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ABSTRACT

This study analyzes whether high IQ investors exhibit superior investment performance. It combines equity return, trade, and limit order book data with two decades of scores from an intelligence test administered to nearly every Finnish male of draft age. Controlling for wealth, trading frequency, age, and determinants of the cross-section of stock returns on each day, we find that high IQ investors exhibit superior stock-picking skills, particularly for purchases, and superior trade execution for both purchases and sales.

Keywords: Intelligence, household finance, trading performance

JEL classification: G11, G14

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The behavioral finance literature finds that individual investors, on average, make major investment mistakes. They under-participate in the stock market, grossly under diversify, enter wrong ticker symbols, buy index funds with exorbitant expense ratios, and lose when actively trading in the stock market.[1] However, a more nuanced and less gloomy portrait emerges when we focus on the heterogeneity of individual investors. Several studies uncover a minority of individual investors whose trades systematically outperform the market[2] and some research establishes that this performance correlates with experience.[3]

It would be useful to understand the fundamental forces that explain why some investors outperform others. However, without better data, empirical work cannot lay a proper foundation for the analysis of this issue. For example, the extant literature cannot assess whether experience or more fundamental investor attributes account for success or failure in the stock market. For obvious reasons, individuals with the innate ability to succeed at most tasks, including investment, tend to obtain vast stock trading experience. Moreover, those endowed with low investment talent may learn from a limited stock trading failure that further experience is to be avoided.

This paper, which makes use of nearly two decades of comprehensive IQ scores from inductees in Finland's mandatory military service, analyzes whether intelligence predicts

[1] See, for example, Odean (1999), Barber and Odean (2000, 2001, 2002), Rashes (2001), Campbell (2006), and Calvet, Campbell, and Sodini (2007, 2009a, 2009b), among others.

[2] See Coval, Hirshleifer, and Shumway (2003), Barber, Lee, Liu, and Odean (2004), and Che, Norli, and Priestley (2008).

[3] See Barber, Lee, Liu, and Odean (2004), Linnainmaa (2009b), Seru, Stoffman, and Shumway (2009), and Nicolosi, Peng, and Zhu (2009).

superior performance. Intelligence is a natural *a priori* choice for an exogenous attribute that could be related to successful stock investing. Using approximately eight years of data, we find that high IQ investors' stock purchases subsequently outperform low IQ investors' purchases by an economically and statistically significant margin, particularly in the near future. The performance differences arise from high IQ investors' exceptionally good stock picks and not from low IQ investors' poor stock picks.

In addition to investigating whether high IQ investors' trades subsequently outperform low IQ investors' trades, we analyze whether IQ influences trading costs. A good portion of this analysis marries the Finnish stock market's second-by-second limit order book with stock trading and stock exchange data. The limit-order data, available for three years, allows us to precisely identify trading costs by comparing the execution price with various bid-ask midpoints throughout the day. It also allows us to analyze trading costs separately for market orders and limit orders and control for historical differences in liquidity across stocks. We are the first to document that high IQ investors are more likely to obtain lower trading costs, both for market and limit orders. The execution prices of stocks bought by high IQ investors—in comparison to the bid-ask midpoint 0, 1, and 5 minutes after the trade, as well as to the day's and next day's closing transaction price—are relatively lower than those of stocks bought by low IQ investors. Moreover, the execution prices for stocks sold by high IQ investors are relatively higher. The results control for the typical bid-ask spread of a given stock. Thus, the market orders of smart investors are placed at times when bid-ask spreads temporarily narrow. The limit orders of smart investors face less adverse selection—that is, they are less likely to execute against an order placed by an investor with superior private information about the stock.

No paper in the literature has data that so cleanly addresses the issue of whether intellectual ability generates investment performance. Instruments for cognitive ability, notably age, have been shown to be related to investment performance.[4] Studies also find that a mutual fund's performance is predicted by the average SAT score at the fund manager's undergraduate institution or average GMAT score at the fund manager's MBA program.[5] However, age may proxy for other performance-related variables, like trading experience or facility with computer-based information gathering. Moreover, attending a school with a higher average test score tends to generate a more valuable network of alumni connections.[6] For research to properly address the causal link from cognitive ability to investment performance, it is important to measure each investor's IQ. Our study meets this standard using a sample that is comprehensive for males born in a developed country over a two-decade period.

The timing of our IQ assessment also helps address the issue of causation. Because our data set assesses intelligence years, and sometimes decades, before the observed trading occurs, IQ is exogenous to the trading outcome. Other investor characteristics considered in the literature cannot easily address the direction of causality. For example, financial literacy may be positively related to stock market participation, not because financially literate individuals understand that a large equity premium makes stocks attractive, but because financial literacy arises from stock market participation. And if certain behavioral patterns, such as under-diversification or the

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[4] See Korniotis and Kumar (2009).

[5] See Chevalier and Ellison (1999) and Gottesman and Morey (2006).

