

# **IQ and Stock Market Trading**

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## **ABSTRACT**

We analyze whether IQ influences trading behavior, combining equity trade data with two decades of scores from an intelligence test administered to nearly every Finnish male of draft age. Controlling for a remarkable variety of factors, we find that high-IQ investors are less subject to the disposition effect, more aggressive about tax-loss trading, and more likely to supply liquidity when stocks experience large price movements.

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## 1. Introduction

The media and our culture, exemplified by the abundance of books on the subject, promote the belief that successful investors possess some innate or acquired wisdom. However, do smart investors trade differently from others? These are straightforward empirical questions, but addressing them has been hindered by an absence of data—until now. To assess whether intelligence accounts for differences in trading patterns and conveys an advantage in financial markets, we analyze nearly two decades of comprehensive IQ scores from inductees in Finland’s mandatory military service and eight years of trading data.

The paper studies IQ’s effect on factors likely to influence trading behavior. We investigate both the sell-versus-hold and sell-versus-buy decisions. Our study finds that high-IQ investors are less subject to the disposition effect (the tendency to sell winning stocks and hold losers), more likely to engage in tax-loss selling, and more likely to buy (sell) a stock at a one-month low (high). High-IQ investors also herd less than low-IQ investors. These findings, which control for wealth and age, as well as hundreds of other regressors, suggest that high-IQ investors may be less susceptible to behavioral biases, more rational about minimizing taxes, and more likely to supply liquidity in response to large movements in stock prices.

The paper also analyzes the portfolio holdings of investors stratified by IQ and wealth. There is evidence that high-IQ investors’ portfolios earn upwards of 200 basis points per year more than those of below-average IQ investors, when controlling for wealth. The gap is considerably larger, over 400 basis points per year, when we account for relative differences in the timing of stock market participation by high- and low-IQ investors. These differences are unlikely to be accounted for by differences in risk: high- and low-IQ investors’ portfolios exhibit similar sensitivities to risk factors.

Our study of IQ and trading behavior analysis builds on mounting evidence that individual

investors exhibit wealth-reducing behavioral biases. Research, exemplified by Barber and Odean (2000, 2001, 2002), Grinblatt and Keloharju (2001), Rashes (2001), Campbell (2006), and Calvet, Campbell, and Sodini (2007, 2009a, 2009b), shows that these investors grossly under-diversify, trade too much, enter wrong ticker symbols, are subject to the disposition effect, and buy index funds with exorbitant expense ratios. Behavioral biases like these may partly explain why so many individual investors lose when trading in the stock market (as suggested in Odean (1999), Barber et al. (2010), and, for Finland, Grinblatt and Keloharju (2000)). IQ is a fundamental attribute that seems likely to correlate with wealth-inhibiting behaviors. By showing that IQ is a significant driver of trading behavior and performance we contribute to a growing literature that identifies heterogeneity in investor performance and attributes like wealth and trading experience that help account for that heterogeneity.<sup>1</sup>

No paper so cleanly addresses the issue of whether intellectual ability generates differences in trading behavior and investment performance. Studies like Chevalier and Ellison (1999) and Gottesman and Morey (2006) find that a mutual fund's performance is predicted by the average SAT score at the fund manager's undergraduate institution or average GMAT score at his or her MBA program. Of course, these studies recognize that sorting investors by their university's average SAT or GMAT score may simply group investors by the value of their alumni network (direct evidence for which is found in Cohen, Frazzini and Malloy (2008)). Our study's IQ assessment generally occurs prior to college entrance and is scored at the individual rather than the school level.

The paper is organized as follows: Section 2 describes the data and discusses summary statistics. Section 3 presents results on IQ and trading behavior. Section 4 presents performance

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<sup>1</sup> See, for example, Coval, Hirshleifer, and Shumway (2003), Ivković and Weisbenner (2005), Ivković, Sialm, and Weisbenner (2008), Che, Norli, and Priestley (2009), Korniotis and Kumar (2009), Nicolosi, Peng, and Zhu (2009), Seru, Stoffman, and Shumway (2010), Barber et al. (2011), and Linnainmaa (2011).

results arising from portfolio holdings, trades, and trading costs. Section 5 concludes the paper.

## 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 are 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) provide 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. We employ the data from January 1, 1994 through November 29, 2002.

**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 “IQ,” 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.

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.<sup>2</sup> The country is also racially homogeneous and compared to other countries, income is distributed fairly equally.<sup>3</sup> These factors make it more likely that differences in measured IQ in Finland reflect genuine differences in innate intelligence.

### *B. Summary Statistics*

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 4.83.

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<sup>2</sup> See, for example, an article in the Economist (December 6, 2007) and Garmerman (2008).

<sup>3</sup> Figure 1.1 in OECD (2008) indicates that Finland has the seventh lowest Gini coefficient among OECD countries.

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 1 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-market rank, 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.

Each average reported in the panel first computes an investor-specific value for the attribute by applying equal weight to every trade by an investor. It then equally weights the investor-specific

values across investors of a given stanine. These stock attributes do not differ across the stanine categories. Although the size rank difference is statistically significant, it is too small to generate material differences in average returns across the stanines. Grinblatt, Keloharju, and Linnainmaa (2010) find stronger results in a similar analysis: high-IQ investors hold small, low-beta stocks with high book-to-market ratios. Whereas Panel D includes only trades but uses the entire sample, Grinblatt et al. (2010) examine the characteristics of investors' holdings at just one point in time. The differences between Panel D and Grinblatt et al. (2010) thus arise from the fact that the characteristics of the stocks that high- and low-IQ investors trade vary over the sample period.

Panel E reports averages of five other characteristics of the stocks purchased by high- and low-IQ investors. The overall averages reported in Panel E (like Panel D) first compute the average characteristic for each investor and then equal weight the investor-specific values across investors of a given stanine. The characteristics in the first two columns are the purchased stocks' past return ranks (0 being the lowest and 1 being the highest rank). High-IQ investors tend to buy stocks that performed relatively worse in the past month and relatively better in the past year. The stocks bought by high-IQ investors tend to have marginally lower monthly return rank (0.424) than those bought by low-IQ investors (0.432). The difference in one-year return ranks is 0.021 with a  $t$ -value of 4.3. These differences in trading behavior may translate into differences in performance due to the 1-month reversal and 1-year momentum patterns documented in Jegadeesh (1990) and Jegadeesh and Titman (1993).

Panel E also suggests that high-IQ investors are relatively more likely to buy stocks on the days they hit one-month lows and are less likely to buy stocks when they hit one-month highs. More than 20 per cent of their purchases occur on days these stocks hit monthly lows. Only about 16 per cent of low-IQ investors' purchases close at their 1-month low on purchase day. IQ's effect on this "low-water mark" purchase motivation is stronger than its effect on the "high water mark" purchase



motivation, but the latter effect is still significant.

