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IQ, trading behavior, and performance ☆

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ABSTRACT

We analyze whether IQ influences trading behavior, performance, and transaction costs. The analysis combines equity return, trade, and limit order book data with two decades of scores from an intelligence (IQ) test administered to nearly every Finnish male of draft age. Controlling for a 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 a one-month high. High-IQ investors also exhibit superior market timing, stock-picking skill, and trade execution.

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 and make better trades? 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

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inductees in Finland's mandatory military service and eight years of trading data.

The paper begins with a study of IQ's effect on factors likely to influence trading behavior. Investigating the sell-versus-hold decision, our study finds that high-IQ investors have a relatively greater tendency to sell losing stocks, more likely to engage in tax-loss selling, and more likely to sell (hold) a stock at a 30-day high (low). 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 the disposition effect, more rational about minimizing taxes, and more likely to supply liquidity in response to large movements in stock prices. Complementing these findings is a study of group behavior, which finds that IQ-grouped investors herd more with investors of similar IQ than with investors of dissimilar IQ.

Known return patterns, tax liabilities, and trading costs often diminish returns when trades are motivated by behavioral factors. For example, low-IQ investors' greater sensitivity to the disposition effect realizes gains on winning stocks and trades against momentum, which tends to reduce returns. Low IQ also is disadvantageous if access to private information or superior ability to interpret public information is positively linked to cognitive ability.

Motivated by these findings and hypotheses, the second part of the paper studies whether high-IQ investors' trades outperform low-IQ investors' trades, controlling for each investor's trading experience, wealth, and age. High-IQ investors' aggregate stock purchases subsequently outperform low-IQ investors' purchases, particularly in the near future. This performance is not offset by larger transaction costs: the purchases and sales of high-IQ investors are executed at better prices and at better times than low-IQ investors' trades. The analysis generating these transaction-cost results controls for the typical bid-ask spread of a given stock and separately studies market and limit orders. Smart investors place market orders at times when bid-ask spreads temporarily narrow and their limit orders face less adverse selection—and thus are less likely to be picked off by an investor with superior private information about the stock.

High-IQ investors' exceptional stock picks and lower trading costs contribute to the 2.2% per year spread between the portfolio returns of high- and low-IQ investors. This 2.2% spread ignores differences in market timing arising from moving cash into and out of the market. The spread jumps to 4.9% per year when we account for IQ-related differences in market timing, including the tendency of high-IQ investors to avoid market participation when, in hindsight, returns to stock investing appear to be low.

Our findings relate to three strands of the literature. First, the 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, Lee, Liu, and Odean (2009); and, for Finland, Grinblatt and Keloharju (2000)). IQ is a fundamental attribute that seems likely to correlate with wealth-inhibiting behaviors.

Second, our study of the performance of IQ-sorted investors' trades fits into a body of research that seeks to assess the degree to which markets are efficient. Grossman (1978) and others point out that perfect market efficiency eliminates the incentive to collect information and therefore cannot exist. Understanding how close markets are to perfect efficiency requires study of investor attributes that plausibly generate successful investing. IQ is a natural a priori candidate for this role.

Third, by showing that IQ is a significant driver of trading behavior, performance, and trading costs, we contribute to a growing literature that identifies attributes like wealth and trading experience that help account for heterogeneity in investor performance.[1] If IQ influences performance, and performance influences other investor attributes, failure to control for IQ could lead to a spurious relation between an attribute and performance. For example, less wealthy households may be less wealthy because their IQ-related behavioral biases generate wealth-reducing investment decisions. And individuals who are talented investors (and have high IQ) may rationally pursue vast stock trading experience while those endowed with low investment talent (and IQ) may learn from a limited stock trading failure that further experience is to be avoided. In these examples, wealth and trading experience do not enhance performance per se: rather, the arrow of causation runs in reverse but is not perceived when IQ is omitted as a control. Measured at the individual level and at an early age, IQ's link to behavior and performance is far less subject to a reverse causality bias than other performance and trading-behavior correlates studied in the literature.

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 Scholastic Aptitude Test (SAT) score at the fund manager's undergraduate institution or average Graduate Management Admission Test (GMAT) score at his or her Master of Business Administration (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. Some studies link genetic variation to differences in financial decision-making. Barnea, Cronqvist, and Siegel (2010) and

[1] 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, Lee, Liu, and Odean (2011), and Linnainmaa (2011).

Cesarini, Johannesson, Lichtenstein, Sandewall, and Wallace (2010), for example, show that the genetic factor accounts for one-third of the variation in stock market participation rates and one-quarter of the variation in portfolio risk. However, these studies do not examine differences in investment performance or sort investors by IQ scores.

The paper also contributes to the literature by providing one of the most exhaustive studies of the disposition effect and December tax-loss trading. With approximately 1.25 million observations of sell vs. hold decisions, it is possible to be agnostic about the disposition effect's functional form, while controlling for more than 500 other regressors. We find that both the disposition effect and tax-loss trading, as well as any IQ-linked moderation or exacerbation of these effects, are based on the sign of the gain or loss. However, while the magnitude of the loss influences trading behavior, the magnitude of the gain does not. We are unaware of any theory of the disposition effect or tax-loss trading that would predict such a functional form.

Finally, the paper introduces innovative methodology. To study IQ and performance, we employ a Fama-MacBeth (1973) regression approach. Each of the approximately 2,000 cross-sectional regressions studies how a stock's daily return is predicted by trading decisions in prior days by IQ-categorized investors. What is unique here is the application of the Fama-MacBeth regression to units of observation consisting of each pairing of an investor and a trade in a stock. This approach facilitates study of IQ's marginal effect on performance while controlling for both investor and stock attributes. The intercept in the cross-sectional regression effectively removes the influence of each day's market movement. Moreover, each cross-sectional regression controls for a large number of variables that might explain a simple correlation between high IQ and successful stock investing. These include wealth, trading frequency, and age, all of which also proxy for the investment experience obtained prior to the trades analyzed. The regression also removes the impact of IQ-related differences in investment style or style timing by employing the usual set of controls for stock characteristics including beta, book-to-market ratio, firm size, and past returns (measured over several intervals). As a consequence, we measure IQ-related differences in the performance of trades that cannot be explained by an IQ-related tendency to follow value or size strategies, or exploit either short-term reversals or momentum.

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

2. Data

2.1. Data sources

We merge five data sets for our analysis.

2.1.1. 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.

2.1.2. 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 assess trading performance. We employ the data from January 1, 1994 through November 29, 2002.

2.1.3. 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.

2.1.4. HEX microstructure data

This is a September 18, 1998 through October 23, 2001 record of every order submitted to the fully electronic, consolidated limit order book of the Helsinki Exchanges. The limit order book for a HEX-listed stock is known to market participants at the time of order submission. We have the original HEX supervisory files, so these data are complete and highly reliable. The data set tracks the life of each order submitted to the Exchanges, detailing when the order is executed, modified, or withdrawn. We first reconstruct second-by-second limit order books for all HEX-listed stocks, paying special attention to executed orders. Only executed orders can be combined with FCSD trading records to identify the investor placing the order. Ultimately, we construct a data set that contains each investor's executed order type—limit or market order—and what the limit order book looked like at any instant prior to, at, and after the moment of order execution. Both market and limit orders originate from the limit order book. Thus, market orders are orders that receive immediate execution by specification of a limit price that matches the lowest ask price when buying or highest bid price when selling. Details are provided in Linnainmaa (2010).

2.1.5. 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 intelligence 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 (2011) 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.[2] The country is also racially homogeneous and compared to other countries, income is distributed fairly equally.[3] These factors make it more likely that differences in measured IQ in Finland reflect genuine differences in innate intelligence.

2.2. 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.

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 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 Security 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.[4] 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 barely differ across the stanine categories. Although the size rank difference is statistically significant, it is economically negligible.[5]

Panel D reports averages of five other characteristics of the stocks purchased by high- and low-IQ investors. The overall averages reported in Panel D (like Panel C) 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 (zero being the lowest and one being the highest rank). High-IQ investors tend to buy stocks that performed relatively worse in the past month and relatively

[2] See, for example, an article in *The Economist* (December 6, 2007) and Garmerman (2008).

[3] Fig. 1.1 in OECD (2008) indicates that Finland has the seventh lowest Gini coefficient among OECD countries.

[4] The beta of the average stock traded by individuals is below one (only 0.77) because of the relatively lower frequency with which individuals trade Nokia. Nokia accounted for two-thirds of the market portfolio in 2000 but only 35% of (Finnish) individuals' trades.

[5] Grinblatt, Keloharju, and Linnainmaa (2011), focusing on holdings rather than trades, find that high-IQ investors hold small, low-beta stocks with high book-to-market ratios.

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 average betas, as well as average size and book-to-market ranks for trades sorted by investor IQ score. Panel D 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 the prior 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 C and D, each investor's average for a variable, computed from that investor's purchases and sales (Panel C) or purchases only (Panel D), receives equal weight. The IQ data are from 1/1982 to 12/2001 and the other data from 1/1995 to 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
No. 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 (%)
	No. 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: Average of beta, book/market rank, and size rank by IQ score

IQ score	Beta	B/M rank	Size rank
1 – 4	0.759	0.312	0.797
5	0.777	0.305	0.795
6	0.771	0.308	0.793
7	0.770	0.307	0.794
8	0.773	0.305	0.792
Highest	0.758	0.308	0.789
Highest – lowest	– 0.001	– 0.004	– 0.007
t-Value	– 0.12	– 1.10	– 3.05

Panel D: 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
t-Value	– 1.88	4.31	– 4.84	8.99	– 3.34

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 one-month reversal and one-year momentum patterns shown in Jegadeesh (1990) and Jegadeesh and Titman (1993).

Panel D 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% of their purchases occur on days these stocks hit monthly lows. Only about

16% of low-IQ investors' purchases close at their one-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 D 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 analyzes the relationship between IQ and trading behavior. Table 2 first extends Grinblatt and Keloharju's (2001) (henceforth GK) study of the factors motivating individuals' buys and holds, lengthening the sample by several years and adding interaction variables to capture IQ's marginal effect on potential trade-influencing regression coefficients. Table 2 also uses a sufficiently wide range of capital gain and loss dummies to capture a relatively unconstrained functional form for the disposition effect, and adds a family of new regressors that measure herding among IQ-partitioned investors. Table 3 complements the GK approach, reporting four additional panel regressions that study trading interactions at the IQ-group level.