[6] See Chevalier and Ellison (1999). Their networking hypothesis is supported by the findings of other papers. Coval and Moskowitz (2001) document superior performance that arises from a geographic connection between fund managers and the companies they invest in. Cohen, Frazzini and Malloy (2008) identify a direct connection between mutual fund managers and the CEOs of companies they invest in.

disposition effect (the tendency to sell winning stocks more than losers) are indeed wealth destroying, causality between wealth and trading success may run in reverse: less wealthy households are less wealthy because their behavioral biases generate wealth-reducing investment decisions. Our innate intelligence measure is not subject to this argument, as the test scores of military inductees cannot be influenced by stock trading that takes place years later.

The IQ findings employ a Fama-MacBeth (1973) regression methodology. Each of the approximately two thousand cross-sectional regressions studies how a stock's daily return is predicted by trading decisions in prior days by IQ-categorized investors. (A nearly identical Fama-MacBeth methodology, partly making use of intra-day returns, also is used to study how IQ influences trade execution costs.) There is clear evidence that high IQ investors' stock purchases predict price increases. Sells of higher IQ investors have little predictive power for price decreases. This asymmetry is consistent with the argument that it is easier to profit from a positive signal because fewer trading restrictions exist on the buy side.[7] The performance result is strongest for the 4% of the population with the highest score on the intelligence test. The return difference between high and low IQ investors' purchases is about the same for stocks bought one and two days prior; the return difference drops for purchases made in the more distant past, becoming negligible for purchases made more than one month prior.

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

[7] Chan and Lakonishok (1993) and Saar (2001) advance this hypothesis. Papers by Kraus and Stoll (1972), Choe, McInish, and Wood (1995), Cohen, Frazzini, and Malloy (2008), and Busse and Green (2002) find evidence that the market acts as if buys are more informative than sales.

investing. These include wealth, trading frequency, and age, all of which also proxy for the investment experience obtained prior to the trades analyzed. We also employ the usual set of controls for stock characteristics, including beta, book-to-market ratio, firm size, and past returns from four horizons. Thus, differences in the exposures of high and low IQ investors' trades to known return predictors cannot account for our results. These results are economically significant: the abnormal returns of a portfolio constructed from yesterday's (or the day before yesterday's) purchases of the highest IQ investors, which control for the variables described above, exceed the abnormal returns of below-average IQ investors by an average of about 11% per year.

Our paper is organized as follows. We begin with a description of the data and summary statistics on our sample. We follow this with a results section, which first studies IQ-related performance and then IQ-related trading costs. We end with a summary and conclusion section.

I. Data

A. Data Sources

We merge five data sets for our analysis.

Finnish Central Securities Depository (FCSD) registry. The FCSD registry reports the daily portfolios and trades of all Finnish household investors from January 1, 1995 through November 29, 2002. The electronic records we use are exact duplicates of the official certificates of ownership and trades, and hence are very reliable. Details on this data set, which includes date-stamped trades, holdings, and execution prices of registry-listed stocks on the Helsinki

Exchanges, are reported in Grinblatt and Keloharju (2000).[8] The FCSD registry also contains investor birth years which we use to control for age.[9]

HEX stock data. The Helsinki Exchanges (HEX) provide daily closing transaction prices for all stocks traded on the HEX, as well as daily data on two stock indexes. The daily stock prices are combined with the FCSD data to measure daily financial wealth[10] and assess trading performance. We employ the data from January 1, 1994 through November 29, 2002.

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

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 electronic copies of the original Helsinki Exchanges Supervisory files, so these data are complete and highly reliable. The data set tracks the life of each order submitted to the Exchanges, indicating 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 orders that are executed. Only executed orders contain certain markers

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[8] 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.

[9] Feng and Seasholes (2005) and Korniotis and Kumar (2009) document that age and experience influence investor behavior and performance.

[10] Vissing-Jørgensen (2003) documents that wealth moderates behavioral biases.

that enable us to combine the limit order book with FCSD trading records to precisely identify the investor placing the executed order. Ultimately, we construct a data set that contains each investor's executed order type—limit or market order[11]—and what the limit order book (including unexecuted orders) looked like at any instant prior to, at, and after the moment of order execution. Details are provided in Linnainmaa (2009a).

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. The results from this test are aggregated into a composite ability score. The FAF composite intelligence score, which we use and refer to as IQ, is standardized to follow the stanine distribution (integers 1 through 9 with 9 being most intelligent).[12] A higher composite score is more predictive of several successful life outcomes[13] and is significantly related to stock market participation.[14] We have test results for all exams scored between January 1, 1982 and December 31, 2001.

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[11] All trades 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 the lowest bid price when selling.

[12] A stanine distribution partitions the normal distribution into nine intervals. Value 9 contains the subjects whose test scores are at least 1.75 standard deviations above the mean, or approximately 4% of the population.

[13] For example, Grinblatt, Ikäheimo, and Keloharju (2008) find a significantly positive correlation between the IQ measure and future income, typically in the 0.25-0.30 range depending on the subject's age cohort.

[14] See Grinblatt, Keloharju, and Linnainmaa (2009).

All investors in the sample were born between 1953 and 1983 due to a combination of two facts. First, our IQ data commence in 1982 and one must enter the military before turning 29 years old. Thus, we lack IQ data on older investors. In addition, 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, i.e. end-1998) 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.[15] The country is also racially homogeneous and compared to other countries, income is distributed fairly equally.[16] These factors make it more likely that differences in measured IQ in Finland reflect genuine differences in innate intelligence.