The final Panel E column indicates that herding is less likely to motivate high-IQ investors' purchases. The panel's buy-sell imbalance ranks are based on the prior week's individual investor "order imbalance" for each stock—aggregate shares they bought divided by the sum of the number of shares they bought and sold in the prior week. This ratio, a measure of individual investor sentiment about a stock, generates a "popularity ranking" for each stock. The averages of these ranks indicate that high-IQ investors' purchases were not as popular in the prior week as the stocks bought by low-IQ investors. The buy-sell imbalance rank difference of -0.010 has a significant  $t$ -value of -3.3. Grinblatt and Keloharju (2000), using a subset of our data, find that individual investors underperform foreign investors and finance and insurance institutions. Low-IQ investors' greater tendency to herd with other individual investors could thus be disadvantageous.

### **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.

Tables 2 and 3 report coefficients and test statistics (clustered at the stock-day level) for GK's sell-versus-hold and sell-versus-buy regressions, respectively. The IQ score in these regressions is

recoded with a linear transformation to range from -1 (a stanine 1 investor) to +1 (a stanine 9 investor). The “benchmark” coefficients thus belong to stanine 5 and can be compared with the estimates in GK (Tables I and II). The transformation also allows us to simply add or subtract the interaction coefficient from the benchmark coefficient to assess how each trade-motivating regressor influences the trades of the stanine 9 and 1 investors, respectively. Table 4 supplements the GK approach, reporting four additional panel regressions that study trading interactions at the IQ-group level.

#### *A. Intelligence and the Sell vs. Hold Decision*

Table 2 reports coefficients from a sell-versus-hold logit panel regression that uses more than 1.2 million data points. Each day an investor sells stock, we generate observations for all stocks in the investor’s portfolio. The dependent variable (before the logit transformation) is “1” for stocks sold and “0” for stocks held. The regression analyzes the relation between this sell-versus-hold decision and 519 regressors. Table 2 reports coefficients for both the original 54 trade-influencing variables reported in GK, for a collection of herding variables (described below), and for the interactions of all of these variables with the IQ score. The regressions also include the same (unreported) fixed effects as those used in GK. (See GK for a full discussion of these controls.) For brevity, our discussion largely concentrates on those determinants of trade that IQ materially affects in either the sell vs. hold or sell vs. buy regression.

**Past Returns.** The 22 past return variables represent either positive or negative market-adjusted returns over 11 non-overlapping horizons. Some benchmark coefficients are statistically significant. Although a few interactions with IQ are significant, these coefficients exhibit no consistent pattern and their observed significance most likely stems from the large number of

comparisons. An exception is the day 0 interaction coefficient, which probably arises from the greater use of limit orders by high-IQ investors.

In short, there is no evidence that high-IQ investors are more likely to follow a momentum strategy. Moreover, high-IQ investors do not take advantage of modest short-term reversals. However, because the regression also contains dummies for monthly highs and lows, which proxy for extreme short-term returns, the failure to take advantage of reversals, documented by the interaction coefficients on the past return regressors, may not apply in the case of large price movements. We defer discussion of this until later.

**The Disposition Effect and Tax-Loss Selling.** Table 2 assesses whether the disposition effect influences trading by including extreme ( $> 30\%$ ) and moderate ( $\leq 30\%$ ) capital loss dummies as regressors. The omitted dummy represents either a capital gain or no price change. Interaction variables between the December dummy and capital loss dummies capture the effect of tax losses on the December sell decision. Odean (1998), among others, observes that tax losses tend to be realized at the end of the year. As in GK, both the moderate and large loss dummies have significantly negative coefficients. These estimates are consistent with the disposition effect: individuals tend to sell winners more than losers. This is the opposite of tax-loss selling and as Grinblatt and Han (2005) have shown, also detrimental to pre-tax returns. The products of a December dummy and the two loss dummies exhibit significant positive coefficients, indicating that the median-IQ investor engages in December tax-loss selling.

The interactions of the loss dummies with IQ score are positive and statistically significant with  $t$ -values of 7.9 for large losses and 2.1 for moderate losses. These interaction coefficients indicate that low-IQ individuals are less likely to realize capital losses. Such behavior generates unnecessary tax liabilities as Finland places no limit on deductions for losses. IQ's interaction with

the large-loss December dummy has a  $t$ -value of 5.3, indicating high-IQ investors are more likely to sell (large) losers to an even greater extent in December. High-IQ investors' greater tendency to realize losses, especially large ones, suggests that they would enjoy superior after-tax returns even if IQ had no influence over pre-tax returns.

IQ's interaction with the large-loss variable also yields a coefficient that implies economically significant differences in IQ-related behavior. Table 2's coefficients for the large loss regressor (-1.13) and its interaction with IQ (0.25) imply that the large capital loss coefficient is -1.38 ( $= -1.13 - 0.25$ ) for stanine 1 investors and -0.88 ( $= -1.13 + 0.25$ ) for stanine 9 investors. To better understand these coefficient magnitudes, consider an investor who wants to sell one of two stocks he owns but is indifferent about which one to sell. Now assume that one of the two stocks has a large loss. The large-loss interaction coefficient indicates that the probability of a sale of the large loss stock decreases from 0.5 to 0.20 ( $= 1 / (1 + e^{1.38})$ ) for the low-IQ investor. The corresponding drop is from 0.5 to 0.29 for the high-IQ investor.

**Reference Price Effects.** The propensity to sell is positively related to whether a stock has hit its high price within the past month. The benchmark estimates indicate that median-IQ investors are less likely to sell when a stock hits the monthly low and to sell when it hits the monthly high. The interactions with IQ score, which have  $t$ -values of -3.7 and 2.7, suggest that IQ strengthens these patterns. High-IQ investors thus appear to be more contrarian than low-IQ investors with respect to these reference prices.

These two reference price dummies capture marginal effects of large intra-month stock-price movements: conditional on reaching the monthly low, the past one-week return in excess of the market averages -11%; and conditional on reaching the monthly high, this one-week return is 12%. The significant coefficients on the two IQ-reference price interactions are therefore consistent with

high-IQ investors supplying liquidity in response to large stock price movements.

The inclusion of these reference price variables allows us to interpret the insignificant IQ-interaction coefficients documented in the previous “past returns” subsection in a more concrete way. The insignificance of the interactions with the more recent of the 22 past return variables indicates that high- and low-IQ investors adjust their sell propensity for small price movements in similar ways. However, the significant reference price interaction coefficients indicate that high- and low-IQ investors’ responses to recent large stock price movements are quite different. By selling stocks at monthly highs and by holding stocks at monthly lows, high-IQ investors appear to follow a liquidity provision strategy. Kaniel, Saar, and Titman (2008) find that individuals profit by supplying liquidity to institutions. Gutierrez and Kelley (2008) (and, using Finnish data, Linnainmaa (2010)) document that trading against extreme price movements earns abnormal profits for short holding periods.