3.1. Intelligence and the sell vs. hold decision

Table 2 reports coefficients and test statistics (clustered at the stock-day level) for GK's sell-versus-hold logit panel regression, using about 1.25 million data points. Each day an investor sells stock, we generate observations for all stocks in the investor's portfolio. The dependent variable is "1" for stocks sold and "0" for stocks held. The regression analyzes the relation between this sell-versus-hold decision and 595 regressors. The IQ score in the regression 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 (Table 1). The transformation also allows the reader to simply add or subtract the interaction coefficient from the benchmark coefficient to infer the coefficients for stanines 9 and 1, respectively.

Table 2 reports coefficients for the trade-influencing variables reported in GK (allowing for the more complex disposition effect specification), 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 but do not report the same fixed effects as those used in Grinblatt and Keloharju (2001): a set of dummies for each stock, month, number of stocks in the investor's portfolio, and investor age dummies, as well as past market returns over the 11 horizons and products of a capital loss dummy and the past market return variables. For brevity, our discussion mostly concentrates on those determinants of trade that IQ materially affects.[6]

3.1.1. The disposition effect and tax-loss selling

Table 2's regressors include 21 dummies for various ranges of paper capital gains and losses. The omitted dummy represents a capital loss between zero and 5%. Coefficients on these dummies assess whether the disposition effect influences trading outside December. Interaction variables between the December dummy and the 21 gain/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.

Table 2's (non-December) loss dummies have significantly negative benchmark coefficients while the gain dummies are significantly positive. This pattern is consistent with the disposition effect: individuals tend to sell winners more than losers. Such a strategy is the opposite of momentum trading, generates larger taxes, and as Grinblatt and Han (2005) have shown, is likely to be detrimental to pre-tax returns even after controlling for momentum's effect on returns. The products of a December dummy and the loss dummies generally exhibit significant positive benchmark coefficients. This finding is consistent with Grinblatt and Keloharju (2001), who note that the tendency to hold losing stocks is tempered in December.

The coefficients on the ten (non-December) loss dummies are approximately linear in the magnitude of the loss. All ten are statistically significant with t-values ranging from -9.95 (for losses between -5% and -10%) to -44.99 for the largest losses (more than 50%). Thus, median-IQ investors tend to hold big losers more than they hold small losers. While stocks with gains have a significantly greater tendency to be sold than stocks from the omitted category (losses from zero to 5%), there is no greater tendency to sell stocks with large gains than stocks with small gains. This asymmetry between the coefficient pattern for gains and losses extends to the December benchmark coefficients. The coefficients for stocks with losses in December (while of opposite sign from the non-December coefficients) are approximately linear in the size of the loss. The products of the December dummy and the 11 gain dummies are largely insignificant.

[6] In addition to the logit coefficients, we computed (but do not report) the marginal effects of Table 2's regressors at their means, as well as their 25th, 50th, and 75th percentile values. We also estimated Table 2's specification as a linear probability model (for which coefficients represent marginal effects). In every instance where a logit interaction coefficient is significant, all five of the associated marginal effect computations (described above) are of the same sign as the logit interaction coefficient. This finding suggests that the concerns expressed in Ai and Norton (2003) about interpreting the direction of marginal effects from the signs of interaction coefficients in non-linear models are unlikely to apply to our analysis.

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), using a more complex disposition effect specification, adding herding variables, and interacting the regressors with individuals' IQ scores. The "benchmark" column reports on the following a) 21 dummies for various ranges of paper capital gains or losses, measured at the close the day prior to the trading decision day; b) 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 21 gain/loss dummies; c) two reference price dummy variables associated with the stock being at a one-month high or low; d) 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, market-adjusted return) and min (0, market-adjusted return); e) 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 (d); 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 section 3.1. 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 the 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		*t*-Values	
	Benchmark	× IQ	Benchmark	× IQ
IQ	−0.295***		−6.23	
Size of holding period return dummy				
[−1.00, −0.50)	−0.956***	0.384***	−44.99	11.59
[−0.50, −0.45)	−0.692***	0.244***	−23.14	4.64
[−0.45, −0.40)	−0.640***	0.229***	−23.29	4.73
[−0.40, −0.35)	−0.607***	0.313***	−22.96	6.75
[−0.35, −0.30)	−0.505***	0.213***	−20.43	4.96
[−0.30, −0.25)	−0.447***	0.125***	−19.51	3.08
[−0.25, −0.20)	−0.410***	0.149***	−19.42	4.03
[−0.20, −0.15)	−0.338***	0.176***	−17.63	5.17
[−0.15, −0.10)	−0.251***	0.123***	−14.40	4.01
[−0.10, −0.05)	−0.154***	0.077***	−9.95	2.82
[0,0.05)	0.451***	−0.004	24.17	−0.12
[0.05,0.10)	0.618***	0.003	30.52	0.10
[0.10,0.15)	0.559***	0.014	25.56	0.41
[0.15,0.20)	0.509***	0.041	21.37	1.07
[0.20,0.25)	0.489***	0.058	19.06	1.42
[0.25,0.30)	0.448***	0.120***	16.03	2.59
[0.30,0.35)	0.462***	0.011	15.25	0.22
[0.35,0.40)	0.415***	0.094*	12.52	1.69
[0.40,0.45)	0.404***	−0.084	11.13	−1.31
[0.45,0.50)	0.414***	0.099	10.41	1.47
[0.50,∞)	0.271***	0.114***	11.42	3.09
December × size of holding period return dummy				
[−1.00, −0.50)	1.238***	0.256***	20.69	4.85
[−0.50, −0.45)	0.739***	0.308**	8.25	2.16
[−0.45, −0.40)	0.811***	−0.013	8.99	−0.10
[−0.40, −0.35)	0.531***	0.201	6.10	1.63
[−0.35, −0.30)	0.560***	0.216*	6.75	1.78
[−0.30, −0.25)	0.347***	0.254**	4.56	2.23
[−0.25, −0.20)	0.136*	0.320***	1.90	2.76
[−0.20, −0.15)	0.213***	−0.002	3.20	−0.02
[−0.15, −0.10)	0.097	0.075	1.54	0.85
[−0.10, −0.05)	0.095	−0.061	1.64	−0.73
[0,0.05)	−0.054	−0.083	−1.14	−1.40
[0.05,0.10)	0.035	−0.101	0.64	−1.45
[0.10,0.15)	−0.109*	−0.058	−1.79	−0.74
[0.15,0.20)	−0.109	−0.166*	−1.48	−1.79
[0.20,0.25)	−0.172**	−0.060	−2.12	−0.52
[0.25,0.30)	−0.210***	−0.051	−2.80	−0.44
[0.30,0.35)	−0.158*	−0.198	−1.80	−1.38
[0.35,0.40)	−0.239**	−0.036	−2.23	−0.22
[0.40,0.45)	−0.011	−0.072	−0.10	−0.35
[0.45,0.50)	−0.309**	0.128	−2.31	0.57
[0.50,∞)	−0.294***	−0.096	−4.79	−1.37
Last month low dummy	−0.106***	−0.093***	−5.07	−4.25
Last month high dummy	0.198***	0.045**	9.87	2.51

Table 2 (*continued*)

Independent variables	Coefficients		*t*-Values	
	Benchmark	× IQ	Benchmark	× IQ
Max [0, Market – adjusted return] in the given interval of trading days before the sell vs. hold decision				
0	4.510***	0.999***	15.76	2.87
−1	1.912***	0.178	8.33	0.63
−2	0.559***	0.010	2.83	0.04
−3	0.319*	0.015	1.67	0.06
−4	0.087	−0.616**	0.47	−2.14
[−19, −5]	−0.038***	−0.066***	−3.76	−3.37
[−39, −20]	−0.004	−0.008	−0.45	−0.55
[−59, −40]	0.011	−0.044*	0.77	−1.65
[−119, −60]	0.030**	0.030	2.49	1.48
[−179, −120]	−0.001	−0.006	−0.13	−0.30
[−239, −180]	−0.055***	−0.014	−3.36	−0.52
Min [0, Market – adjusted return] in the given interval of trading days before the sell vs. hold decision				
0	−1.003***	0.411	−2.70	0.82
−1	−0.899***	−0.170	−2.81	−0.43
−2	−0.414	−0.212	−1.43	−0.55
−3	−0.276	−0.870**	−1.17	−2.44
−4	−0.548**	−0.219	−2.37	−0.62
[−19, −5]	−0.881***	−0.230*	−10.97	−1.92
[−39, −20]	−0.430***	0.021	−6.55	0.21
[−59, −40]	−0.143**	−0.057	−2.08	−0.57
[−119, −60]	−0.332***	−0.092	−8.05	−1.45
[−179, −120]	−0.174***	−0.114*	−3.91	−1.72
[−239, −180]	0.074	−0.063	1.63	−0.93
Max [0, Holding period capital loss dummy × Market – adjusted return] in the given interval of trading days before the sell vs. hold decision				
0	−1.483***	0.199	−5.05	0.49
−1	−2.109***	−0.353	−7.92	−0.93
−2	−0.705***	−0.394	−2.88	−1.02
−3	−0.525**	−0.592	−2.18	−1.46
−4	−0.474*	0.961**	−1.83	2.55
[−19, −5]	0.030**	−0.002	1.99	−0.05
[−39, −20]	0.012	−0.001	1.33	−0.08
[−59, −40]	0.004	0.014	0.30	0.48
[−119, −60]	−0.001	−0.027	−0.04	−1.19
[−179, −120]	0.025**	−0.008	2.30	−0.33
[−239, −180]	0.080***	0.016	4.65	0.55
Min [0, Holding period capital loss dummy × Market – adjusted return] in the given interval of trading days before the sell vs. hold decision				
0	−1.558***	−1.118**	−3.68	−1.97
−1	−0.199	−0.402	−0.55	−0.86
−2	0.047	0.160	0.15	0.35
−3	−0.204	1.367***	−0.71	3.03
−4	0.295	−0.413	0.99	−0.87
[−19, −5]	0.752***	0.227	8.12	1.52
[−39, −20]	0.548***	−0.009	6.84	−0.07
[−59, −40]	0.067	0.103	0.82	0.79
[−119, −60]	0.296***	0.009	5.96	0.11
[−179, −120]	0.027	0.166**	0.52	1.97
[−239, −180]	−0.263***	0.023	−5.00	0.27
Average $(\text{return})^2$ of stock over days [−59.0]	1.339*	2.145**	1.80	1.98
Average $(\text{market return})^2$ of stock over days [−59.0]	33.812	−94.913*	0.24	−1.84
ln(Portfolio value)	−0.037***	0.014***	−16.06	4.19
No. days between purchase and sale	−0.000***	−0.000**	−14.09	−2.52
Herding in the given interval of trading days before the sell vs. hold decision				
0	0.683***	−0.001	65.40	−0.11
[−4, −1]	0.149***	0.021	16.09	1.56
[−19, −5]	0.085***	−0.002	7.36	−0.11
[−59, −20]	0.059***	−0.012	4.08	−0.69

The interactions of the ten (non-December) loss dummies with IQ score are uniformly positive and statistically significant with *t*-values ranging from 2.82 (for losses between −5% and −10%) to 11.59 for the largest losses (more than 50%). These loss-interaction coefficients indicate that low-IQ investors are less likely to realize capital losses, particularly large capital losses, than high-IQ investors. However, despite joint significance of the largely positive gain interaction coefficients at the 1% level, IQ has a relatively small influence on the propensity to sell winning stocks.