B. Summary Statistics

Table 1 provides summary statistics on the data. We necessarily restrict the sample to those trading at least once over the sample period. Panel A describes means, medians, standard deviations, and interquartile ranges for a number of investor characteristics. The sample contains both investors who enter the market for the first time and those who are wealthy and experienced

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

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

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 median number of trades is only 5 but the mean, 24.1, is considerably higher. The monthly turnover measure, calculated as in Barber and Odean (2001), also reveals heterogeneity in turnover activity across investors but the heterogeneity is relatively small in comparison to the heterogeneity in the number of trades.

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.[17]

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 all subsequent analyses. We later refer to these investors as the "below average IQ" group or as the "benchmark" group.

[17] The gap in IQ remains about the same if we expand our sample to investors with no trading in their portfolio throughout the eight-year sample period.

Panel C describes means and medians for portfolio size and trading activity measures conditional on investors' intelligence scores. Here, the average and median portfolio value and number of trades show nearly monotonic patterns across the categories: high IQ investors both have more financial wealth and trade more often. Despite a larger number of trades, high IQ investors display, if anything, lower portfolio turnover. This is particularly evident for the two highest IQ categories, which have the largest portfolio values.

Panel D presents means and standard deviations for the returns of the two primary Finnish stock indexes over the sample period. The first column shows that the restricted HEX portfolio index—a general index limiting the weight of any one stock to 10% of the index—returned an average of 12.4% per year during the sample period. The second column indicates that the unrestricted HEX General Index, the standard value-weighted portfolio for Finland, performed better than the weight-restricted HEX Portfolio Index. This is mostly because Nokia, the Finnish telecommunications giant, performed exceptionally well during the sample period. These averages mask the market's considerable price fluctuations during the sample period: the period includes not only the five years of the late-1990s bull market, but also more than two years of the bear market that began in 2000.

Panel E reports summary statistics for bid-ask spreads (as a percentage of the bid-ask midpoint) for the average trade of a given order type: market order or limit order. For limit orders, the spreads are computed the instant before the order is executed. When submitting a market order, the average investor pays a spread of 0.97%. When an investor submits a limit order that is ultimately executed, the average bid-ask spread faced by the investor at execution is somewhat higher, 1.38%.[18]

Panel F reports the average Scholes-Williams (1977) beta,[19] book-to-market rank, and firm size rank[20] (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. 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. As Panel F indicates, these stock attributes do not differ across the stanine categories. IQ does not seem to affect the types of stocks one trades. The finding suggests that controlling for these attributes, while an innocuous exercise, is unlikely to alter inferences about IQ and returns.

II. Results

High IQ investors may have superior access to private information, be 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, high IQ investors should outperform low IQ

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[18] This difference in the bid-ask spreads is consistent with findings on order type choice by Biais, Hillion, and Spatt (1995).

[19] We estimate the Scholes-Williams betas using the same computation as the Center for Research in Securities Prices. For details, see http://www.crsp.com/documentation/product/stkind/calculations/scholes-williams_beta.html. The day *t* beta calculation of a stock 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.

[20] The 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.

investors before transaction costs. We begin by analyzing this issue. Later, we study the role of IQ in mitigating the costs of trading.

A. Intelligence and Stock-Picking Ability

We first assess the degree to which high IQ investors' stock purchases and sales predict future returns relative to low IQ investors' trades. Each column of Table 2 corresponds to one regression specification. A single column reports the average of coefficients from approximately two thousand cross-sectional regressions[21] along with Fama-MacBeth *t*-statistics.[22] 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. The formation period windows skip the immediately prior day (which we analyze later), but otherwise roughly correspond to non-overlapping windows representing a day, a week, a month, and three months prior to the return.

For each of the eight regression specifications, the left-hand side variable is the day t return of the stock (in percent). The right-hand side variables consist of seven stock characteristics known to influence returns and fifteen regressors for investor attributes. The stock-specific controls are stock *j*'s Scholes-Williams beta, book-to-market percentile rank, and

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[21] We exclude any day *t* regression that lacks trades in at least 30 stocks.

[22] Because *t*-statistics are computed from the time-series of daily coefficient estimates in the Fama-MacBeth procedure, the validity of our inference only requires that daily portfolio returns are close to being serially uncorrelated. To verify this, we bootstrapped and jackknifed the standard errors and found them to be essentially identical with those obtained from asymptotic thoery.

size percentile rank, along with four returns, each cumulated over one of four past return intervals: [-1, -1], [-5, -2], [-21, -6], and [-252,-22].[23] The fifteen investor-specific variables are age (scaled by dividing by 100), as well as fourteen dummy variables for IQ, trading activity, and portfolio wealth categories. For brevity, Table 2 does not report regression coefficients for the seven stock-specific control variables.[24]

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.[25] 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. We treat multiple trades by the same investor in a stock on the same day as either a single purchase or 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 14, 1998 for formation period [-2, -2] has (in contrast

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[23] The four past return variables in Table 2's regression control for both the short-term as well as for the short- (up to one-month) reversal and long-term (one month to one year) momentum return reversals documented in the literature. See, for example, French and Roll (1986), Jegadeesh (1990), Lehmann (1990), Jegadeesh (1990), Jegadeesh and Titman (1993, 1995), and Kaniel, Saar, and Titman (2008). The past return intervals, [-1, -1], [-5, -2], [-21, -6], and [-252, -22], roughly correspond to the return cumulated over the prior trading day, the prior week excluding the prior day, the prior month excluding the prior week, and the prior year excluding the prior month.