**Herding.** We measure benchmark herding (that is herding for stanine 5) as the regression coefficient on the natural logarithm of the ratio:

$$\text{Herd}_j(-t_0, -t_1) = \text{Log}[\# \text{ of sell trades by other investors in stock } j \text{ in period } [-t_0, -t_1] / (\# \text{ of sells} + \text{ holds by other investors in stock } j \text{ in period } [-t_0, -t_1])].$$

Because the regression controls for other significant determinants of the sell-versus-hold decision (like tax-loss selling),  $\text{Herd}_j(-t_0, -t_1)$  measures marginal differences in the extent to which a stanine 5 investor’s day  $t$  sales of a stock tend to parrot *other* individual investors’ tendencies to sell the stock in the period from  $t_0$  to  $t_1$  days prior to day  $t$ . The IQ-score interaction measures whether having higher IQ exacerbates or tempers the benchmark tendency to herd. We compute the herding regressor for four non-overlapping mimicking periods over which we measure the trades of others: same day, past week excluding the same day, past month excluding the past week, and past three months excluding the past month.

Table 2's significantly positive benchmark estimates for all four mimicking periods indicate that individuals' sell-versus-hold decisions are correlated. This finding is consistent with studies such as those by Dorn et al. (2008) and Barber et al. (2009) who find correlated trades among individual investors at daily, weekly, monthly, and quarterly horizons. The herding variables do not interact significantly with IQ scores. Thus, high-IQ investors do not appear to be any more or less coordinated when deciding which stocks to sell from their portfolios.

### *B. Intelligence and the Sell-versus-Buy Decision*

Table 3 analyzes IQ's influence on the sell-versus-buy decision using a logit regression framework similar to that used to study sells-versus-holds. Here the dependent variable (before the logit transformation) is a dummy variable that, conditional on a transaction, obtains the value of one if the transaction is a sell and zero if it is a buy. The regressors are identical to those in Table 2, except that we exclude (non-computable) variables related to the disposition effect, tax-loss selling, and holding period. The panel consists of about one million data points.

**Past Returns.** Table 3 reports coefficients on past market returns, positive market-adjusted returns, and negative market-adjusted returns, each over 11 return intervals, to assess the degree to which investors follow momentum or contrarian strategies. Investors appear to be contrarian with respect to both positive and negative day 0 returns. The two day 0 interaction terms, both significantly positive, probably indicate only that high IQ investors use limit orders to a greater extent than low-IQ investors. Outside of day 0, no clear pattern emerges except that the interaction terms for past negative returns tend to be of larger magnitude than for positive returns. When significant, the IQ interaction terms for past negative returns tend to be negative, consistently so for past return intervals between three and twelve months ago. This is weak evidence that high-IQ

investors' trades are less likely to be purchases of losing stocks (as measured over these periods). However, it would certainly be an embellishment of the truth to argue from this evidence that high-IQ investors are momentum traders.

**Reference Price Effects.** The coefficients on the reference price variables—being at a monthly high or low—are significant in the sell-versus-buy decision, suggesting that high-IQ investors are more contrarian with respect to extreme price movements. The IQ-score interactions have even larger  $t$ -values than the benchmark coefficients. Thus, high-IQ investors' sell-versus-buy decisions respond dramatically to extreme price movements in a contrarian way. The literature on liquidity supply and extreme price movements, discussed with the sell vs. hold analysis, suggests that this contrarian strategy could be profitable.

**Herdling.** We measure baseline herding (that is herding for stanine 5) as the regression coefficient on the natural logarithm of the ratio:

$$\text{Herd}_j(-t_0, -t_1) = \text{Log}[\# \text{ of sell trades by other investors in stock } j \text{ in period } [-t_0, -t_1] / (\# \text{ of sells} + \text{buys by other investors in stock } j \text{ in period } [-t_0, -t_1])].$$

These regressors are the sell vs. buy analogues of the measures used to study herding in the sell vs. hold decision. The interaction term measures whether having higher IQ tends to exacerbate or temper sell vs. buy herding.

The benchmark herding coefficients are significantly positive, while the IQ interaction coefficients are significantly negative except for the one-month estimate. Thus, higher IQ clearly mitigates buy-sell herding. The mitigation probably derives from mimicking of buy trades, as Table 3's significant negative interactions stand in contrast to Table 2's insignificant herding interactions reported for sells versus holds.

### *C. Intelligence and Trading: Analysis of Group Interactions*

The herding results, discussed above, address whether IQ is correlated with sensitivity to aggregate trading behavior, but offer little detail on group trading interactions. For example, do the highest- and lowest-IQ investors have a greater tendency to trade like investors with similar IQ (what we call “dog-pack behavior”) or do only smart investors trade like other smart investors? To examine how one IQ group’s trades influence those of other groups, we regress group trading behavior in a stock on a given day—measured as a sell vs. hold or sell vs. buy ratio—against average trading of all other groups and every other group’s current and lagged excess trading behavior. As with Table 2 and 3’s herding analysis, the lagged ratios are computed from non-overlapping intervals of the past week, month, and quarter. Coefficients on the lagged excess ratios study whether some investor groups follow the “lead” of other investor groups. For example, high-IQ investors could be the first to trade on a useful signal, only to be followed by low-IQ investors who receive the same signal with delay.

Let  $S_{jt}(g)$  denote group  $g$ ’s day  $t$  ratio of sell trades to sells plus holds (or sells plus buys for the sell-buy regression) in stock  $j$ . For the lowest IQ group ( $g=1-4$ ), we regress this variable on (i) the analogous average of the current and lagged ratios of IQ groups 5, 6, 7, 8, and 9, which captures a common component of trading, and (ii) current and prior excess ratios of groups 5, 6, 8, and 9, measured as deviations from the average, which capture differences in influence across the IQ groups. For the highest-IQ group, we regress  $S_{jt}(9)$  on the corresponding current and lagged average of the ratios of group 1-4, 5, 6, 7, and 8, as well as current and prior excess ratios of groups 1-4, 5, 6, and 8. One category, here stanine 7, has to be omitted to avoid perfect multicollinearity. We also add (unreported) control regressors for missing observations.