The IQ interactions with the ten December loss dummies are largely positive. Four of the coefficients are individually significant at the 5% level and, taken together, all ten are jointly significant in a Wald test (p-value < 0.00001). Thus, high-IQ investors are more likely than median-IQ investors to sell losers in all months. As Finland places no limit on deductions for losses, high-IQ investors' greater tendency to realize losses suggests that they would enjoy superior after-tax returns even if IQ had no influence over pre-tax returns.

Summing of December and non-December capital loss benchmark coefficients indicates that during December, median-IQ investors are better characterized as modest sellers of losers than as disposition traders. For example, when losses exceed 50%, median-IQ investors have a coefficient of -0.956 outside of December, but this changes to 0.282 ($=-0.956+1.238$) in December. High-IQ investors engage in December tax-loss selling to an even greater extent. Stanine 9 investors' large-loss coefficient increases from a non-December value of -0.572 ($=-0.956+0.384$) to 0.922 ($=-0.956+1.238+0.384+0.256$) in December.

To better understand these coefficient magnitudes, consider an investor in December 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 loss in excess of 50% and the other stock is trading just below the price it was purchased for. The 0.282 and 0.922 coefficient sums above imply that the probability of a sale of the large-loss stock increases from 0.5 to 0.57 ($=1/(1+e^{-0.282})$) for the median-IQ investor, and from 0.5 to 0.72 for the high-IQ investor ($=1/(1+e^{-0.922})$).

3.1.2. Reference price effects

The propensity to sell is positively related to whether a stock has hit its high price within the past month (specifically, the prior 20 trading days). The benchmark estimates indicate that median-IQ investors are more likely to hold 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 having high IQ strengthens these patterns. High-IQ investors thus appear to be more contrarian than low-IQ investors with respect to these reference prices.

Absent further evidence on whether such trading behavior enhances or diminishes returns, one cannot determine whether the significant IQ interaction coefficients on the two reference price variables are rational or indicative of greater behavioral bias by high-IQ investors. We do know that returns from selling at a monthly high and holding at a monthly low are undiminished by momentum (because we are in the month after the formation period). Moreover, because we control for the capital gain or loss on the stock, the significant benchmark and interaction coefficients on the reference prices have no tax implications. We also know that the reference price behavior is a contrarian strategy and the reference price signal is based on relatively short-term extreme returns. 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%. Lehmann (1990), Jegadeesh (1990), Gutierrez and Kelley (2008), and, using Finnish data, Linnainmaa (2010) document that trading against recent extreme price movements earns abnormal profits for short holding periods.[7] Kaniel, Saar, and Titman (2008) find that individuals who engage in such contrarian behavior profit by supplying liquidity to institutions. This suggests that by selling stocks at monthly highs and holding stocks at monthly lows, high-IQ investors are more likely to be following a rational liquidity provision strategy than a psychological bias that diminishes returns.

The sensitivity of the high-IQ investors' sell vs. hold decision to these reference price variables stands in contrast to the largely insignificant interactions with the 22 past return variables. While the significant reference price interaction coefficients indicate that high- and low-IQ investors respond to large recent returns to differing degrees, but in the same direction, their responses to the typically smaller past price movements are about the same. Positive day-0 return coefficients are an exception but this phenomenon likely arises from high-IQ investors' greater use of sell limit orders, which execute only if the price increases. As Linnainmaa (2010) shows, this phenomenon generates a positive correlation between trades and same-day returns.

3.1.3. Herding

Table 1 Panel D suggested that low-IQ investors have a greater tendency to purchase stocks that were popular in the prior week. Table 2 allows us to measure sell vs. hold herding with respect to any prior period for measuring popularity. Herding with respect to a prior period is given by the regression coefficient on

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

Because the regression controls for other significant determinants of the sell-versus-hold decision (like tax-loss selling), $\text{Herd}_j(-t_0, -t_1)$'s coefficient 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

[7] High-IQ investors' sell-versus-buy decisions also respond dramatically to extreme price movements in a contrarian way. A similarly specified regression (not reported here) that studies all trades, with sells corresponding to a dependent variable of one and buys corresponding to a zero, has significantly positive (negative) benchmark and interaction coefficients on the one-month high (low) dummy. The other regressors are the same as those in Table 2, except that we exclude (non-computable) variables related to the disposition effect, tax-loss selling, and holding period.

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, Huberman, and Sengmueller (2008) and Barber, Odean, and Zhu (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 herd neither more nor less than lower-IQ investors when deciding which stocks to sell and which to hold onto.

3.2. Intelligence and trading: analysis of group interactions

The herding results, discussed above, do not study purchases, nor do they offer 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 by all other groups together and against each of the other group's current and lagged excess trading behavior. As with Table 2's herding analysis, the lagged ratios are computed from non-overlapping intervals representing 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.[8]

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 groups 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 3 Panel A reports 20 (four groups and one group average × four 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 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 three of the four 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 of 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—being more correlated with the past trades of stanine 5 investors than with those of stanine 8 or 9 investors—exhibit material differences in sensitivity to the prior trades of other IQ groups.

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's benchmark coefficients for herding and with the summary statistics in Table 1 Panel D.

4. IQ-related performance and transaction costs

4.1. Intelligence and the performance of portfolio holdings

Fig. 1 plots the cumulative distribution of portfolio returns for those in the highest (stanine 9) and lowest (stanines 1–4) IQ categories. We restrict the sample to those who participate in the market for at least 252 trading days (about one 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.

The differences between the two distributions are economically significant. The Kolmogorov-Smirnov test, based on the maximum distance between the estimated cumulative distribution functions, rejects the equality of the distributions (p-value < 0.0001). However, the test assumes that return observations are sampled independently, which is unlikely to hold in reality.

Table 4 remedies this statistical concern by organizing the panel into time-series vectors of daily portfolio

[8] Kaustia and Knüpfer (this issue) find that neighbors' recent stock returns influence an individual's stock market entry decision. If the residences or workplaces of those of similar IQ cluster geographically, IQ-linked dog-pack behavior may arise from neighbors' sharing of trade-motivating information.

Table 3
Interactions in trading behavior between IQ groups.

Table 3 reports coefficients and t-values from a panel regression of the IQ 1–4 or IQ 9 groups' 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.

Dependent variable		Independent variables: Other group's sell-hold ratios IQ score						t-Value, closest–most distant
	Interval	1–4	5	6	8	Highest	Average	
Panel A: Sell-hold ratios								
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								
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	

returns for 36 groups (five equal-sized wealth groups, subsequently sorted by six IQ categories plus six groups sorted only by IQ). Each day's group return, a single element of the time-series vector, equally weights the returns of every investor within the category. We can then generate a simple t-test for the difference in the time-series mean of any pair of vectors by differencing corresponding elements of the pair and testing whether the mean of the difference vector is zero.[9]

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 former 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

[9] We do not report alphas because IQ-linked alpha differences are similar to the differences in the raw returns. This finding is robust to whether alphas are computed with CAPM, Fama-French (1993) three-factor, or Carhart (1997) four-factor benchmarks.

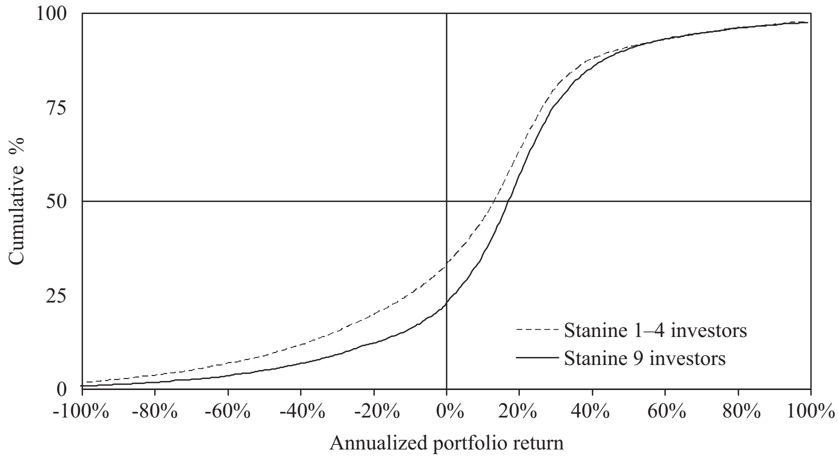

Fig. 1. Cumulative distribution of the cross-section of investors' annualized portfolio returns. This figure plots the cumulative distribution (CDF) of the cross-section of investors' annualized returns for subgroups of investors sorted by IQ (stanines 1–4 or stanine 9). The sample excludes investors 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.

Table 4
Intelligence and the returns of portfolio holdings.

Table 4 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 initial public offering (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 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.

IQ score	Wealth quintile					
	Lowest	2	3	4	Highest	All
Panel A: Equal-weighted returns						
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						
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						
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

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 4 Panel A's "All" column indicates that the portfolio returns of stanine 9 investors averaged 14.84% per year, which is 2.2% more per year than the average of the stanine 1–4 investors. This difference is significant at the 10% level. Panel B, which accounts for the timing of participation intensity, increases the IQ-return gap to 4.9% per year, which is significant at the 5% level.

Panels A and B also suggest that when we control for wealth quintile, high-IQ investors' portfolios still outperform those of their lower-IQ counterparts. The wealth-controlled differences are of similar magnitude to the uncontrolled differences. Panel A's wealth-controlled differences range from 1.51% to 2.72%, excluding the lowest wealth category, and often are significant. The lowest wealth quintile, (which has a noisier estimate due to small sample size arising from relatively few stanine 9 investors) has a far smaller IQ-related return gap, 0.35%. Panel B's far larger difference of about 5% also persists when we control for wealth quintile and it is insignificant only for the lowest wealth quintile. 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 Fig. 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 4'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. Moreover, similar-sized differences exist if we compare the time-series of median returns of high- and low-IQ investors, as opposed to equally weighted returns. For example, the difference in medians in the "All" column would be 3.01% and 6.29% per year for the unweighted and participation-weighted averages, respectively.

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.