[24] The beta and firm size rank 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 coefficients are statistically significant.

[25] 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.

to Table 2) one regressor—a dummy variable for a stanine 9 IQ. In this case, the slope coefficient is the July 14 return difference between two sets of July 12 purchases. A positively significant coefficient indicates that on July 14, the typical July 12 stock purchase by the highest IQ investors outperformed the typical July 12 purchase by others of lower IQ.

The portfolio interpretation for the hypothetical example illustrates that the OLS slope coefficient is a self-financing portfolio with portfolio weights determined by the regressor, the highest IQ dummy. Thus, each July 14 return observation generated by a stanine 9 July 12 purchase receives identical positive weight, while each observation generated by the July 12 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 receiving one vote for each 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 in the vote-weighted portfolios.

In Table 2's multivariate regression setting, 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.

In Table 2, quintile dummies for trading activity and stock portfolio wealth are formed from the number of trades and value of stockholdings, respectively. 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. 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 2 shows that all of the sixteen estimated IQ coefficients for the above-average stanine dummies (6-9) are positive. The IQ stanine 9 coefficient is significant at the 5% level in all the regressions for formation periods up to a month prior to the return and the IQ stanine 8 coefficient is significant for two of the same three formation periods at the 5% level, and one at the 10% level. The economic significance is often impressive. The stanine 9 investors' purchases two days prior, [-2, -2], outperform the purchases of the benchmark investors (stanines 1-4 pooled) by 4.4 basis points per day, or about 11% per year. Moreover, for all but the most distant formation period, the coefficients monotonically increase as the IQ stanine increases. This performance also controls for stock returns over a variety of past return horizons and skips the prior day as a formation period. It seems unlikely that the advantage high IQ investors have over their less cognitively gifted peers arises from market microstructure or liquidity considerations.

For each of the above-average IQ stanine investors (6-9), the performance pattern for purchases is 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 standard errors of the differences in coefficients are large. 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, rational expectations theory suggests that trades, and not just public disclosures, reveal private valuations. In light of this, we remain agnostic about whether the performance of high IQ investors arises from advance access to information that will be publicly disclosed.

In contrast to the buys, one cannot infer that high IQ generates superior sell-side performance. All but one of the IQ coefficients on the right half of Table 2 are statistically insignificant. The lone significant coefficient indicates that high IQ investors' sales underperform those in the lowest IQ category, but only at one horizon and by 1.1 basis points.

This strikes as a chance result, arising from the fact that if one stares at twenty *t*-statistics, at least one is likely to clear the 5% significance hurdle, even in the absence of any effect.

Figure 1 illustrates the coefficient pattern for buys and sells. Panel A graphs the buy IQ coefficients from Table 2; Panel B graphs the negative of the sell IQ coefficients from Table 2. As we move towards higher IQ and a more recent purchase in Panel A—the rear of the graph—the coefficients rise dramatically. By contrast, Panel B does not display the same monotonicity.

In addition to the analyses detailed above, we performed five different robustness checks of Table 2's findings. We summarize them as follows: First, netting purchases and sales in the same stock over the entire given formation period (rather than each day) does not alter the results. Second, eliminating some or all of the stock-specific controls generally produces the same or a marginally stronger IQ-performance relationship. Third, non-parametric tests, geared towards coefficient estimation in the presence of fat or skewed tails, strengthens the statistical significance of our findings. Fourth, breaking the sample into early and late sub-periods yields similar findings about the positive relationship between IQ and performance for both sub-periods. Fifth, excluding trades in Nokia from the sample does not alter any of our results.

B. Performance at Shorter Horizons

Table 3 presents results for prior-day and same-day formation periods. For the same-day formation period, we compute "same-day returns" from the execution price to the closing price that day. Otherwise, the methodology of Table 3 is identical to that of Table 2 and makes use of the same control variables (including stock characteristics and past returns over several horizons, for which coefficients are omitted for brevity). Table 3 illustrates that the prior-day buys of stanines 8 and 9 significantly outperform the prior-day buys of the benchmark investors in stanines 1-4 by about the same amount as found for the skip-day formation period, [-2, -2], in Table 2. For example, stanine 9's prior-day buys outperform the benchmark by 4.5 basis points while the skip-day buys outperform the benchmark by 4.4 basis points

IQ's influence on same-day returns is even greater than its influence on next-day returns. Table 3 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.

In contrast to Table 2, Table 3 indicates that over shorter horizons, the sales of high IQ investors influence future returns. The same-day returns from sales by the highest IQ category are significantly below the comparable returns of the benchmark group's sales. Moreover, the next-day returns from sales are also below the returns from the benchmark group's sales (albeit, with a *t*-statistic of merely -1.87).