The top half of Table 4 Panel A reports 20 (4 groups and one group average x 4 intervals) coefficients for the low-IQ group’s sell vs. hold regression while the bottom half reports the



coefficients for the high-IQ group. Panel B reports analogous coefficients for the two sell vs. buy regressions. The  $t$ -statistic in the rightmost column indicates whether there is a difference in the coefficients of the extreme IQ groups in the row. These regressions indicate that an IQ group's behavior is influenced the least by the current excess ratios of investors at the opposite end of the IQ spectrum. The difference in the same-day coefficients between the extreme-IQ groups is significant with a  $p$ -value  $< 0.001$  in 3 of the 4 regressions. While coefficient differences are occasionally more modest, the coefficient pattern is remarkably monotonic: in all four regressions, stanine 1-4 investors' trading behavior is more influenced by the same-day behavior of stanine 5 or stanine 6 investors than by the behavior by stanine 8 or 9 investors; likewise, stanine 9 investors' are more influenced by stanines 6 or 8 than by stanines 1-4 or 5.

Coefficient differences across the proximate and distant IQ groups for the prior-week coefficients achieve similarly high levels of significance in the sell vs. buy regressions, but not in the sell vs. hold regressions. At more distant lags, only the lowest-IQ investors' buy-sell decisions exhibit differences in sensitivity to the prior trades of other IQ groups. Similar to the same-day results, low-IQ investors' behavior here is more similar to the past behavior of stanine 5 investors than that of stanine 8 or 9 investors.

While the analysis here focuses on coefficient differences, the far larger levels of the coefficients on the average of all other groups signify that all investors tend to herd with the current and lagged trades of all investors in the market. This finding is consistent with Table 2 and 3's benchmark coefficients for herding.

#### **4. IQ-Related Performance**

##### *A. Intelligence and the Performance of Portfolio Holdings*

Figure 1 plots the cumulative distribution of portfolio returns for those in the highest (stanine 9) and lowest (stanine 1-4) IQ categories. 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. This restriction, 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 IQ earn, high-IQ investors have a larger probability of earning at least the same return realization or more than low-IQ investors.

The differences between the two distributions are economically significant. The Kolmogorov-Smirnov test, which takes as its test statistic the maximum distance between the estimated cumulative distribution functions, rejects the equality of the distributions with a  $p$ -value  $< 0.001$ . However, this rejection should be interpreted cautiously because the test assumes that observations are sampled independently. In reality, the correlations could be nonzero and vary depending on the days investors participate and the composition of the portfolios they hold.

Table 5 remedies these statistical concerns by reducing the panel data into time series vectors of daily portfolio returns for each of 30 groups (5 equal-sized wealth groups, subsequently sorted by IQ stanine). Differencing the elements of paired IQ-linked vectors and computing  $t$ -tests for the mean of a difference vector is then straightforward. Each day's group return equally weights the returns of every investor within the category. The rightmost column reports results for groups based only on an IQ sort. Table 5 does not report alphas because risk-factor betas vary negligibly across the stanines, generating IQ-linked alpha differences that are similar to the differences in the raw returns. This finding is robust to whether factor betas are measured with CAPM, Fama-French (1993) 3-

factor, or Carhart (1997) 4-factor benchmarks.

Panel A reports the annualized average of the time series of daily returns for each group. Panel B weights each group's daily return observations by the number of investors within the group participating in the stock market that day. This weighting, which is scaled to sum to one, adjusts for variation in the group's participation intensity over the sample period. For example, if the number of investors in wealth quintile 4 and stanine 9 participating in the market on May 10, 2000 is twice the number participating on May 10, 1996, Panel B gives the latter observation twice the weight. By construction, each group's participation-weighted portfolio return in Panel B is Panel A's return, plus the scaled covariance between the daily participation fraction of the group and the return of the group portfolio. The scaling divides the covariance by the average daily participation fraction over all days. Panel C reports the difference between Panels B and A, reflecting the contribution to returns from periods when investors in the group "over" or "under participate" in the market relative to the group's average participation rate.

Without wealth sorting, Table 5 Panel A indicates that the portfolio returns of stanine 9 investors averaged 14.84 per cent per year, which is 2.2 per cent more per year than the average of the stanine 1-4 investors. This difference is significant at the 10% level. The five columns to the left suggest that when we control for wealth quintile, high-IQ investors' portfolios still outperform those of their lower-IQ brethren. The difference is of a similar magnitude, ranging from 1.51% to 2.72%, excluding the lowest wealth category, and often significant. The lowest wealth quintile has a far smaller IQ-related return gap, 0.35%. The smaller gap could be due to the relatively few stanine 9 investors with such low wealth.

Proper timing of participation intensity increases the IQ-return gap to 4.9 per cent per year, as seen in Panel B, which is significant at the 5% level. Again, this difference persists when we control

for wealth quintile and it is insignificant only for the lowest wealth quintile, which has far fewer stanine 9 investors.

Looking from top (lowest IQ) to bottom (highest IQ) of each column in Panels A or B, the average (or weighted-average) returns exhibit a remarkable degree of monotonicity. Moreover, for all but Panel A's lowest wealth category, the highest stanine investors earn the highest average returns. This finding is consistent with Figure 1, which suggests that high-IQ investors' portfolios outperform the portfolios of their lower-IQ brethren.

To assess the significance of the IQ-stratified return difference, the bottom rows of Table 5's panels report statistics from paired  $t$ -tests of the mean difference between the two time series of daily returns generated by the highest- and lowest-IQ investors in the column. The  $t$ -values for the full sample are 1.77 (Panel A;  $p$ -value = 0.076) and 2.56 (Panel B;  $p$ -value = 0.01). We also know that outliers do not explain the high- minus low-IQ return difference. For example, stanine 9's daily portfolio return in Panel A (without wealth controls) is larger than stanine 1-4's portfolio return on 53% of the sample days, which is significant at the 5% level.

The stark difference between Panels A and B suggests that low-IQ investors tend to time their participation when returns are low. Panel C represents the covariance between the daily participation intensity of the group and the daily return earned by the group. We obtain Panel C by subtracting Panel A's numbers from the corresponding numbers in Panel B. Panel C confirms that low-IQ investors exhibit significantly worse market timing than high-IQ investors. For example, focusing on the rightmost column, Panel C reports a return difference of 2.73% with a  $t$ -value of 2.26 from IQ-linked differences in participation timing.

### *B. Intelligence and the Performance of Portfolio Holdings*

The “heat map” in Figure 2 illustrates this result by plotting the entry rate of new investors into technology stocks each week from each IQ stanine—computed by dividing the number of entrants to technology stocks by the number of investors already holding technology stocks. 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.

The results on IQ-partitioned entries in Figure 2 are consistent with Table 5. The most interesting part of the figure is the 1999-2001 period when the index peaked. Above-median-IQ investors were entering the market in significant numbers until the latter half of 1999. After this point, it is the below-median IQ investors who dominate entry, a pattern that continues for most of 2000 and 2001. This finding lends support to the view that sophisticated and less-sophisticated investors entered the market at different times around the year-2000 peak in stock valuations.