The "heat map" in Fig. 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 Fig. 2 are consistent with Table 4. 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

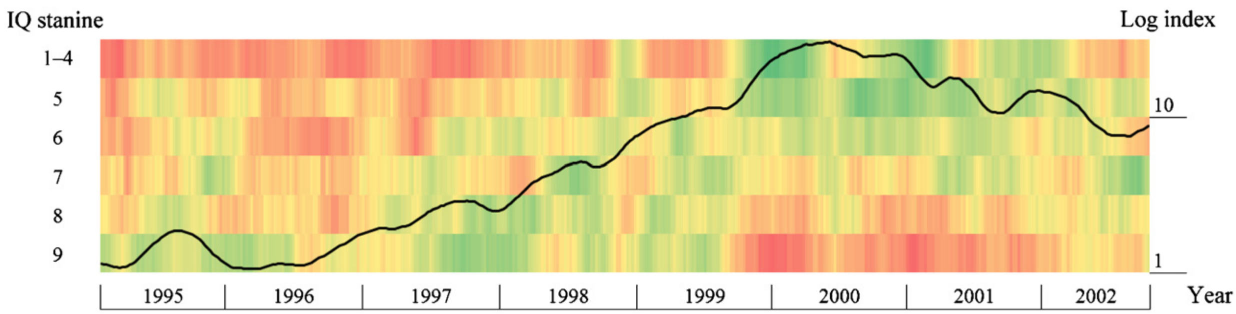

Fig. 2. Entries into technology stocks as a function of time and IQ stanine. This figure analyzes investors' entry into technology stocks as a function of time and IQ. We calculate for each IQ group and week the proportional entry rate, and the ratio of number of entrants into technology stocks to the 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.

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.

4.2. Intelligence and the performance of stock trades

Fig. 1 and Table 4 suggest that high-IQ investors earn higher returns than low-IQ investors. It is certainly possible that high-IQ investors have superior access to private information, are better or quicker at processing information into a useful trade signal, or excel at distinguishing useful information from noise. If any of these considerations apply, the trades of high-IQ investors should outperform low-IQ investors' trades before transaction costs.

One motivation for studying trades is that portfolios do not properly capture the active management of individuals' portfolios. Risk sharing incentives, which arise in equilibrium for risky assets, dictate that there may be a sizable passive component that tends to dilute the performance of portfolio holdings. Support for this hypothesis is found in the Chen, Jegadeesh, and Wermers (2000) observation that the trades of fund managers, but not their holdings, predict the future returns of stocks. Studying trades also is consistent with decompositions of performance from active management, like that in Grinblatt and Titman (1993). Their decomposition suggests that performance may better be measured from changes in holdings rather than from holdings themselves.

Because so many factors besides wealth influence returns, one cannot use Table 4's methodology to analyze the marginal impact of IQ on the performance of trades. There are far fewer trades than there are holdings. Thus, analyzing trades for investors sorted by IQ, wealth, age, and trading experience, while at the same time controlling for stock attributes that might influence returns, will generate mostly missing observations of daily returns. There is an alternative methodology that resolves this problem and yet provides quantities for the marginal influence of IQ that can be interpreted as portfolio returns. This methodology, which involves a novel implementation of Fama-MacBeth (1973) cross-sectional regression methodology, is also capable of separating the influence of IQ on the performance of purchases from IQ's influence on the performance of sales.

Table 5 assesses whether high-IQ investors' stock purchases and sales predict returns relative to low-IQ investors' trades. Each column of Table 5 corresponds to one regression specification. A single column reports the average of coefficients from approximately 2,000 cross-sectional regressions along with Fama-MacBeth t-statistics.[10] We exclude any day t regression that lacks trades in at least 30 stocks. The data points for each cross-sectional regression are purchases (left half of the table) or sales (right half of the table) in a trade formation period given by the column label. Columns listed as $[-t_0, -t_1]$ have a trade formation period from t_0 trading days before date t to t_1 trading days before date t. For each of six regression specifications for buys and six for sells, the left-hand side variable is the day t return of the stock (in percent). For the [0, 0] specification, the day t return is computed from day t's execution price to the closing price, ensuring that the return is measured after the trade. In Panel A, the right-hand side variables are the five IQ-score dummy variables. Panel B's regressions also control for seven stock characteristics known to influence returns and for ten variables based on investor attributes.

Panel B's stock-specific controls are stock j's Scholes-Williams beta, book-to-market percentile rank, and size percentile rank, along with four returns, each computed over one of four non-overlapping past return intervals. Returns over these intervals control for both the short-term (up to one month) reversal and long-term (one month to one year) momentum effects documented in the literature.[11] For brevity, Table 5 does not report regression coefficients for the stock-specific controls.[12] Panel B's investor-specific controls are age and quintile dummies for trading activity and stock portfolio wealth. The trading activity quintiles are based on number of trades from the start of the sample period in January 1995 to one day prior to the start of the most distant formation period (day $t-64$), where t is the date of the returns used for the regression. Portfolio wealth is computed using the market value of stocks held by the investor on the day prior to the start of the lengthiest formation period ($t-64$). Zero trading activity and a pool consisting of the lowest quintile of positive portfolio wealth and zero portfolio wealth are the omitted trading activity and wealth categories.

Because the unit of observation is a buy trade or sell trade, the return of a given stock can appear multiple times on the left-hand side of the same cross-sectional regression. For example, suppose that on January 27, 1999, there were 420 purchases of Nokia and 87 purchases of Finnair. In the formation period $[-2, -2]$ buy regression for January 29, 1999, Nokia would appear as a data point 420 times while Finnair would appear 87 times.[13] We treat multiple trades by the same investor in a stock on the same day as either a single purchase or

[10] Because t-statistics are computed from the time-series of daily coefficient estimates in the Fama-MacBeth procedure, the validity of our inferences only requires that daily portfolio returns are close to being serially uncorrelated, which they are. Moreover, Newey-West adjusted standard errors in Table 6 Panel B for lags up to one month do not alter our inferences. For example, the t-values for stanine 9 investors' $[-2, -2]$ and $[-5, -3]$ formation periods change from 2.34 and 2.58 to 2.24 and 3.16, respectively.

[11] See, for example, French and Roll (1986), Lehmann (1990), Jegadeesh (1990), Jegadeesh and Titman (1993, 1995), and Kaniel, Saar, and Titman (2008).

[12] One can summarize their unreported coefficients as follows: The beta and firm size ranks are insignificantly related to returns while book-to-market rank is strongly and positively related to returns. Generally, the lagged return coefficients are negative for returns up to one month in the past and positive for the more distant horizons. Only the short-term horizons exhibit statistically significant coefficients.

[13] The data structure implies that we would obtain identical results if we ran one regression for all formation periods, with coefficients obtained (as in seemingly unrelated regression) from the interactions of the current regressors with dummies for the formation periods.

Table 5
Intelligence and the performance of trades.

Table 5 reports average coefficients and Fama-MacBeth *t*-statistics (in parentheses), computed from 12 specifications of daily cross-sectional regressions. We exclude any day *t* regression that lacks trades in at least 30 stocks. The dependent variable in the first stage of the two-stage procedure is the day *t* daily return of stock *j* for data point *n* if stock *j* was purchased (left six columns) or sold (right six columns) in the formation period corresponding to the columns. The same-day return in column [0, 0] is computed from trade price to the closing price on day *t*. The investor-related regressors are IQ stanine, number of trades prior to day $t-64$, stock portfolio wealth at $t-64$, and age/100 which are described in Section 4.2. IQ stanines 1–4, zero trading activity, and the pool of zero portfolio wealth and the lowest quintile of portfolio wealth are the omitted categories. The firm-level regressors are the stock's Scholes-Williams beta, size rank of the firm, book-to-market rank of the firm, and past returns of the stocks over intervals [−1, −1], [−5, −2], [−21, −6], and [−252, −22]. See Section 2.2 for details. After collecting coefficient estimates from each day in the 1/1995–11/2002 sample period, the second stage computes the means of these coefficient estimates and the associated *t*-statistics from the time-series of coefficients. The left half of the table reports buy coefficients and the right half reports sell coefficients. Panel A (Panel B) reports the estimates without (with) controls. Coefficients denoted with *, **, *** are significant at the 10%, 5%, and 1% level, respectively. IQ data are from 1/1982 to 12/2001.