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. Buys artificially lower post-trade returns because the temporary price impact is positive and sells raise post-trade returns because the temporary price impact is negative. These effects certainly distort same-day returns but they could spill over to the next-day return if the temporary alteration in the stock price has not fully dissipated by the close on the day of execution. The latter case may be particularly relevant for trades near the close of the day. Hence, if high IQ reduces trading costs, we would observe positive coefficients for high IQ dummies for buys and negative coefficients for sells with both same-day and previous-day formation periods. For this reason, it is difficult to assess whether the significant coefficients in Table 3 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.

There is some evidence that trading costs may be contaminating our inferences here. In Table 2, the investor's prior degree of trading is unrelated to performance. However, for the same-day and next-day returns in Table 3, prior trading activity seems to be a more important predictor of returns than IQ. Moreover, for the same-day formation period, there is a clear relationship between trading activity and returns for both purchases and sales. 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 points below those stocks sold by the lowest trading activity quintile.

C. 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. Thus, we would expect to observe Table 3's findings even if investors with high IQ or vast amounts of trading experience lack any other advantage at selecting stocks. 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 trading experience to be better able to choose an order strategy (including order type) that best fits the prevailing liquidity environment.

To better 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 Tables 2 and 3, 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 4's Fama-MacBeth methodology is similar to Table 2's performance analysis. As before, we analyze 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 various minutes after the trade. Table 4, like Table 3, 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 4 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 Tables 2 and 3, are also included in Table 4's regressions. Once again, we omit these coefficients from the table for brevity. Finally, Table 4 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.

Panel A reports the coefficients of buy and sell regressions for market-order trades and Panel B reports regression coefficients for executed limit orders. Column labels depict the horizon for the dependent variable: an intraday holding period return measured from the point of execution to the bid-ask midpoint 0, 1, and 5 minutes after the transaction, as well as to the closing transaction price of the day.

Table 4 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 this is what happens, but only for the highest IQ investors.

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.[26] 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 4 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

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

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. Investors with the greatest number of trades in the past experience the lowest bid-ask spreads when placing market-order buys and sells. With few exceptions, Panel A's intraday return coefficients tend to monotonically increase for buys and decrease for sells as trading experience increases. This indicates that the effective trading costs 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 1-minute and 5-minute intraday returns of the highest trading activity quintile have *t*-statistics of about 12 for purchases, and range from -4 to -6 for sales.

Past trading activity also is an important determinant of the ability to avoid adverse selection costs for limit orders. After the trade executes, 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 have learned how to 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 appears to reduce trading costs, but only for market orders. In Table 4 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 2, which stands in marked contrast to other studies.

The highly significant trading experience and wealth regressors in the microstructure analysis punctuate the importance of IQ in Table 2's long-run return analysis. In Table 2, trading activity, wealth, and age do not exhibit a significant positive relationship with performance.[27] 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 the Table 4'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

[27] In Table 2, 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 stocks sold by the wealthiest in the same formation period also have significantly higher returns (1.3 basis points) than those of investors in the least wealthy quintile.

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.

III. Conclusion

Employing IQ measures for a large population of investors, we uncover a connection between intellectual ability and skill at both picking stocks and mitigating trading costs. High IQ investors' purchases are informative about future stock price movements. IQ's influence on stock-picking skill is particularly strong for returns measured two days later, when the purchases of high IQ investors outperform the purchases of their low IQ peers at an annualized rate of about 11% per year. However, high IQ investors' purchases also earn superior and significant returns up to one month in the future. These findings control for trading experience, wealth, age, and relevant stock characteristics like beta, book-to-market, firm size, and past returns. The controls allay concerns that characteristics related to average returns or simple technical trading strategies account for our results.

The evidence on stock-picking skill and IQ is not generated by a market microstructure phenomenon. One reason for this is that we skip a day between formation period and test day. Moreover, even if we skip a week, we obtain performance that is not only significant but also statistically indistinguishable from the performance observed using the skip-day formation period.

Because high IQ investors trade more, one might erroneously conclude that their superior skill at picking good stocks might be offset by trading costs. This conjecture ignores our study of intraday and next-day returns, which indicates that if trading costs influence the returns earned, trading costs per trade are lower for high IQ investors. The stocks purchased by high IQ investors earn superior profits on the day of the trade as well as the next day. High IQ investors' market orders and executed limit orders also outperform those of low IQ investors within the first five minutes of a trade. In contrast to the conclusion about stock-picking skills, this finding applies both to buys and sells. Moreover, high IQ investors' portfolios, which are much larger than the portfolios of low IQ investors, have lower turnover.

The evidence of superior stock-picking ability existing only on the buy side is not only consistent with the extant empirical evidence, but with arguments in the literature about short sales restrictions. If short sales frictions prevent many high IQ investors from taking advantage of their stock-picking skill, models with information production also need to incorporate them. Along these lines, uninformed sellers who use limit orders face larger adverse selection costs than buyers of stocks if there are more informed buys than sells in the market. This warrants greater use of market orders when selling stock, all else equal. Of course, equilibrium bid and ask prices are determined by a marginal trader who is indifferent between the two order types. In light of this, it would be useful to further our theoretical understanding of how markets determine bid and ask prices when buyers generate far more adverse selection risk.