#### **4. Conclusion**

Employing IQ measures for a large population of investors, we uncover a connection between intellectual ability, trading behavior, and skill both at picking stocks and timing the market. High-IQ investors are less likely to be swayed by the disposition effect or the actions of other individual investors, and are more likely to provide liquidity or engage in tax-motivated stock sales. High-IQ investors’ portfolio holdings outperform low-IQ investors’ portfolios, especially when adjusted for differences in market timing. Because our performance analysis is based on pre-tax returns and because high-IQ investors are far more willing to realize (large) losses, the differences in

high- and low-IQ investors' after-tax returns are likely to be greater.

These findings tie well with current research and raise interesting questions. Barber and Odean (2008) and Barber, Odean, and Zhu (2009) contend that investors trade in response to the same attention-grabbing events and that these events influence buying more than selling. We find that low-IQ investors are more likely to herd in their buy vs. sell decisions but IQ has little influence on sell vs. hold herding. Investigating whether attention-grabbing events are more influential in the buys of low-IQ investors offers a promising avenue for future research.

Our results on IQ 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. Goetzmann 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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**Table 1**  
**Descriptive statistics**

Panel A reports statistics on birth year, ability (IQ), wealth, and two measures of trading frequency. Panel B reports the distribution of IQ scores. Panel C reports portfolio size and trading activity statistics by IQ score. Panel D reports average betas, as well as average size and book-to-market ranks for trades sorted by investor IQ score. Panel E reports averages of prior one-week and one-year return percentile ranks (1 = highest return) of purchases, frequencies at which the purchased stock's closing price is at the monthly high or low on the day of purchase, and the percentile rank of purchased stock based on one-week buy-sell imbalance by individual investors (1 = most bought), for purchases sorted by investor IQ score. In computing averages for an IQ group in Panels D and E, each investor's average for a variable, computed from that investor's purchases and sales (Panel D) or purchases only (Panel E), receives equal weight. The IQ data are from 1/1982 to 12/2001 and the other data from 1/1995-11/2002.

Panel A: Investor characteristics

Variable	Mean	Std. dev.	Percentiles			N
			25	50	75	
Birth year	1969.78	5.63	1965	1969	1974	87,914
IQ score	5.75	1.86	5	6	7	87,914
Average portfolio value, EUR	16,464	721,406	1183	2808	6910	87,914
# of stock trades	24.10	129.65	2	5	16	87,914
Portfolio turnover	0.818	1.504	0.135	0.316	0.786	86,703

Panel B: Distribution of IQ score

IQ score	This sample		Full sample	Stanine distribution
	# of observations	% of scores	% of scores	
1 (low IQ)	1,505	2%	5%	4%
2	3,452	4%	9%	7%
3	4,419	5%	9%	12%
4	11,167	13%	18%	17%
5	17,894	20%	21%	20%
6	20,378	23%	18%	17%
7	12,620	14%	9%	12%
8	9,146	10%	6%	7%
9 (high IQ)	7,333	8%	4%	4%
Totals	87,914	100%	100%	100%
Average		5.75	4.83	5.00

Panel C: Portfolio size and trading activity by IQ score

IQ score	Average portfolio characteristics			Median portfolio characteristics		
	Portfolio value	# trades	Portfolio turnover	Portfolio value	# trades	Portfolio turnover
1-4	10,543	18.90	0.834	2,496	4	0.316
5	13,351	22.73	0.835	2,622	5	0.319
6	11,091	25.89	0.816	2,806	5	0.316
7	14,299	24.32	0.819	2,923	6	0.320
8	18,285	28.10	0.781	3,277	7	0.310
Highest	57,031	31.61	0.782	3,510	7	0.305

Panel D: Mean and standard error of beta, book/market rank and size rank by IQ score

IQ score	Beta	B/M rank	Size rank
1-4	0.7587 (0.0026)	0.3119 (0.0018)	0.7967 (0.0013)
5	0.7767 (0.0028)	0.3053 (0.0018)	0.7951 (0.0013)
6	0.7708 (0.0025)	0.3081 (0.0017)	0.7935 (0.0012)
7	0.7700 (0.0032)	0.3066 (0.0021)	0.7944 (0.0015)
8	0.7728 (0.0037)	0.3052 (0.0024)	0.7917 (0.0018)
Highest	0.7581 (0.0041)	0.3082 (0.0027)	0.7893 (0.0020)
<i>t</i> -value Highest - Lowest	-0.12	-1.10	-3.05

Panel E: Average characteristics of buy transactions by IQ score

IQ score	One-month return rank	One-year return rank	One-month high	One-month low	One-week imbalance rank
1-4	0.432	0.465	0.132	0.164	0.672
5	0.430	0.465	0.125	0.178	0.668
6	0.428	0.466	0.125	0.184	0.664
7	0.424	0.471	0.115	0.188	0.667
8	0.432	0.474	0.118	0.193	0.659
Highest	0.424	0.486	0.114	0.201	0.662
Highest - Lowest	-0.008	0.021	-0.018	0.037	-0.010
<i>t</i> -value	-1.88	4.31	-4.84	8.99	-3.34

**Table 2****IQ and the determinants of the propensity to sell versus hold**

Table 2 reports coefficients and  $t$ -values from a logit regression in which the dependent variable takes the value of one when an investor sells a stock for which the purchase price is known. Each sell is matched with all stocks in the investor's portfolio that are not sold the same day and for which the purchase price is known. In these "hold" events, the dependent variable obtains the value of zero. All same-day trades in the same stock by the same investor are netted. The regression extends the specification in Grinblatt and Keloharju (2001) by adding a herding variable and by interacting the regressors with individuals' IQ scores. The "benchmark" column reports on the following a) 11 pairs of regressors for each of 11 past return intervals, each member of the pair depending on the return sign, i.e.,  $\max(0, \text{market-adjusted return})$  and  $\min(0, \text{market-adjusted return})$  b) two capital loss dummies associated with moderate (below 30%) or extreme (above 30%) capital losses; c) two interaction variables representing the product of a dummy that takes on the value of one if the sell or hold decision is in December, and the two capital loss dummies; d) 22 interaction variables representing the product of a dummy that takes on the value of one if there is a realized or paper capital loss and the 22 market-adjusted returns described above in (a); e) two reference price dummy variables associated with the stock being at a one-month high or low; f) variables related to the stock's and market's average squared daily return over the prior 60 trading days; g) portfolio size; h) holding period; and i) four herding variables described in the body of the paper. The coefficients in the "IQ interaction" column are for variables that multiply the corresponding regressors with an individual's IQ score. We linearly transform the IQ stanine in these regressions to range from -1 (for a stanine 1 investor) to +1 (for a stanine 9 investor); the value represented in the benchmark column, 0, corresponds to the median-IQ investor. Unreported are coefficients on a set of dummies for each stock, month, number of stocks in the investor's portfolio, investor age dummies, past market return variables, and products of a capital loss dummy and past market return variables. Standard errors are clustered at stock-day level. Coefficients denoted with \*, \*\*, \*\*\* are significant at the 10%, 5%, and 1% level, respectively. The logit regression has 1,252,010 observations and a pseudo  $R^2$  of 0.266. Data in the panel are daily and taken from January 1, 1995 through November 29, 2002.

