IQ and Mutual Fund Choice*

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Abstract

We show that cognitive ability influences mutual fund choice: high-IQ investors avoid funds with high management fees. Two competing stories can explain this phenomenon. One is that high-IQ consumers benefit less from costly services, as they find it easier to make informed financial decisions without external help. The alternative story is that these investors are less likely to overpay for the services they receive because they either are better judges of value or more capable of discerning the price charged for these services. A comprehensive dataset of Finnish males' fund holdings supports both stories: Consistent with the first story, high-IQ investors tend to avoid funds sold via expensive service-intensive channels and prefer a mix of equity and bond funds to expensive readily-packaged balanced funds. Consistent with the alternative story, IQ and fees are inversely correlated, even after controlling for many fund services, including any operating at the fund family level.

JEL classification: G11, G23, D12, D22

Consumer choice often seems like a battle pitting the buyer's ability to find "the best deal" against the seller's skill at obfuscating the terms of purchase.[1] The advent of the Internet promised price comparisons at lower cost. However, most consumers are now barraged with a seemingly endless array of online coupons, loyalty rewards, registrations for discounts, and purchase restrictions that make price comparisons almost impossible. Even in industries with relatively homogeneous products, like retail financial services, consumers must consider features and product differences that complicate assessments of whether the price being charged is fair. A bank account bears a known interest rate, but also a vector of fees for banking services—from statement printing to cancelled checks and infrequent debit card use. Credit cards, once pieces of plastic evaluated at a single borrowing rate, have morphed into rewards programs offering rebates on purchases—provided one signs up for timely registration of categories, inquires about merchant exclusions, and recognizes purchase limits and minimums during reward cycles.

In light of this newfound complexity in consumer choice, and recent theoretical work on the role of cognitive ability in consumer welfare,[2] does the smart consumer possess an advantage? Lack of data has limited inquiry into this issue—until now. We analyze how cognitive ability influences consumer price elasticity with data on IQ and choices of mutual funds, measured at the level of the individual consumer. Controlling for wealth, education, and profession, we find that intelligent consumers are more price-sensitive about mutual fund fees. The data used to draw this conclusion come from a test specifically designed to measure intellectual ability. The IQ test, administered to virtually every Finnish male who reaches military draft age, mimics other well-known IQ tests, like the Wechsler Adult Intelligence Scale, and is noteworthy for its timing—at the age of induction into military service (about 19 or 20). This is prior to significant participation in financial markets or post-high school education. Indeed, we generally observe the inductees' mutual fund choices many years and sometimes decades after their IQ assessment. The data set contains every Finnish male's score since 1982.

The dearth of research on IQ and price elasticity is unsurprising in light of the difficult task at hand. For most products, a plethora of private attributes hinders the identification of price elasticity. If smart consumers are willing to pay more for a Honda than a Ford, it is hard to know which of many attributes—like safety, reliability, drivability, gas mileage, design, or resale value—accounts for the choice. By contrast, some financial products,

[1] Gabaix and Laibson (2006), Carlin (2009), Ellison and Ellison (2009), and Carlin and Manso (2011) model product design and marketing intended to generate a more complex consumer search problem.

[2] Cognitive costs play a role in consumption choice and contracting models (e.g., Chetty, Looney, and Kroft, 2007 and Tirole, 2009). Models also link cross-sectional differences in the cognitive cost of search to consumer demand elasticity, product choice, pricing, and consumer welfare. For example, in Gabaix and Laibson's (2006) model, sophisticated consumers with high "consumer IQ" earn rents from those with "low consumer IQ."

in particular mutual funds, are relatively simple. No consumer likes them in the way they like a particular car, facilitating the econometrician's ability to identify the link between IQ and the price paid for the same good.

The key service mutual funds render is a post-fee risk-return tradeoff, linked to fees by prior research using the extensive historical data on fund returns. This research suggests that risk-adjusted returns largely vary because of fees,[3] leading many researchers to believe that fee magnitudes dominate assessments of whether an investor has overpaid for fund services.[4] The pervasiveness of regulation confirms widespread belief that cognitive costs are significant in the mutual fund industry, at least for some investors, despite the relative simplicity of the product. In most developed countries, regulators require funds to disclose the expenses borne by their shareholders and in some jurisdictions can prohibit what they consider to be excessive fees.[5] Even if differing fund attributes—like asset class, service speed, degree of "handholding," tax help, or report quality—drive some fee variation, it is easy to control for them: Compared to products like autos, most fund attributes are either observed (e.g., asset class) or are identical for all funds within the same fund family (e.g., service speed, handholding, and tax help).[6]

Concerns about statistical power also motivate our focus on fees. Unlike expected returns and alphas, fund fees are directly observed and measured without noise. OLS panel regressions of fees on IQ and fund asset class later show that the smartest investors, at best, pay 10% less in fees than the least smart investor group.