Independent variables	Dependent variable: One-day return, percent											
	Buys						Sells					
	[0,0]	[−1,−1]	[−2,−2]	[−5,−3]	[−21,−6]	[−63,−22]	[0,0]	[−1,−1]	[−2,−2]	[−5,−3]	[−21,−6]	[−63,−22]
Panel A: IQ score regressors only												
IQ score												
5	0.042***	0.015	0.017	−0.007	−0.004	−0.006	0.002	−0.002	−0.016	0.001	0.002	−0.003
	(2.69)	(0.79)	(0.94)	(−0.54)	(−0.67)	(−1.43)	(0.14)	(−0.08)	(−0.99)	(0.10)	(0.53)	(−0.88)
6	0.076***	0.013	0.034*	0.028**	−0.007	−0.008	−0.023*	−0.007	−0.025*	0.003	0.002	0.002
	(4.94)	(0.67)	(1.91)	(2.10)	(−1.04)	(−1.45)	(−1.92)	(−0.39)	(−1.65)	(0.29)	(0.37)	(0.38)
7	0.070***	0.048**	0.047**	0.030*	0.006	−0.005	0.003	−0.013	−0.009	−0.000	0.008	0.003
	(3.99)	(2.14)	(2.25)	(1.93)	(0.71)	(−0.88)	(0.20)	(−0.66)	(−0.49)	(−0.01)	(1.40)	(0.78)
8	0.108***	0.070***	0.045*	0.046***	0.007	−0.001	−0.023	−0.031	−0.039**	−0.008	0.009	0.004
	(6.00)	(2.86)	(1.89)	(2.81)	(0.75)	(−0.10)	(−1.61)	(−1.51)	(−2.08)	(−0.66)	(1.53)	(0.75)
Highest	0.147***	0.075***	0.080***	0.050***	0.016	0.004	−0.065***	−0.027	−0.034*	0.006	0.008	0.008
	(7.63)	(2.81)	(3.26)	(3.08)	(1.48)	(0.51)	(−4.05)	(−1.24)	(−1.75)	(0.46)	(1.06)	(1.32)
Panel B: IQ score regressors and all controls												
IQ score												
5	0.068***	0.015	0.012	−0.010	−0.001	−0.003	−0.012	−0.035**	−0.024*	0.005	−0.003	−0.004*
	(3.25)	(1.00)	(0.80)	(−1.06)	(−0.13)	(−1.06)	(−0.94)	(−2.31)	(−1.69)	(0.65)	(−0.86)	(−1.70)
6	0.084***	0.012	0.022	0.002	0.002	−0.000	−0.023*	−0.006	−0.016	0.004	−0.000	−0.002
	(3.82)	(0.84)	(1.57)	(0.15)	(0.45)	(−0.14)	(−1.75)	(−0.43)	(−1.23)	(0.55)	(−0.14)	(−0.80)
7	0.092***	−0.006	0.024	0.011	0.007	0.000	−0.010	−0.025	−0.015	0.005	0.003	0.000
	(3.33)	(−0.36)	(1.47)	(0.94)	(1.43)	(0.02)	(−0.69)	(−1.63)	(−0.96)	(0.63)	(0.81)	(0.04)
8	0.106***	0.038**	0.041**	0.018*	0.011**	0.007	−0.016	−0.026	−0.006	0.009	0.005	0.003
	(4.31)	(2.01)	(2.24)	(1.65)	(2.03)	(1.63)	(−1.01)	(−1.45)	(−0.36)	(1.01)	(1.13)	(0.85)
Highest	0.150***	0.045**	0.044**	0.033***	0.016***	0.005	−0.068***	−0.033*	0.011	0.009	0.011**	0.003
	(5.36)	(2.19)	(2.34)	(2.58)	(2.58)	(0.97)	(−4.11)	(−1.87)	(0.63)	(0.88)	(2.32)	(0.76)
Trading activity quintile												
Lowest	0.038	−0.004	−0.006	−0.006	0.004	−0.005	−0.019	−0.012	0.005	0.015	0.002	0.008
	(1.60)	(−0.26)	(−0.31)	(−0.57)	(0.82)	(−1.49)	(−1.17)	(−0.69)	(0.27)	(1.39)	(0.26)	(0.98)
2	−0.001	0.009	−0.013	0.012	−0.006	−0.005	−0.027	0.000	−0.002	0.016	0.014*	0.013
	(−0.03)	(0.52)	(−0.75)	(1.02)	(−1.11)	(−1.18)	(−1.57)	(0.02)	(−0.10)	(1.41)	(1.89)	(1.51)
3	−0.020	0.029	−0.005	−0.014	−0.003	−0.012***	−0.042**	−0.008	0.016	0.012	0.006	0.014
	(−0.53)	(1.56)	(−0.27)	(−1.12)	(−0.59)	(−2.73)	(−2.45)	(−0.44)	(0.88)	(0.97)	(0.76)	(1.46)
4	0.122***	0.049**	0.014	−0.010	−0.002	−0.011**	−0.052***	−0.008	−0.019	0.014	0.006	0.008
	(4.35)	(2.46)	(0.78)	(−0.86)	(−0.32)	(−2.18)	(−2.87)	(−0.40)	(−1.01)	(1.19)	(0.70)	(0.83)
Highest	0.182***	0.090***	0.007	0.010	−0.002	−0.009	−0.087***	−0.028	−0.008	0.009	−0.001	0.008
	(6.60)	(4.23)	(0.29)	(0.73)	(−0.23)	(−1.48)	(−4.69)	(−1.34)	(−0.38)	(0.68)	(−0.10)	(0.75)

Table 5 (*continued*)

Portfolio value quintile												
2	0.041*	−0.005	0.021	0.007	0.003	−0.000	0.007	−0.023	−0.006	−0.001	0.005	−0.000
	(1.83)	(−0.33)	(1.05)	(0.75)	(0.62)	(−0.13)	(0.49)	(−1.62)	(−0.42)	(−0.14)	(1.14)	(−0.13)
3	−0.010	−0.012	−0.018	−0.007	0.001	−0.001	0.021	0.011	−0.004	−0.005	0.008	−0.002
	(−0.48)	(−0.78)	(−1.16)	(−0.63)	(0.19)	(−0.24)	(1.56)	(0.76)	(−0.28)	(−0.59)	(1.50)	(−0.40)
4	0.079***	−0.003	−0.023	0.011	0.009*	0.003	−0.000	−0.018	−0.013	0.002	0.005	0.002
	(3.05)	(−0.19)	(−1.50)	(1.05)	(1.76)	(0.85)	(−0.00)	(−1.22)	(−0.89)	(0.19)	(0.87)	(0.47)
Highest	0.093***	−0.010	0.032*	0.015	0.020***	0.006	−0.004	0.025	0.001	0.010	0.013**	0.008
	(3.19)	(−0.56)	(1.75)	(1.32)	(3.22)	(1.33)	(−0.27)	(1.30)	(0.05)	(1.03)	(2.01)	(1.25)
Age	0.009	0.069	0.008	0.066	−0.021	0.026	−0.065	0.081	−0.007	−0.001	0.013	0.017
	(0.07)	(0.78)	(0.09)	(1.18)	(−0.76)	(1.34)	(−0.80)	(0.93)	(−0.08)	(−0.02)	(0.51)	(0.86)

a single sale or no trading after netting all shares bought against those sold. This mitigates the influence of high-frequency day traders.

A hypothetical example clarifies why the Fama-MacBeth approach is sensible. Suppose that the cross-sectional regression on July 15, 1998 for formation period $[-2, -2]$ has (in contrast to Table 5) one regressor—a dummy variable for a stanine 9 IQ. In this case, the slope coefficient is the July 15 return difference between two sets of July 13 purchases. A significantly positive coefficient indicates that on July 15, the typical July 13 stock purchase by the highest-IQ investors outperformed the typical July 13 purchase by others of lower IQ.

The hypothetical example's portfolio interpretation illustrates that the ordinary least squares (OLS) slope coefficient is a self-financing portfolio with portfolio weights determined by the regressor, the highest-IQ dummy. Thus, each July 15 return observation generated by a stanine 9 July 13 purchase receives identical positive weight, while each observation from the July 13 purchases of others receives identical negative weight. The sum of all positive and negative weights is zero because the regression has a constant. The coefficient on the IQ variable is thus the difference in the returns of two portfolios: the vote-weighted purchases of the highest-IQ investors and the vote-weighted purchases of the lower-IQ investors (with each buy contributing one vote for the stock purchased). When we average the time-series of coefficients in the second stage of the Fama-MacBeth process, we compute the average return difference between the two vote-weighted portfolios.

Table 5's columns roughly correspond to non-overlapping windows representing the current day, prior day, prior skip-day, prior week, prior month, and prior three months for the trade. The estimates in Panel A, which control for neither stock nor investor characteristics, represent raw average return differences between IQ-categorized investors' trades. The 0.080 coefficient in the last row of the "Buys $[-2, -2]$" column, for example, indicates that the stocks bought by the highest-IQ investors two days prior outperformed, on average, the stocks bought by the stanine 1–4 investors by 8 basis points. This spread is significant with a t-value of 3.3.

Because Panel A lacks controls, its IQ-related performance estimates could be due to omitted IQ correlates. For example, wealthier investors may make better trades or the characteristics of the stocks that investors trade may vary with IQ stanine. The multivariate regressions in Panel B address these concerns. In these regressions, coefficients on IQ dummies are still interpretable as the return difference between a high-IQ investor purchase (or sale) and a low-IQ investor purchase (or sale). The additional regressors merely change the voting system to a vote based on the component of the IQ dummy that is orthogonal to the other regressors. Like the IQ coefficients, the coefficients for trading activity and wealth categories in Panel A represent marginal effects on future returns from a purchase (left four columns) or sale (right four columns) by an investor in these categories relative to a purchase or sale from the omitted category.

The left (purchase) half of Table 5 Panel B shows that all but two of the 24 IQ coefficients for the above-average stanine dummies (6–9) are positive. Moreover, with just a handful of exceptions, the coefficients increase monotonically as the IQ stanine increases. All but one of the IQ stanine 8 and 9 coefficients are significant at the 5% level for formation periods up to a month prior to the return; the lone exception (stanine 8) is significant at the 10% level.

The most striking numbers in the left half of Table 5 Panel B are in the stanine 9 row. The stanine 9 investors' purchases one, and two days prior, [−1, −1] and [−2, −2], outperform the purchases of the benchmark investors (stanines 1–4 pooled) by 4.5 and 4.4 basis points per day, respectively. Each represents an annualized spread of about 11% per year, a figure interpreted as the difference in alphas between portfolios tied to stanine 9 and stanine 1–4 trades that are rebalanced either daily or every other day. Summing the prior-day coefficient and the products of the earlier formation period coefficients and the number of trading days in the respective formation period means that a single buy from a stanine 9 investor is expected to generate about 44 basis points more alpha than a buy from a stanine 1–4 investor in the month after the buy, an annualized rate (to a monthly rebalanced portfolio) of 5.3%.[14]

IQ's influence on same-day returns for purchases is even greater than its influence on next-day returns. Table 5's Panel B [0, 0] column indicates that stanine 9 purchases earn same-day returns that exceed the returns of the benchmark IQ group's purchases by a highly significant 15 basis points, while stanine 8 purchases earn 10.6 basis points more than the benchmark group.

For each of the above-average IQ stanines (6–9), Panel B's performance pattern for purchases is almost perfectly monotonic in the distance of the formation period from the return date. The dying off of the performance advantage as the formation period recedes into the more distant past generates an insignificant performance advantage of half a basis point per day (about 1.25% per year) for the purchases of the most intellectually gifted at the most distant horizon, [−63, −22]. We also verified that the IQ-related performance advantage is absent at more distant horizons up to one year in the past—but spare the reader further details for brevity.

The evidence for purchases, particularly with stanine 9, is consistent with the same phenomenon driving the superior performance at all horizons up to one month in the past: a better understanding of fundamental values on the part of high-IQ investors. One cannot with certainty distinguish whether this better understanding of fundamental values is driven by material private information or by better processing of public information. Some might argue that the decay in economic significance as the formation period recedes into the past seems to favor material private information, publicly disclosed within a month, as playing some (if not the major) role in our finding. However, for the three formation periods within the month, the t-statistics for the differences in coefficients are small. For example, the t-statistic for the difference between the IQ stanine 9 coefficients for [−2, −2] and [−21, −6] is 1.28; it is even smaller for the [−2, −2] and [−5, −3] difference. Moreover, even if the coefficient differences across the horizons are not a statistical fluke, theory, such as Kyle (1985), suggests that trades, and not just public disclosures, can reveal private valuations over relatively short periods of time. In light of this, and additional evidence discussed in the conclusion, we remain agnostic about the source of high-IQ investors' superior returns.