Independent variables	Coefficients		<i>t</i> -values	
	Benchmark	x IQ	Benchmark	x IQ
IQ	-0.282 ***		-6.30	
Max [0, Market-adjusted return]				
in the given interval of trading days before the sell vs. hold decision				
0	4.440 ***	1.075 ***	15.31	3.07
-1	1.782 ***	0.226	7.84	0.80
-2	0.453 **	0.040	2.33	0.18
-3	0.208	0.056	1.09	0.22
-4	-0.033	-0.561 *	-0.18	-1.93
[-19,-5]	-0.044 ***	-0.066 ***	-4.30	-3.56
[-39,-20]	-0.007	-0.008	-0.75	-0.54
[-59,-40]	0.004	-0.042	0.31	-1.52
[-119,-60]	0.027 **	0.036 *	2.16	1.78
[-179,-120]	0.000	-0.004	0.03	-0.20
[-239,-180]	-0.056 ***	-0.011	-3.37	-0.43
Min [0, Market-adjusted return]				
in the given interval of trading days before the sell vs. hold decision				
0	-0.975 ***	0.400	-2.63	0.80
-1	-0.866 ***	-0.144	-2.68	-0.36
-2	-0.438	-0.176	-1.49	-0.45
-3	-0.329	-0.851 **	-1.38	-2.39
-4	-0.593 **	-0.190	-2.55	-0.54
[-19,-5]	-0.974 ***	-0.188	-12.13	-1.57
[-39,-20]	-0.498 ***	0.020	-7.63	0.20
[-59,-40]	-0.175 **	-0.054	-2.52	-0.54
[-119,-60]	-0.344 ***	-0.102	-8.32	-1.60
[-179,-120]	-0.185 ***	-0.127 *	-4.16	-1.91
[-239,-180]	0.067	-0.060	1.48	-0.88
Large loss dummy	-1.134 ***	0.251 ***	-52.29	7.91
Moderate loss dummy	-0.636 ***	0.048 **	-38.67	2.05
December * large loss dummy	1.084 ***	0.219 ***	23.05	5.30
December * moderate loss dummy	0.242 ***	0.045	7.66	1.20
Max [0, Holding period capital loss dummy x Market-adjusted return]				
in the given interval of trading days before the sell vs. hold decision				
0	-1.522 ***	0.179	-5.09	0.43
-1	-1.972 ***	-0.419	-7.38	-1.10
-2	-0.585 **	-0.426	-2.41	-1.11
-3	-0.419 *	-0.632	-1.78	-1.56
-4	-0.347	0.860 **	-1.37	2.30
[-19,-5]	0.038 ***	-0.007	2.64	-0.18
[-39,-20]	0.015	-0.002	1.55	-0.16
[-59,-40]	0.011	0.010	0.75	0.33
[-119,-60]	0.001	-0.033	0.09	-1.45
[-179,-120]	0.023 **	-0.008	2.15	-0.34
[-239,-180]	0.080 ***	0.015	4.67	0.51

Independent variables	Coefficients		<i>t</i> -values	
	Benchmark	xIQ	Benchmark	xIQ
Min [0, Holding period capital loss dummy x Market-adjusted return] in the given interval of trading days before the sell vs. hold decision				
0	-1.334 ***	-1.226 **	-3.14	-2.16
-1	-0.084	-0.498	-0.23	-1.06
-2	0.212	0.051	0.65	0.11
-3	0.001	1.240 ***	0.00	2.75
-4	0.461	-0.512	1.53	-1.07
[-19,-5]	0.964 ***	0.116	10.41	0.79
[-39,-20]	0.702 ***	-0.049	8.85	-0.38
[-59,-40]	0.159 *	0.064	1.93	0.50
[-119,-60]	0.370 ***	-0.007	7.46	-0.08
[-179,-120]	0.087 *	0.139 *	1.69	1.65
[-239,-180]	-0.212 ***	-0.005	-4.01	-0.06
Last month low dummy	-0.120 ***	-0.081 ***	-5.77	-3.70
Last month high dummy	0.193 ***	0.048 ***	9.56	2.69
Average (return) <sup>2</sup> of stock over days [-59,0]	1.424 **	2.312 **	1.97	2.15
Average (market return) <sup>2</sup> of stock over days [-59,0]	28.824	-79.290	0.20	-1.54
ln(Portfolio value)	-0.036 ***	0.013 ***	-15.65	3.90
# days between purchase and sale	-0.001 ***	0.000	-23.84	0.50
Herding				
in the given interval of trading days before the sell vs. hold decision				
0	0.689 ***	-0.001	65.72	-0.12
[-4,-1]	0.156 ***	0.022 *	16.85	1.68
[-19,-5]	0.083 ***	0.000	7.29	0.00
[-59,-20]	0.060 ***	-0.012	4.14	-0.73

**Table 3****IQ and the determinants of the propensity to sell versus buy**

Table 3 reports coefficients and  $t$ -values from a logit regression in which the dependent variable takes the value of one for sales and zero for purchases. All intraday purchases and sales of a given stock by a given investor are netted separately. This regression extends the specification in Grinblatt and Keloharju (2001) by adding a herding variable and by interacting the regressors with individuals' IQ scores. The "benchmark" column reports on the following regressors: a) 33 regressors for market-adjusted returns and market returns for 11 past return intervals, with positive and negative market-adjusted returns represented separately; b) two reference price dummy variables associated with the stock being at a one-month high or low; c) variables related to the stock's and market's average squared daily return over the prior 60 trading days; d) a set of age dummy variables; e) portfolio size; f) holding period; and g) four herding variables described in the body of the paper. The coefficients in the "IQ interaction" column multiply the corresponding regressors with an individual's IQ score. We linearly transform the IQ stanine in these regressions to range from -1 (for a stanine 1 investor) to +1 (for a stanine 9 investor); the value represented in the benchmark column, 0, corresponds to the median-IQ investor. Unreported are coefficients on a set of dummies for each stock, month, and the number of stocks in the investor's portfolio. Standard errors are clustered at stock-day level. Coefficients denoted with \*, \*\*, \*\*\* are significant at the 10%, 5%, and 1% level, respectively. The logit regression has 991,762 observations and a pseudo  $R^2$  of 0.108. Data in the panel are daily and taken from January 1, 1995 through November 29, 2002.