[3] Blake, Elton, and Gruber (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Christofferson and Musto (2002), Otten and Bams (2002), Elton, Gruber, and Busse (2004), and Gil-Bazo and Ruiz-Verdú (2009) find that higher mutual fund fees tend to reduce the risk-adjusted returns earned by fund investors.

[4] Fama and French (2010) write, "… [alpha] estimated on the net (post-expense) returns realized by investors is negative by about the amount of fund expenses" and any attempt to identify positive alpha managers "… is largely based on noise." This point is echoed in the 2008 presidential address to the American Finance Association, in which French (2008) observes, "a representative investor who switches to a passive market portfolio would increase his average annual return by 67 basis points from 1980 to 2006." The 67-basis point enhancement is entirely due to the larger expense ratio of actively managed funds. For a contradictory view, see Berk and Green (2004) who model active management that compensates investors for the fees charged. The latter view is supported by Del Guercio and Reuter (2014), who show that in the U.S., actively managed funds do not underperform index funds directly distributed to investors.

[5] In Jones et al. v. Harris Associates L.P. (2010), the United States Supreme Court ruled that the court has the jurisdiction to regulate mutual fund fees when those fees are excessive and in breach of fiduciary duty.

[6] To assess whether services differ across funds within a fund family, a research assistant, posing as a "fund shopper," met with a financial advisor at each of the five largest Finnish mutual fund families. Each advisor assured our shopper that the services provided would be identical for any fund purchased within the family.

Even if we grossly exaggerate the normal fee for a group of funds to be as high as 400 basis points, 10% translates into a mere 40-basis point difference. Only a far lengthier time series than we have could reliably detect a 40-basis point difference in risk-adjusted returns attributable to IQ differences. For our sample, which identifies each draftee's fund ownership over five years, significance requires the funds held by different IQ groups to exhibit a risk-adjusted return difference of about 220 basis points per year. Thus, being "smart about fees" may improve risk-adjusted performance, but there is little hope of detecting this from risk-adjusted returns. No reasonable fee difference across investor groups is sufficient to meet a 220-basis point hurdle for statistical significance in the presence of noisy returns: a hurdle of this magnitude exceeds not just the 40-basis point difference alluded to above, but also the 170-basis point fee difference between the 90^{th} and 10^{th} percentile-fee funds within the asset class exhibiting the greatest variation in fees![7]

We show that high-IQ investors tend to avoid high-fee funds in two ways. First, they avoid categories of funds that tend to charge higher fees, including actively managed funds, balanced funds, and funds distributed through expensive service-intensive channels known as "retail networks." The demand for some of these fund categories does not prove that low-IQ investors pay too much for their mutual fund services; instead, low-IQ investors are likely to invest in such funds because they need better (but more costly) service. Second, we find that high-IQ investors avoid high-fee funds even after holding investor characteristics, fund asset class, distribution channel (retail vs. non-retail), investment philosophy (active vs. passive), minimum investment requirement (above vs. below 5,000 Euros), and any omitted service variables operating at the fund family level fixed. IQ's sensitivity to this "idiosyncratic component" of fees lowers the fees paid by high-IQ investors beyond that obtainable from a low-fee asset class, distribution channel, investment philosophy, minimum investment, or fund family. For example, among actively managed equity funds in the same fund family without large minimums, high-IQ investors tend to choose funds with the lowest management fees.

The fund selection logit regressions that demonstrate the latter finding—a high-IQ preference for low-fee funds *per se*—draw inferences from IQ-fee interaction coefficients. The methodological choice is a natural one for addressing the challenge of inferring IQ's marginal impact on fee sensitivity. The challenge arises because an observed relationship between IQ and fund fees may be influenced both by investor attributes besides

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[7] Consistent with the argument, Fama-MacBeth regressions of general equity funds' raw and benchmark-adjusted returns on their quartile rank for the fraction of investors with high IQ has positive but insignificant average coefficients (t = 0.25 for raw returns, t = 1.46 when benchmark adjusted). Analogous regressions of the returns of general equity funds on fees and a passive fund dummy have negative but insignificant fee coefficients (t = −0.69 for raw returns and t = −0.35 when benchmark adjusted). Here, the passive dummy coefficient is negligibly negative and insignificant, which is not surprising given the relatively short sample period and small number of passively managed funds.

IQ and by fund attributes besides fees. Moreover, it is not just the attributes per se, but the interactions between other investor attributes and other fund attributes that influence the simple correlation between IQ and fund fees. For example, emerging markets equity funds, which tend to have higher fees, may be more appealing to wealthy (and generally higher-IQ) investors than to less wealthy investors. Our methodology controls for the asset class-wealth interaction as well as interactions between other correlates of fees and IQ that influence the fund selection decision. The methodology used to study IQ-fee interactions also facilitates the analysis of preferences across asset classes, distribution channel, and investment philosophy separate from fees. For example, we show that high-IQ investors would have no significant preference for passively managed funds if they charged the same fees as actively managed funds within their asset class; only the fee difference leads high-IQ investors to gravitate towards passive funds.