In contrast to the buys, the right side of Table 5 suggests that one cannot infer that high IQ generates superior sell-side performance. Sales lack the same monotonicity and except for stanine 9's same-day return coefficients, every coefficient's magnitude is below 4 basis points. All but two of the IQ coefficients in the right half of Table 5 Panel A and three in Panel B are statistically insignificant at the 5% level, and the only common one is the [0, 0] coefficient for stanine 9. The remaining three significant coefficients strike us as chance results, arising from the multiple comparison of 60 t-statistics; one even indicates that high-IQ investors' sales underperform those in the lowest-IQ category, but only at one horizon and by 1.1 basis points.

The same- and next-day returns from sales by the highest-IQ category are, however, significantly below the comparable returns of those of the benchmark group. For example, the next-day returns from sales are 3.3 basis points below the returns from the benchmark group's sales with a t-value of −1.87 and the same-day returns associated with stanine 9 sales are 6.8 basis points below the benchmark group with a t-value of −4.11. It seems unlikely that both of these coefficients are chance events, but it is hard to assess if these coefficients represent real performance, of the type associated with superior information, or a market microstructure phenomenon. The price at which a trade is executed, as well as the price path for a short period afterwards, can vary with an investor's skill at mitigating trading costs. If high IQ reduces trading costs, we would observe positive coefficients for high-IQ dummies for buys and negative coefficients for sells at least on the day of the trade. The previous-day formation period could also be affected if liquidity shocks can last for more than a day. For this reason, it is difficult to assess whether the significant coefficients in Table 5's nearest formation periods arise from the high-IQ investors' superior information about future stock returns or the ability of high-IQ investors to trade intelligently in a market with trading costs.

Table 5 Panel B offers evidence that trading costs may be contaminating our inferences here. For all but the same- and prior-day formation periods, the investor's prior degree of trading is unrelated to performance. However, for the same- and next-day returns in Table 5, and for both buys and sells, prior trading activity seems to be a more important predictor of returns than IQ. For example, the same-day purchases of the highest prior trading activity quintile earn 18.2 basis points more that day than the purchases of the lowest trading activity quintile; the same-day returns of stocks sold are 8.7 basis

[14] A portfolio constructed at the end of trading day t earns 4.5 basis points on day $t+1$, 4.4 basis points on day $t+2$, 3.3 basis points per day on days $t+3$ through $t+5$, and 1.6 basis points per day on days $t+6$ through $t+21$. Thus, the return on a portfolio that is rebalanced once a month is $12*(0.045+0.044+3*0.033+16*0.016)=5.3\%$ per year.

points below those stocks sold by the lowest trading activity quintile.

Fig. 3 summarizes these performance results by cumulating the return effect from the coefficients observed in Table 5 Panel B. Fig. 3 Panel A graphs the buy IQ coefficients, Panel B graphs the sell IQ coefficients, and Panel C plots the difference between buys and sells. As we move towards higher IQ in Panel A—the rear of the graph—the coefficients rise dramatically. By contrast, Panel B does not display the same monotonicity.

4.3. Intelligence and trading costs

If some investors are better at mitigating trading costs, one should not be surprised if the short-term returns of their buys are larger and those of their sells are smaller than others' returns. For example, a market order performs better when the price impact of a trade is low and the bid-ask spread is narrow. By contrast, a limit order performs better (ceteris paribus) when there is little or no adverse selection from execution against informed traders. One expects investors with higher IQ and more trading experience to be better able to choose an order strategy (including order type) that best fits the prevailing liquidity environment.

To address the issue of who achieves better trade execution, we analyze the HEX microstructure data set described earlier. Although the three-year sample length is shorter than the eight-year sample analyzed in Table 5, the microstructure data set allows us to separately analyze market orders and limit orders, as well as second-by-second movements in bid and ask prices.

Table 6's Fama-MacBeth methodology is similar to Table 5's performance analysis. As before, we analyze

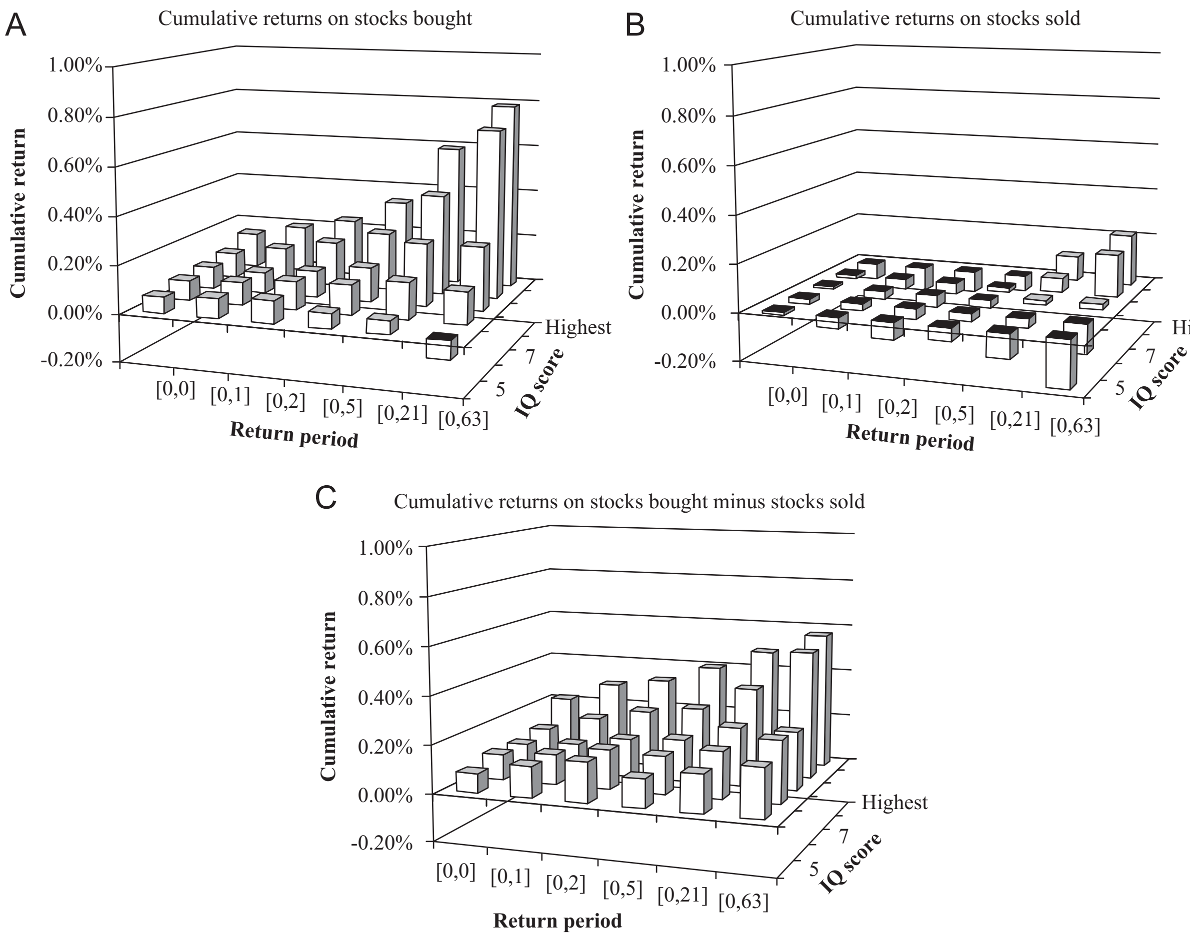

Fig. 3. Performance of investor trades by IQ and formation period. Each panel of Fig. 3 plots average IQ-related coefficients for six daily cross-sectional regressions reported in Table 6. We exclude any day t regression that lacks trades in at least 30 stocks. Panel A (Panel B) plots the cumulative returns on stocks bought (sold) by investors, imputed using the buy-side coefficients in Table 6. Panel C plots the difference between buys and sells. The dependent variable in the first stage of the two-stage procedure is the day t daily return of stock j for data point n if stock j was purchased (Panel A) or sold (Panel B) in the formation period corresponding to the columns. The investor-related regressors are IQ stanine, number of trades prior to day $t-64$, and stock portfolio wealth at $t-64$, which are described in the text. IQ stanines 1–4, zero trading activity, and the pool of zero portfolio wealth and the lowest quintile of portfolio wealth are the omitted categories. The firm-level regressors are the stock's Scholes-Williams beta, size rank of the firm, book-to-market rank of the firm, and past returns of the stocks over intervals $[-1, -1]$, $[-5, -2]$, $[-21, -6]$, and $[-252, -22]$. See the text for details. After collecting coefficient estimates from each day in the 1/1995–11/2002 sample period, the second stage computes the means of these coefficients. IQ data are from 1/1982 to 12/2001.

Table 6

Intelligence and intraday returns.

Table 6 reports average coefficients and Fama-MacBeth t-statistics (in parentheses), computed from daily cross-sectional regressions. We exclude any day t regression that lacks trades in at least 30 stocks. Panel A reports on eight regressions from market-order trades and Panel B reports on eight regressions associated with executed limit orders. The dependent variable in the first stage of the two-stage procedure is the intraday return of stock s for the data point of investor j and stock s, which is defined differently across the eight regressions in each panel. The first and fifth columns measure the return from the execution price to the bid-ask midpoint an instant before the trade executes. The second, third, sixth, and seventh columns measure returns from the execution price to the bid-ask midpoint of the stock t minutes after the trade executes, where t is the column label. The fourth and eighth columns compute the intraday return from the execution price to the closing transaction price for the day. The investor must be a seller or a buyer of some stock on day t using a market order to be included in the Panel A regressions and a buyer or seller of some stock on day t using a limit order to be included in the Panel B regressions. The investor-related regressors are categorical variables representing the investor's IQ stanine, number of trades prior to day t-64, and stock portfolio wealth at t-64, which are described in the text. IQ stanines 1–4, zero trading activity, and the pool of zero portfolio wealth and the lowest quintile of portfolio wealth are the omitted categories. Although not reported, there are seven stock-level regressors: the stock's Scholes-Williams beta, size rank of the firm, book-to-market rank of the firm, past returns of the stock over intervals [−1, −1], [−5, −2], [−21, −6], and [−252, −22], and the stock's average bid-ask spread (computed over the prior 21 trading days). We report only on the bid-ask spread regressor. Each cross-sectional regression is estimated separately for purchases and sales and for each intraday return horizon. After collecting coefficient estimates from each day in the September 18, 1998 through October 23, 2001 sample period, the second stage computes the means of these coefficient estimates and the associated t-statistics from the time-series of coefficients. Coefficients denoted with *, **, *** are significant at the 10%, 5%, and 1% level, respectively.