The source of high IQ investors' stock-picking skill is unresolved. Either high IQ investors are better at accessing non-public information or they are better at processing information—public or private. Whichever it is, market prices incorporate the valuations of high IQ investors within a relatively short period of time—one month. Because there is no 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 they know will shortly be publicly disclosed. However, in unreported work, we find no evidence that the abnormal returns of high IQ investors' purchases cluster in time or around events like earnings announcements. This leads us to believe that there are likely to be other factors, besides public disclosure of private information, that drive market prices to the beliefs of high IQ investors within a month. 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.

Our study is related to the literature on mutual fund performance. Like mutual fund studies, we identify an *ex ante* investor trait ("IQ" as opposed to "professional investor") that could plausibly generate abnormal performance. Unlike these studies, the data we analyze are not confounded by expense ratios, infrequent reporting, or missing subjects. Our paper relates even more closely to prior work on individual investor performance, but focuses on a more obvious choice for an exogenous variable that influences performance. By demonstrating that this variable, IQ, accounts for significant differences in the future performance of individual investors' stock purchases, we reinforce the findings from this literature. Unlike this prior research, however, reverse causality cannot plausibly account for the performance differences we find because of the early age at which we measure IQ.

We are fortunate here to benefit from unique data, the likes of which will be difficult to duplicate. No study that we are aware of, or that is likely to appear in the near future, combines multi-year second-by-second records of trades and offers to trade with comprehensive individual-level IQ data. These unique data show that in the absence of transaction costs, mimicking the aggregate buys of high IQ investors is a highly profitable endeavor. Admittedly, the typical smart buyer, trading once per year, earns far less per year than the aggregate buys of an IQ peer group that trades every day. The approximately 50 basis point per year advantage to such a buyer is about one order of magnitude larger than the 4.4 basis points earned two days hence because the IQ-related buy influences returns for at least one month. However, the investment game is reasonably fair to even those with below average intelligence if they lose out to the smartest investors by a mere 50 basis points per year.

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Table 1

Descriptive statistics

Panel A reports summary statistics on birth year, ability (IQ), wealth, and two measures of trading frequency. Panel B reports the distribution of IQ scores. Panel C reports portfolio size and trading activity statistics by IQ score. Panel D reports average annual return and standard deviations for the Finnish General Index and Portfolio Index for the sample period, where the latter index caps the weight of individual stocks in the index to 10%. Panel E reports average bid-ask spreads as a percentage of the spread midpoint, based on order type, with each spread recorded at the time of the transaction. In computing average spreads, each day receives equal weight. Panel F reports average betas, as well as average size and book-to-market ranks across investors sorted by IQ score. In computing averages for an IQ group, each investor's average beta, size rank, and book-to-market, computed from that investor's purchases and sales, receive equal weight. IQ data are from 1/1982 to 12/2001. Remaining data are from 1/1995-11/2002.

Panel A: Investor characteristics

			Percentiles			
Variable	Mean	Std. dev.	25	50	75	N
Birth year	1969.78	5.63	1965	1969	1974	87,914
IQ score	5.75	1.86	5	6	7	87,914
Average portfolio value, EUR	16,464	721,406	1183	2808	6910	87,914
# of stock trades	24.10	129.65	2	5	16	87,914
Monthly portfolio turnover	0.068	0.125	0.011	0.026	0.066	86,703

Panel B: Distribution of IQ score

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

Panel C: Portfolio size and trading activity by IQ score

	Average portfolio characteristics			Median portfolio characteristics		
IQ score	Porfolio value	# of trades	Portfolio turnover	Porfolio value	# of trades	Portfolio turnover
1-4	10,543	18.90	0.0695	2,496	4	0.0263
5	13,351	22.73	0.0696	2,622	5	0.0266
6	11,091	25.89	0.0680	2,806	5	0.0263
7	14,299	24.32	0.0683	2,923	6	0.0267
8	18,285	28.10	0.0651	3,277	7	0.0258
Highest	57,031	31.61	0.0652	3,510	7	0.0254

Panel D: Finnish stock market returns 1/1995-11/2002

	Portfolio Index	General Index
Annualized average return	12.4%	24.6%
Standard deviation	23.5%	34.6%

Panel E: Spread by order type

	2 * (Ask - Bid) / (Ask + Bid)					
		Standard	Percentiles			
Order type	Average	deviation	25	50	75	N
Market order	0.97%	0.28%	0.78%	0.92%	1.13%	776
Limit order	1.38%	0.33%	1.14%	1.32%	1.57%	776

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

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

Table 2

Intelligence and investment performance

Table 2 reports average coefficients and Fama-MacBeth *t*-statistics (in parentheses), computed from eight 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 four columns) or sold (right four columns) in the formation period corresponding to the columns. 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 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 coefficient estimates and the associated *t*-statistics from the time-series of coefficients. Left half of the table reports buy coefficients, right half reports sell coefficients. IQ data are from 1/1982 to 12/2001. Coefficients denoted with ***, **, * are significant at the 0.1%, 1%, and 5% level, respectively.