Independent variables	Coefficients		$t$ -values	
	Benchmark	x IQ	Benchmark	x IQ
IQ	-0.126 ***		-3.78	
Max [0, Market-adjusted return] in the given interval of trading days before the transaction				
0	0.234	0.841 ***	1.41	4.35
-1	-0.251	0.253	-1.38	1.30
-2	0.194	0.094	1.15	0.52
-3	0.155	0.499 ***	1.09	2.82
-4	-0.237 *	0.256	-1.81	0.89
[-19,-5]	-0.005	-0.001	-0.64	-0.07
[-39,-20]	0.000	0.028 *	-0.05	1.78
[-59,-40]	0.001	0.021	0.14	1.14
[-119,-60]	0.001	0.007	0.23	0.79
[-179,-120]	-0.001	-0.002	-0.25	-0.23
[-239,-180]	0.004	-0.004	0.71	-0.41



Independent variables	Coefficients		t-values	
	Benchmark	x IQ	Benchmark	x IQ
Min [0, Market-adjusted return]				
in the given interval of trading days before the transaction				
0	2.453 ***	0.459 *	8.77	1.80
-1	0.592 ***	-0.230	3.11	-1.04
-2	0.085	-0.245	0.54	-1.11
-3	-0.215	-0.429 **	-1.49	-2.26
-4	-0.203	-0.599 ***	-1.50	-3.01
[-19,-5]	-0.306 ***	-0.133 *	-6.63	-1.83
[-39,-20]	-0.046	0.079	-1.11	1.25
[-59,-40]	-0.111 ***	0.069	-2.66	1.07
[-119,-60]	-0.021	-0.073 *	-0.75	-1.80
[-179,-120]	0.025	-0.170 ***	0.84	-4.17
[-239,-180]	0.032	-0.077 *	1.14	-1.82
Market returns				
in the given interval of trading days before the transaction				
0	1.197 ***	0.514	4.27	1.44
-1	-0.225	-0.067	-0.87	-0.19
-2	-0.269	-1.180 ***	-1.00	-3.34
-3	-0.809 ***	0.049	-2.85	0.14
-4	-1.512 ***	-0.261	-5.34	-0.72
[-19,-5]	-0.703 ***	-0.113	-5.10	-1.24
[-39,-20]	-0.445 ***	0.019	-3.09	0.25
[-59,-40]	-0.465 ***	0.071	-3.04	0.93
[-119,-60]	-0.025	-0.078 **	-0.17	-2.12
[-179,-120]	-0.083	-0.029	-0.56	-0.71
[-239,-180]	0.054	0.029	0.47	0.73
Last month low dummy	-0.273 ***	-0.173 ***	-19.01	-9.24
Last month high dummy	0.235 ***	0.151 ***	16.05	8.81
Average (return) <sup>2</sup> of stock over days [-59,0]	1.889 **	-2.555 *	2.42	-1.89
Average (market return) <sup>2</sup> of stock over days [-59,0]	291.252 *	-9.916	1.92	-0.19
1951-55 dummy	-0.204 ***	-0.013	-4.17	-0.14
1956-60 dummy	-0.136 ***	-0.054 *	-7.69	-1.72
1961-65 dummy	-0.089 ***	-0.075 ***	-14.00	-6.00
1971-75 dummy	0.100 ***	-0.041 ***	13.23	-2.87
1976-80 dummy	0.193 ***	0.022	18.80	1.14
1981-85 dummy	0.071 ***	-0.183 ***	2.82	-3.66
ln(Portfolio value)	0.109 ***	-0.002	52.00	-0.68
Herding				
in the given interval of trading days before the transaction				
0	1.098 ***	-0.083 ***	102.25	-6.73
[-4,-1]	0.396 ***	-0.030 **	39.59	-2.22
[-19,-5]	0.206 ***	0.009	17.63	0.53
[-59,-20]	0.129 ***	-0.068 ***	9.89	-3.77

**Table 4****Interactions in trading behavior between IQ groups**

Table 4 reports coefficients and *t*-values from a panel regression of the IQ 1-4 or IQ 9 group's aggregate trading behavior against average (across all other groups) and excess current and prior trading behavior of other groups. The regressions in Panel A (Panel B) use IQ-stratified sell/(sell+hold) (or sell/(sell+buy)) ratios computed for each stock and day. In regressions explaining the stanine 1-4 group behavior, the regressors are average and excess current and prior ratios for groups 5, 6, 8, and 9. The regressor groups in the stanine 9 regressions are stanines 1-4, 5, 6, and 8. Stanine 7's excess current and lagged ratios are omitted to prevent perfect multicollinearity. Excess ratios are computed by subtracting the across-group average ratio (at the corresponding lag) from each stanine's ratio. The prior ratios are computed for three non-overlapping periods: past week excluding the same day, past month excluding the past week, and past three months excluding the past month. The regressions also contain (unreported) control regressors for missing observations. The *t*-statistic in the rightmost column tests whether there is a difference in the coefficients of the extreme IQ groups in the row. Coefficients denoted with \*, \*\*, \*\*\* are significant at the 10%, 5%, and 1% level, respectively. Data in the panel are daily and taken from January 1, 1995 through November 29, 2002.

Panel A: Sell-hold ratios

Dependent variable	Interval	Independent variables: Other group's sell-hold ratios						<i>t</i> -value, Closest - Most distant
		1-4	5	6	8	9	Average	
Stanine 1-4 sell-hold ratio	0		0.024 ***	0.031 ***	-0.005	-0.008	0.311 ***	3.60 ***
			2.63	3.33	-0.52	-0.90	43.91	
	[-4,-1]		0.008	0.017	-0.012	-0.009	0.251 ***	1.43
			0.63	1.35	-1.07	-0.79	23.30	
	[-19,-5]		-0.002	-0.008	-0.018	-0.022	0.196 ***	1.23
			-0.12	-0.47	-1.14	-1.42	13.91	
	[-59,-20]		0.007	0.015	0.006	0.000	0.164 ***	0.35
			0.31	0.65	0.31	-0.02	11.71	
Stanine 9 sell-hold ratio	0	-0.015 *	-0.005	0.014	0.013		0.292 ***	3.25 ***
		-1.70	-0.62	1.58	1.51		42.41	
	[-4,-1]	0.001	0.000	0.029 **	0.013		0.197 ***	1.14
		0.13	-0.02	2.38	1.21		18.96	
	[-19,-5]	-0.008	0.014	0.019	-0.008		0.135 ***	0.00
		-0.59	0.91	1.14	-0.52		9.98	
	[-59,-20]	0.012	-0.008	0.008	0.027		0.154 ***	0.82
		0.65	-0.43	0.34	1.42		11.18	