Independent variables	Dependent variable: Return from trade to bid-ask midpoint or to closing price, percent							
	Buys				Sells			
	Bid-ask midpoint at			Closing price	Bid-ask midpoint at			Closing price
	0 min	1 min	5 min		0 min	1 min	5 min	
Panel A: Market orders								
IQ score								
5	0.010	−0.002	−0.007	0.003	−0.000	0.002	0.018	0.028
	(1.40)	(−0.14)	(−0.44)	(0.12)	(−0.04)	(0.15)	(1.19)	(0.86)
6	−0.000	0.018	0.023	0.096***	−0.009	−0.007	−0.005	0.010
	(0.01)	(1.61)	(1.32)	(3.58)	(−1.24)	(−0.57)	(−0.30)	(0.34)
7	0.014	0.013	−0.002	0.090***	−0.012	−0.037**	−0.013	0.027
	(1.54)	(0.92)	(−0.14)	(2.63)	(−1.42)	(−2.35)	(−0.77)	(0.59)
8	0.010	0.011	0.017	0.118***	−0.021*	−0.023	−0.012	0.007
	(1.13)	(0.75)	(0.72)	(3.46)	(−1.86)	(−1.29)	(−0.57)	(0.17)
Highest	0.021**	0.034**	0.029	0.139***	−0.037**	−0.036**	−0.042**	−0.040
	(2.25)	(1.98)	(1.25)	(3.82)	(−2.50)	(−2.50)	(−2.09)	(−0.96)
Trading activity quintile								
Lowest	0.006	0.024*	−0.006	0.006	0.034	0.046**	−0.160	0.013
	(0.83)	(1.93)	(−0.33)	(0.18)	(1.60)	(2.11)	(−0.86)	(0.30)
2	0.030***	0.037***	0.070***	0.092***	−0.002	0.010	−0.021	−0.033
	(2.86)	(2.78)	(4.18)	(2.58)	(−0.19)	(0.55)	(−0.99)	(−0.70)
3	0.034***	0.092***	0.100***	0.076**	−0.019	−0.009	−0.044*	−0.079*
	(4.25)	(5.28)	(5.08)	(2.16)	(−1.17)	(−0.41)	(−1.90)	(−1.74)
4	0.054***	0.128***	0.140***	0.128***	−0.030**	−0.026	−0.050*	−0.087**
	(6.04)	(6.91)	(6.58)	(3.27)	(−2.35)	(−1.15)	(−1.69)	(−2.00)
Highest	0.066***	0.196***	0.238***	0.286***	−0.053***	−0.077***	−0.149***	−0.202***
	(8.18)	(12.41)	(12.06)	(7.09)	(−4.95)	(−3.94)	(−5.86)	(−4.27)
Portfolio value quintile								
2	−0.003	−0.012	−0.009	−0.012	0.002	−0.012	−0.002	0.060*
	(−0.37)	(−1.02)	(−0.57)	(−0.44)	(0.22)	(−0.85)	(−0.12)	(1.67)
3	−0.004	−0.004	−0.017	0.014	−0.026***	−0.033***	−0.014	0.030
	(−0.46)	(−0.34)	(−1.03)	(0.41)	(−2.87)	(−2.37)	(−0.87)	(0.90)
4	0.004	0.003	−0.009	0.057*	−0.020	−0.050***	−0.003	0.056
	(0.52)	(0.14)	(−0.46)	(1.85)	(−1.57)	(−2.67)	(−0.13)	(1.48)
Highest	0.019**	0.072***	0.083**	0.117***	−0.016*	−0.078***	−0.056***	−0.011
	(2.00)	(2.89)	(2.49)	(3.30)	(−1.69)	(−4.87)	(−3.07)	(−0.34)

Table 6 (*continued*)

Independent variables	Dependent variable: Return from trade to bid-ask midpoint or to closing price, percent							
	Buys				Sells			
	Bid-ask midpoint at			Closing price	Bid-ask midpoint at			Closing price
	0 min	1 min	5 min		0 min	1 min	5 min	
Age	−0.044	0.121	0.209*	−0.001	−0.008	−0.103	−0.105	−0.103
	(−0.91)	(1.46)	(1.89)	(−0.00)	(−0.14)	(−1.07)	(−0.63)	(−0.51)
Past spread	−29.564***	−13.003***	−14.625***	6.415**	33.545***	21.436***	18.645***	9.806***
	(−35.41)	(−10.11)	(−8.33)	(2.35)	(39.47)	(18.22)	(8.36)	(3.15)
Panel B: Limit orders								
IQ score								
5	−0.014	−0.010	−0.029	0.021	−0.003	−0.005	−0.002	0.024
	(−1.34)	(−0.45)	(−1.33)	(0.58)	(−0.35)	(−0.32)	(−0.12)	(0.73)
6	−0.002	−0.011	−0.046*	0.073**	0.006	−0.040	−0.028*	−0.029
	(−0.23)	(−0.56)	(−1.70)	(1.96)	(0.67)	(−1.33)	(−1.66)	(−0.82)
7	0.002	0.019	0.015	0.010	−0.012	−0.002	−0.020	−0.016
	(0.20)	(0.68)	(0.62)	(0.27)	(−1.36)	(−0.09)	(−1.04)	(−0.37)
8	−0.008	0.011	0.016	0.084**	−0.005	−0.008	−0.011	−0.062
	(−0.71)	(0.46)	(0.65)	(2.24)	(−0.52)	(−0.41)	(−0.45)	(−1.19)
Highest	−0.003	0.047**	0.035*	0.112**	0.005	−0.040**	−0.055***	−0.096**
	(−0.24)	(2.05)	(1.66)	(2.42)	(0.48)	(−2.41)	(−2.74)	(−2.24)
Trading activity quintile								
Lowest	0.005	−0.029	0.003	−0.019	0.005	−0.000	0.027	−0.049
	(0.40)	(−1.13)	(0.10)	(−0.53)	(0.38)	(−0.02)	(1.04)	(−1.17)
2	−0.001	−0.020	0.022	−0.003	0.013	−0.059**	−0.027	0.020
	(−0.12)	(−0.89)	(0.86)	(−0.07)	(1.24)	(−1.99)	(−1.12)	(0.46)
3	0.020	0.047*	0.073***	0.079*	−0.001	−0.063***	−0.042*	−0.012
	(1.60)	(1.94)	(2.72)	(1.94)	(−0.10)	(−2.62)	(−1.78)	(−0.26)
4	0.025**	0.100***	0.129***	0.128***	0.018*	−0.078***	−0.085***	−0.000
	(2.21)	(3.87)	(4.22)	(2.88)	(1.77)	(−3.36)	(−3.67)	(−0.00)
Highest	0.055***	0.148***	0.182***	0.246***	−0.010	−0.124***	−0.122***	−0.139***
	(5.16)	(6.07)	(6.12)	(5.47)	(−0.95)	(−5.24)	(−4.50)	(−3.20)
Portfolio value quintile								
2	−0.003	−0.005	0.005	0.047	−0.018*	0.032	0.032*	−0.007
	(−0.31)	(−0.23)	(0.21)	(1.29)	(−1.89)	(1.42)	(1.86)	(−0.19)
3	−0.002	0.018	0.015	0.079**	−0.010	0.049*	0.038**	0.018
	(−0.20)	(0.90)	(0.79)	(2.29)	(−1.00)	(1.73)	(2.25)	(0.53)
4	−0.015	0.053**	0.050*	0.104***	−0.004	0.006	0.032	−0.013
	(−1.42)	(2.03)	(1.81)	(2.85)	(−0.41)	(0.24)	(1.54)	(−0.35)
Highest	−0.023**	0.024	0.025	0.050	0.001	−0.004	0.006	0.011
	(−2.19)	(0.99)	(1.11)	(1.32)	(0.09)	(−0.20)	(0.30)	(0.32)
Age	0.072	−0.039	−0.002	0.094	−0.007	0.080	−0.071	−0.282
	(1.32)	(−0.33)	(−0.01)	(0.45)	(−0.11)	(0.79)	(−0.62)	(−1.09)
Past spread	38.637***	13.103***	12.747***	13.134***	−40.118***	−14.822***	−15.912***	8.112***
	(43.89)	(9.61)	(9.38)	(5.39)	(−48.24)	(−9.62)	(−10.96)	(3.46)

average coefficients from cross-sectional regressions with returns on the left-hand side. Here, however, returns are computed from the execution price of the trade to the average of the bid and ask prices at the time of the trade, or one or five minutes after the trade. Table 6, like the same-day return column of Table 5, also computes intraday returns from the execution price to the closing transaction price. It is useful to think of both sets of intraday returns as measures of whether the execution price of a trade is high or low in comparison to relevant benchmarks throughout the day. A high intraday return means a low execution price, which is good for a purchase and bad for a sale.

Because trading costs might differ between market and limit orders, and between buys and sells, Table 6 employs 16 regressions—each representing whether the trade is buy or sell, whether the trade originates from a market or limit order, and which of four different return horizons apply. Data points for each regression are all pairings of investors and the stocks traded on day t with the relevant order type (market or limit and buy or sell). In rare instances when an investor has multiple trades of the same order type in a given stock on the same day, we employ the average intraday return for the stock. The average equal weights all of the investor's same-order-type trades (market or limit) in a given stock.

The regressors, as before, consist of investor age and dummy variables representing IQ, trading activity, and portfolio wealth categories. The dummy coefficients estimate the marginal return effects that arise from purchases (left-hand side) or sales (right-hand side) by investors belonging to these categories. Stock attributes, using the same beta, book-to-market, firm size, and past returns controls as in Table 5 are also included in Table 6's regressions. Once again, we omit these coefficients from the table for brevity. Finally, Table 6 also makes use of an additional regressor, which controls for the recent bid-ask spread of a stock. This regressor is the average spread of the stock, sampled every minute, over the prior 21 trading days.

Table 6 Panel A indicates that the market orders of high-IQ investors face significantly lower bid-ask spreads than the market orders of the benchmark investors. The "0" minutes intraday return is measured to the bid-ask midpoint an instant before execution and is thus always negative for market-order buys and positive for sells. We can infer the relative size of the bid-ask spread faced by the investor categories from the coefficients in this column. The coefficient of 0.021% for the stanine 9 buys indicates that the bid-ask spread is narrower for these smart investors, resulting in a 2.1 basis point less negative intraday return at the time of trade execution. The comparable coefficient of −0.037% for the sells of these investors also is indicative of a smaller spread, which generates a 3.7 basis point larger portfolio return at the margin. Because we control for the stock's average bid-ask spread over the prior 21 trading days, these coefficients indicate that high-IQ investors exhibit better spread timing than low-IQ investors, placing market orders when bid-ask spreads narrow in a stock.

In the absence of private information that could imminently become public, an investor facing a temporarily wide bid-ask spread would be better off waiting for the spread to converge to its norm before placing an order. Similarly, when a spread is unusually narrow, it is time to pounce on an intended trade. The "0" minutes column in Panel A indicates that the highest-IQ investors' market orders exhibit superior spread timing.