	Dependent variable: One-day return, percent							
	Buys				Sells			
Independent variables	[-2,-2]	[-5,-3]	[-21,-6]	[-63,-22]	[-2,-2]	[-5,-3]	[-21,-6]	[-63,-22]
IQ score								
5	0.012	-0.010	-0.001	-0.003	-0.024	0.005	-0.003	-0.004
	(0.80)	(-1.06)	(-0.13)	(-1.06)	(-1.69)	(0.65)	(-0.86)	(-1.70)
6	0.022	0.002	0.002	0.000	-0.016	0.004	0.000	-0.002
	(1.57)	(0.15)	(0.45)	(-0.14)	(-1.23)	(0.55)	(-0.14)	(-0.80)
7	0.024	0.011	0.007	0.000	-0.015	0.005	0.003	0.000
	(1.47)	(0.94)	(1.43)	(0.02)	(-0.96)	(0.63)	(0.81)	(0.04)
8	0.041*	0.018	0.011*	0.007	-0.006	0.009	0.005	0.003
	(2.24)	(1.65)	(2.03)	(1.63)	(-0.36)	(1.01)	(1.13)	(0.85)
Highest	0.044*	0.033**	0.016**	0.005	0.011	0.009	0.011*	0.003
	(2.34)	(2.58)	(2.58)	(0.97)	(0.63)	(0.88)	(2.32)	(0.76)
Trading activity quintile								
Lowest	-0.006	-0.006	0.004	-0.005	0.005	0.015	0.002	0.008
	(-0.31)	(-0.57)	(0.82)	(-1.49)	(0.27)	(1.39)	(0.26)	(0.98)
2	-0.013	0.012	-0.006	-0.005	-0.002	0.016	0.014	0.013
	(-0.75)	(1.02)	(-1.11)	(-1.18)	(-0.10)	(1.41)	(1.89)	(1.51)
3	-0.005	-0.014	-0.003	-0.012**	0.016	0.012	0.006	0.014
	(-0.27)	(-1.12)	(-0.59)	(-2.73)	(0.88)	(0.97)	(0.76)	(1.46)
4	0.014	-0.010	-0.002	-0.011*	-0.019	0.014	0.006	0.008
	(0.78)	(-0.86)	(-0.32)	(-2.18)	(-1.01)	(1.19)	(0.70)	(0.83)
Highest	0.007	0.010	-0.002	-0.009	-0.008	0.009	-0.001	0.008
	(0.29)	(0.73)	(-0.23)	(-1.48)	(-0.38)	(0.68)	(-0.10)	(0.75)
Portfolio value quintile								
2	0.021	0.007	0.003	0.000	-0.006	-0.001	0.005	0.000
	(1.05)	(0.75)	(0.62)	(-0.13)	(-0.42)	(-0.14)	(1.14)	(-0.13)
3	-0.018	-0.007	0.001	-0.001	-0.004	-0.005	0.008	-0.002
	(-1.16)	(-0.63)	(0.19)	(-0.24)	(-0.28)	(-0.59)	(1.50)	(-0.40)
4	-0.023	0.011	0.009	0.003	-0.013	0.002	0.005	0.002
	(-1.50)	(1.05)	(1.76)	(0.85)	(-0.89)	(0.19)	(0.87)	(0.47)
Highest	0.032	0.015	0.020**	0.006	0.001	0.010	0.013*	0.008
	(1.75)	(1.32)	(3.22)	(1.33)	(0.05)	(1.03)	(2.01)	(1.25)
Age	0.008	0.066	-0.021	0.026	-0.007	-0.001	0.013	0.017
	(0.09)	(1.18)	(-0.76)	(1.34)	(-0.08)	(-0.02)	(0.51)	(0.86)

Table 3

Intelligence and investment performance at shorter horizons

Table 3 reports average coefficients and Fama-MacBeth *t*-statistics (in parentheses), computed from four 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 half) or sold (right half) on the same day (day *t*) or the previous day (day *t*-1). The same-day return 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 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 coefficient estimates and the associated *t*-statistics from the time-series of coefficients. Left half of the table reports buy coefficients, right half reports sell coefficients. IQ data are from 1/1982 to 12/2001. Coefficients denoted with ***, **, * are significant at the 0.1%, 1%, and 5% level, respectively.

Independent variables	Buys: Trade price to day t closing price	Buys: Day t closing price to day t+1 closing price	Sells: Trade price to day t closing price	Sells: Day t closing price to day t+1 closing price
IQ score				
5	0.068**	0.015	-0.012	-0.035*
	(3.25)	(1.00)	(-0.94)	(-2.31)
6	0.084***	0.012	-0.023	-0.006
	(3.82)	(0.84)	(-1.75)	(-0.43)
7	0.092***	-0.006	-0.010	-0.025
	(3.33)	(-0.36)	(-0.69)	(-1.63)
8	0.106***	0.038*	-0.016	-0.026
	(4.31)	(2.01)	(-1.01)	(-1.45)
Highest	0.150***	0.045*	-0.068***	-0.033
	(5.36)	(2.19)	(-4.11)	(-1.87)
Trading activity quintile				
Lowest	0.038	-0.004	-0.019	-0.012
	(1.60)	(-0.26)	(-1.17)	(-0.69)
2	-0.001	0.009	-0.027	0.000
	(-0.03)	(0.52)	(-1.57)	(0.02)
3	-0.020	0.029	-0.042*	-0.008
	(-0.53)	(1.56)	(-2.45)	(-0.44)
4	0.122***	0.049*	-0.052**	-0.008
	(4.35)	(2.46)	(-2.87)	(-0.40)
Highest	0.182***	0.090***	-0.087***	-0.028
	(6.60)	(4.23)	(-4.69)	(-1.34)
Portfolio value quintile				
2	0.041	-0.005	0.007	-0.023
	(1.83)	(-0.33)	(0.49)	(-1.62)
3	-0.010	-0.012	0.021	0.011
	(-0.48)	(-0.78)	(1.56)	(0.76)
4	0.079**	-0.003	0.000	-0.018
	(3.05)	(-0.19)	(-0.00)	(-1.22)
Highest	0.093**	-0.010	-0.004	0.025
	(3.19)	(-0.56)	(-0.27)	(1.30)
Age	0.009	0.069	-0.065	0.081
	(0.07)	(0.78)	(-0.80)	(0.93)