Panel B: Sell-buy ratios

Dependent variable	Interval	Independent variables: Other group's sell-buy ratios						<i>t</i> -value, Closest - Most distant
		1-4	5	6	8	9	Average	
Stanine 1-4 sell-buy ratio	0		0.024 **	0.025 **	-0.002	-0.015	0.265 ***	4.04 ***
			2.47	2.46	-0.25	-1.53	42.00	
	[-4,-1]		0.014	0.036 ***	-0.019 *	-0.020 *	0.290 ***	3.03 ***
			1.21	2.90	-1.70	-1.80	31.59	
	[-19,-5]		0.009	-0.010	-0.050 ***	-0.057 ***	0.182 ***	4.38 ***
			0.55	-0.55	-3.22	-3.88	15.89	
	[-59,-20]		0.038 *	-0.005	-0.036 *	-0.076 ***	0.150 ***	5.50 ***
			1.66	-0.20	-1.68	-3.70	13.11	
Stanine 9 sell-buy ratio	0	-0.026 **	-0.010	0.020 *	-0.009		0.289 ***	1.58
		-2.33	-0.84	1.73	-0.76		40.68	
	[-4,-1]	-0.039 ***	-0.004	0.020	0.003		0.258 ***	3.24 ***
		-2.98	-0.28	1.42	0.21		25.12	
	[-19,-5]	-0.022	-0.002	0.014	-0.009		0.156 ***	0.77
		-1.28	-0.14	0.74	-0.53		12.25	
	[-59,-20]	-0.036	-0.043 *	0.044	-0.024		0.102 ***	0.55
		-1.51	-1.76	1.61	-1.00		7.90	

**Table 5****Intelligence and the returns of portfolio holdings**

Table 5 reports annualized returns (or return differences with *t*-statistics in parentheses) of equal-weighted portfolios across investor groups sorted by IQ and beginning-of-day market capitalization (wealth). The time series of each day's equal-weighted portfolio return is averaged over all days before annualizing. Returns are close-to-close returns unless a trade takes place in the stock, in which case the execution price replaces the closing price in the calculation. The returns are adjusted for dividends, stock splits, and mergers. First-day IPO returns are excluded. Portfolio returns are computed each day in the 1/1995-11/2002 sample period. Panel A weights each daily time-series observation equally. Panel B uses weights that are proportional to the number of investors participating in the market from each group. Panel C represents the difference between the Panel B and Panel A with test statistics constructed from differencing the time series of returns implicit in the two panels. Return differences denoted with \*, \*\*, \*\*\* are significant at the 10%, 5%, and 1% level, respectively.

Panel A: Equal-weighted returns

IQ score	Wealth quintile					All
	Lowest	2	3	4	Highest	
1-4	11.60%	11.70%	12.11%	12.60%	15.53%	12.65%
5	11.02%	12.09%	11.75%	12.46%	16.12%	12.64%
6	11.41%	12.75%	12.26%	13.87%	16.30%	13.34%
7	12.32%	12.76%	12.81%	12.86%	16.85%	13.57%
8	11.25%	12.98%	13.44%	13.77%	16.87%	13.87%
9	11.96%	14.33%	13.62%	14.33%	18.25%	14.84%
9 minus 1-4	0.35%	2.63% **	1.51%	1.72%	2.72% *	2.19% *
	0.21	2.15	1.20	1.34	1.88	1.77

Panel B: Participation-weighted returns

IQ score	Wealth quintile					All
	Lowest	2	3	4	Highest	
1-4	7.39%	8.89%	9.31%	8.72%	14.10%	9.52%
5	7.14%	9.24%	9.20%	10.02%	14.97%	10.01%
6	8.01%	10.68%	10.34%	12.16%	14.78%	11.19%
7	10.21%	11.33%	11.52%	12.02%	15.52%	12.14%
8	11.15%	10.75%	11.67%	12.72%	15.62%	12.53%
9	11.59%	13.82%	13.81%	14.12%	17.66%	14.45%
9 minus 1-4	4.21%	4.93% **	4.50% *	5.41% **	3.56% **	4.93% **
	1.56	2.49	1.70	2.41	2.09	2.56

Panel C: Participation-weighted returns minus equal-weighted returns

IQ score	Wealth quintile					All
	Lowest	2	3	4	Highest	
1-4	-4.22%	-2.81%	-2.80%	-3.89%	-1.42%	-3.12%
5	-3.89%	-2.85%	-2.54%	-2.45%	-1.15%	-2.63%
6	-3.40%	-2.07%	-1.91%	-1.71%	-1.52%	-2.15%
7	-2.11%	-1.44%	-1.29%	-0.85%	-1.33%	-1.43%
8	-0.10%	-2.23%	-1.77%	-1.05%	-1.25%	-1.34%
9	-0.36%	-0.51%	0.19%	-0.20%	-0.58%	-0.39%
9 minus 1-4	3.85% **	2.30%	2.99%	3.68% ***	0.84%	2.73% **
	2.20	1.63	1.54	2.69	1.28	2.26

**Figure 1: Cumulative distribution of the cross-section of investors' annualized portfolio returns**

Figure 1 plots the cumulative distribution (CDF) of the cross-section of investors' annualized returns for subgroups of investors sorted by IQ (stanines 1-4 or stanine 9). The sample excludes investors who held stocks for fewer than 252 trading days in the sample period. Returns for each investor are annualized from the average daily portfolio returns computed over days the investor held stocks. The daily portfolio return is the portfolio-weighted average of the portfolio's daily stock returns. The latter are close-to-close returns unless a trade takes place in the stock, in which case execution prices replace closing prices in the calculation. The returns are adjusted for dividends, stock splits, and mergers. IQ data are from 1/1982 to 12/2001. Remaining data are from 1/1995-11/2002.



## Figure 2: Entries into technology stocks as a function of time and IQ stanine

Figure 2 analyzes investors' entry into tech stocks as a function of time and IQ. We calculate for each IQ group and week the proportional entry rate, and the ratio of number of entrants into technology stocks to the number of investors already holding technology stocks. The ratios are ranked within each week from 1 to 6 among the IQ groups. The figure calculates the 12-week average of the ranks and plots these smoothed entry rates. Green (red) color indicates high (low) propensity to enter the market. Technology stocks are defined as stocks that belong to the "Technology" industry according to the official HEX classification. Entry must happen by means of an open market buy (IPOs, seasoned offerings, and exercise of options are excluded). An investor can enter the market at most once in these computations and counts at most as one technology-stock owner regardless of the number of technology stocks owned. The black solid line is the log of the 12-week average of the HEX tech stock index. IQ data are from 1/1982 to 12/2001.