Trading costs for market orders are a function of the bid-ask spread at the time the order is executed, as well as market impact costs, arising from temporary price movements that tend to reverse.[15] For example, consider an investor who buys a stock after its price has been pushed up by others' buy orders. If the price subsequently declines, there was a temporary market impact from prior trades. This is a trading cost to the investor who failed to see that illiquidity, rather than fundamentals, pushed the price up. Because of this temporary impact, it is useful to also see how well an investor's trade performs after execution.

Table 6 Panel A indicates that the market-order buys of high-IQ investors not only do better at the time of execution, but generally have prices that appreciate more (or depreciate less) than the market-order buys of low-IQ investors as the day wears on. The increase in profitability as time elapses could either be consistent with high-IQ investors obtaining superior information about stocks purchased or with high-IQ investors being more capable of exploiting liquidity-related movements in the universe of stocks available for purchase. By contrast, while high-IQ investors' market-order sales also do better at the time of execution, the difference, compared to low-IQ investors, does not change markedly as the day wears on.

The evidence on the value of having a high IQ is equally compelling for limit orders. Panel B suggests that at market close on the day of the trade, high-IQ investors' executed limit orders outperform low-IQ investors' limit orders by 11.2 basis points on the buy side and by 9.6 basis points on the sell side. These differences indicate that the limit orders of high-IQ investors face lower adverse selection costs than those of low-IQ investors.

Panel A's coefficients on the trading activity dummies indicate that experience matters for market orders. The most experienced investors place buy and sell market orders when the bid-ask spreads are the narrowest. With few exceptions, Panel A's intraday return coefficients increase monotonically for buys and decrease for sells as trading experience increases. The effective trading costs thus diminish with trading experience. Moreover, for the highest trading activity quintile, the advantage increases as the day wears on. The t-statistics are substantially larger than those for IQ. For example, the five-minute intraday returns of the highest trading activity quintile have t-statistics of 12.1 and −5.9 for purchases and sales, respectively.

Past trading activity also significantly determines one's ability to avoid adverse selection costs for limit orders. After trade execution, Panel B's coefficients on the highest trading activity quintile are far larger for buys and far smaller for sells than the coefficients on the highest IQ group. Either the most frequent traders learn how to

[15] See, for example, Holthausen, Leftwich, and Mayers (1990) and Keim and Madhavan (1996).

achieve lower adverse selection costs or those endowed with an ability to mitigate adverse selection become the most active traders.

Being in the highest wealth quintile also reduces trading costs, but only for market orders. In Table 6 Panel A, all but two of the eight intraday return regressions to the bid-ask midpoint have significantly positive coefficients on the highest portfolio quintile dummy for buys and significantly negative coefficients for sells. This is all the more remarkable in that the wealthiest investor quintile tends to place orders with the largest trade sizes and we place no greater weight on large-sized trades. Age has no effect, either here or in Table 5, which stands in marked contrast to other studies.

The highly significant trading experience and wealth regressors in the Table 6's microstructure analysis punctuate the importance of IQ in Table 5's long-run return analysis. In Table 5, trading activity, wealth, and age do not exhibit a significant positive relationship with performance.[16] Thus, while increases in wealth and trading experience significantly reduce trading costs, only IQ score appears to correlate reliably with superior stock-picking skills.

The final coefficients of interest are those on the prior bid-ask spread, at the bottom of Table 6's panels. These are negative for market-order buys and limit-order sells and positive for market-order sells and limit-order buys for the three intraday returns computed to the bid-ask midpoint. The coefficient sign pattern arises from the tendency of market-order buys and limit-order sells to execute above the bid-ask midpoint while the reverse is true for market-order sells and limit-order buys. For market-order buys and limit-order sells (which execute against market-order buys), the past bid-ask spread coefficient reverses in sign for the return-to-the-close regression (becoming positive). The sign reversal is consistent with superior information as the motive for market-order buys. By contrast, there is little adverse selection in the remaining pair of trade types (right side of Panel A and left side of Panel B) because neither counterparty's order is a market-order buy.

5. 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 mitigating trading costs. 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, and high-IQ investors' purchases are informative about future stock price movements. 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. Incidental to the effect of IQ, we found that the intensities of both disposition-effect trading behavior and December tax-loss selling depend on the magnitude of a capital loss but not on the magnitude of the capital gain.

We verified that the stock-picking advantage of high-IQ investors is not generated by a market microstructure phenomenon or reduced by higher transaction costs. There are significant performance differences across IQ groups even when we skip a day between the formation period and test day. Moreover, with superior intraday and next-day returns, and both market and limit orders that outperform those of low-IQ investors within the first five minutes of a trade, high-IQ investors bear no additional cost that offsets their stock-picking advantage.

In addition to the paper's reported performance analyses, we performed four robustness checks of performance findings, summarized as follows. First, netting purchases and sales in the same stock over the entire formation period (rather than each day) does not alter the results. Second, non-parametric tests, geared towards coefficient estimation in the presence of fat or skewed tails, strengthen the statistical significance of our findings. Third, breaking the sample into early and late subperiods yields similar findings about the positive relationship between IQ and performance for both subperiods. Fourth, the exclusion of Nokia trades from the sample does not materially influence the results.

We also tested several other specifications but left these out of the paper for brevity. First, we studied whether the interaction of age and IQ influenced the performance findings, but the interactions were insignificant, perhaps due to the fact the IQ sample does not cover investors who are old enough to suffer from age-related cognitive deterioration. Second, we split the sample into "reinvestment" and "liquidity" trades, that is, sales that are followed shortly by buys (reinvestment trade) rather than sells whose proceeds are then removed from the portfolio. Here, interactions of a "repurchase" dummy with IQ dummies yielded insignificant coefficients. Third, excluding small trades and trade-size weighting appeared to increase noise and decreases statistical significance. Finally, we studied high-IQ investors' style timing—for example, do they invest more in value stocks on days when value does well? Here, we estimated daily risk premia for value and size and replaced actual stock returns with these estimates. We then repeated the analysis of performance. This computation effectively drops the idiosyncratic component of a stock's return and focuses on the day-to-day variation in returns arising solely from each stock's characteristics. The estimated IQ-style timing coefficients were not statistically significant at conventional levels.

Our 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

[16] In Table 5, the $[-21, -6]$ formation period purchases of the wealthiest quintile of investors outperform the purchases of the least wealthy quintile by 2 basis points on day t. However, this could be a chance result in that sales by the wealthiest in the same formation period also have significantly higher returns (1.3 basis points) than sales of investors in the least wealthy quintile.

their buy 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, Keloharju, and Linnainmaa (2011) 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. Bailey, Kumar, and Ng (2011) study the choices of mutual fund investors and find that "behaviorally biased investors" make poor decisions about, among other things, fund style and expenses. 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.

We also discovered that high-IQ investors' stock purchases predict price increases but their stock sales say little about price decreases. This asymmetry hypothesis, first advanced by Chan and Lakonishok (1993) and Saar (2001), is supported by evidence from Kraus and Stoll (1972), Choe, McInish, and Wood (1995), Busse and Green (2002), and Cohen, Frazzini, and Malloy (2008). Further study of IQ's asymmetric predictive power may shed light on whether the greater information in stock purchases arises from informative sales being diluted by sales driven by liquidity shocks—or whether it is simply easier to profit from a positive signal because fewer trading restrictions exist on the buy side.

The source of high-IQ investors' stock-picking skill is unresolved. High-IQ investors may have better access to non-public information, they may be better at processing public or private information, or their greater immunity to behavioral biases may boost their returns. Whichever it is, market prices incorporate the valuations of high-IQ investors within a relatively short period of time—one month. Because there is little effect beyond one month, and because the magnitude of the profits from stock-picking ability increases as the formation period moves closer to the trade date, it is tempting to argue that high-IQ investors are merely obtaining inside information that will imminently be disclosed to the public. Since we know that insider trading exists, this phenomenon is likely to play some role in our findings. On the other hand, the coefficient pattern per se does not ensure that more innocuous sources of advantage to high-IQ investors could also be contributing to our findings. Even if the abnormal returns of high-IQ investors' trades arise merely from a superior ability to estimate discounted cash flows, existing models suggest that trades by informed investors could reveal the better valuation to the market over time. This revelation process could plausibly erode any advantage held by smart investors within a month.

Further empirical analysis could potentially assess how high-IQ investors earn their superior returns. However, despite our best efforts, we can only present mixed evidence that does little to resolve the issue. For example, we reran Table 6's performance analysis after filtering out stock-day observations with large absolute returns. Support for the insider-trading story critically depends on the size of the filter. Surprisingly, it is the filters for the larger absolute returns that are least consistent with this story. Moreover, the abnormal returns of high-IQ investors' purchases do not cluster around earnings announcements. Finally, there is nothing in the distribution of portfolio returns of high- and low-IQ investors to suggest that the distribution shift is largely occurring at one end of the distribution function.

So what can we conclude about the degree of market efficiency from this evidence? The answer really depends on one's definition of efficiency. In the Grossman (1978) model, informed traders profit from noisy supply, making it highly profitable to mimic the informed agents' collective trades. This is evidence of inefficiency, in that prices do not fully and instantly reflect the information of all traders. However, the advantage to being informed should be relatively small. Rational expectations inferences generate prices that reduce the value of each informed trader's private information signal. There is a benefit to having a private signal, but most of that benefit is lost to the rational expectation process. Moreover, the benefit from learning about others' private information from prices is fully competed away.

Our findings are consistent with this model. Mimicking high-IQ investors' collective trades is quite profitable: the abnormal returns of a portfolio constructed from yesterday's (or the day before yesterday's) purchases of the highest-IQ investors exceed the abnormal returns of below-average IQ investors by an average of about 11% per year. This difference is comparable to the returns to a portfolio that follows a momentum strategy or mimics the trades of corporate insiders. Even if one limits the mimicking to one trade per month, the strategy earns an extra return of 44 basis points over the subsequent month and 5.3% over the year.

An alternative and perhaps more appropriate view is that market efficiency means that securities prices are fair or nearly fair to all. With this definition, the conclusion is unambiguous. Comparing the least intelligent to the most intelligent group, there is no disadvantage when selling and the disadvantage from a purchase is a mere 44 basis points, entirely borne within a month after the purchase. For someone who trades frequently, 44 basis points per trade is a daunting hurdle to overcome. However, a disadvantage of this magnitude is quite small indeed if you are a low-IQ investor who trades infrequently or with less intelligent segments of the population as counterparties. From this perspective, markets are close to being efficient.

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