Table 4

Intelligence and intraday returns

Table 4 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 intra-day 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 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. IQ data are from 1/1982 to 12/2001. Coefficients denoted with ***, **, * are significant at the 0.1%, 1%, and 5% level, respectively.

Panel A: Market orders

Independent variables	Buys: Bid-ask midpoint at 0 min	Buys: Bid-ask midpoint at 1 min	Buys: Bid-ask midpoint at 5 min	Buys: Closing price	Sells: Bid-ask midpoint at 0 min	Sells: Bid-ask midpoint at 1 min	Sells: Bid-ask midpoint at 5 min	Sells: Closing price
	Dependent variable: Return from trade to bid-ask midpoint or to closing price, percent							
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)
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)

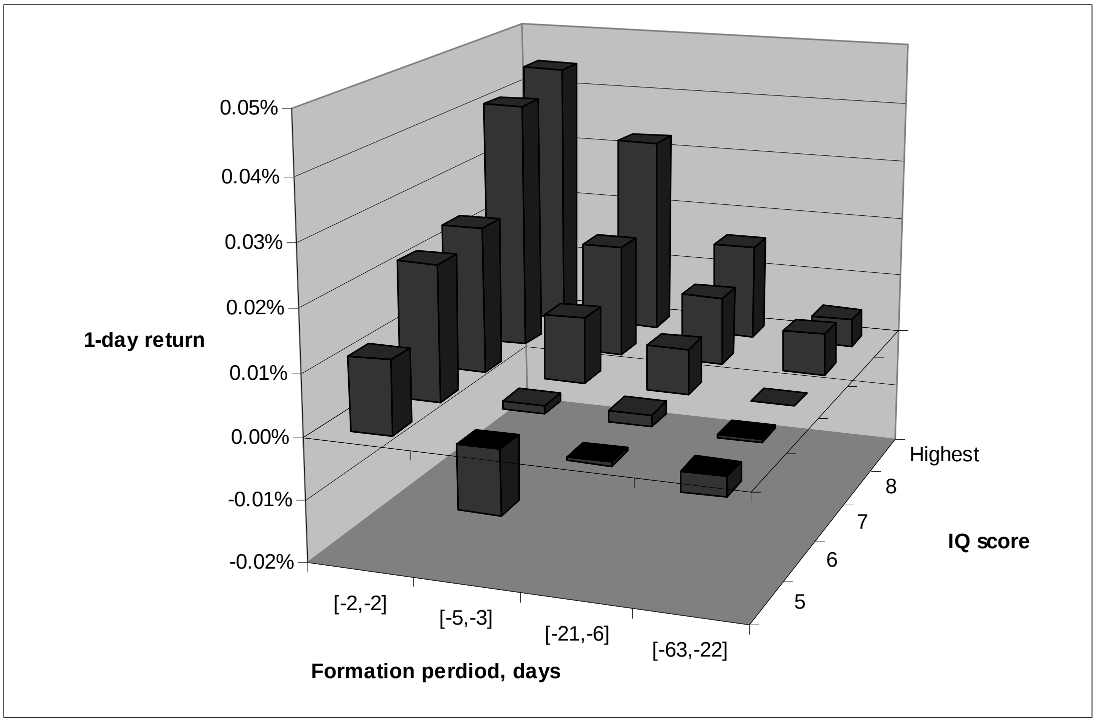
Panel B: Limit orders

Independent variables	Dependent variable: Return from trade to bid-ask midpoint or to closing price, percent							
	Buys				Sells			
	Bid-ask midpoint at			Closing	Bid-ask midpoint at			Closing
	0 min	1 min	5 min	price	0 min	1 min	5 min	price
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)

Figure 1: Investment Performance by IQ and Formation Period

Each Panel of Figure 1 plots average IQ-related coefficients for four daily cross-sectional regressions reported in Table 2. We exclude any day *t* regression that lacks trades in at least 30 stocks. In the case of buys, it plots the coefficients and in the case of sells it plots the negative of the coefficients. 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 coefficient estimates and the associated *t*-statistics from the time-series of coefficients. Panel A reports buy coefficients, Panel B reports sell coefficients. IQ data are from 1/1982 to 12/2001.

Panel A: Buy coefficients by formation period and IQ score



Panel B: Negative of sell coefficients by formation period and IQ score