Business education may also play a role in discriminating fund fees. In most specifications—the most notable exceptions being those with fund family fixed effects—having a business degree leads to lower fees. Indeed, business education is the only educational subfield that is associated with significantly lower fees. An investor having a business degree experiences 4% lower fees when controlling for the fund's asset class, and 2% lower fees with three additional controls for fund attributes.

Our paper builds on three strands of the empirical literature. The first, which analyzes the role of fees and expenses in fund selection, arrives at conflicting conclusions. None of the studies in this category uses real IQ data representative of a broad population or relate IQ to real-world investment choice.[8] The second strand investigates IQ's role in stock market decisions.[9] These studies are silent on IQ's role in generating price sensitivity to offerings of financial (or any other) services and lack individual-level data on education, a control variable highly correlated with IQ. The final strand links various measures of financial literacy and cognitive

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[8] Barber, Odean, and Zheng (2005) contend that investors are sensitive to loads but not to less visible fees. However, Ivković and Weisbenner (2009) find that investors are sensitive to less visible fees. Anagol and Kim (2012), studying changes in India's regulations of fund fees, conclude that demand for closed-end funds diminishes when issuance costs are charged as up-front loads rather than being amortized and thus shrouded by market volatility. Müller and Weber (2010) and Bailey, Kumar, and Ng (2011) report that experience and financial literacy are negatively associated with the loads investors pay for their funds; the association with fees tends to be weaker and generally insignificant. Consistent with this, Choi, Laibson, and Madrian (2010) find no relationship between subjects' SAT scores and fund fees in an experimental setting, using Harvard and Wharton students and staff as subjects. By contrast, Wilcox (2003) and Engström (2007) find that highly educated, wealthy, and more experienced investors exhibit preferences for funds with *high* fees or loads.

[9] Grinblatt, Keloharju, and Linnainmaa (2011, 2012) show that high-IQ investors participate more in the stock market, tend to purchase a stock just before its share price rises, and avoid wealth-destroying behavioral biases.

skill to the use of financial services.[10] The data from our study, drawn from official registers, not only have more controls, but also lack the selection issues and response bias of the survey-based samples that dominate this third strand of the literature.

I. Institutional Setting and Data

A. The Finnish Mutual Fund Market

The market for mutual funds in Finland differs from the U.S. market in six dimensions.

Size. Compared to the U.S., the Finnish mutual fund market is small. According to the 2009 Investment Company Handbook, assets under management and the number of funds are less than 1% and 5% of comparable figures for the U.S., respectively.

Advisory fees. For the vast majority of Finnish mutual funds (and for all funds in the sample we analyze), the "management fee" is equivalent to the expense ratio in the U.S. Management fees, which tend to be modestly higher than expense ratios in the U.S., account for over 90% of Finnish advisory firm revenue.[11] The relatively small amount of other revenue is collected from the loads that most Finnish funds charge. Front-end loads tend to be lower than those for U.S. load funds—on average 1.0% for equity and balanced funds, and 0.3% for bond funds. Because loads are one-time events, are relatively small, and do not vary much across Finnish funds,[12] we do not study their role in mutual fund selection.

Distribution. Finnish investors tend to buy funds directly from an intermediary representing the fund company, most often the local bank branch selling the bank's own financial products; the product mix includes a single family of funds.[13] We refer to the funds distributed by banks with extensive branch outlets as "retail funds," which come with extensive handholding and advice on how to invest. Retail fund sales are concentrated: the three largest banks account for about two-thirds of the market. A retail network generally does not distribute

[10] Hastings and Tejeda-Ashton (2008), Moore (2003), and Lusardi and Tufano (2009) find that financial literacy contributes to informed social security funding and borrowing choices. Agarwal and Mazumder (2013) observe higher-IQ individuals making fewer credit card balance-transfer and rate-changing mistakes; Zagorsky (2007) finds them to be *more likely* to "max out" their credit line, miss payments, or go bankrupt.

[11] We verified this from the year 2006 income statements of the fund management companies in our sample.

[12] 75.1% of equity and balanced funds charge 1% and 83.2% of bond funds charge either 0% or 0.5%.

index funds, which are far less popular in Finland than in the U.S.[14] There also are many smaller asset management houses or other players in the market. We refer to their fund offerings and those of all other funds as "non-retail" because they lack the wide fund distribution network of the banks offering retail funds.[15] Finnish investors acquire non-retail funds in a variety of ways—predominantly via the Internet, but occasionally by telephone, direct mail, or a rare brick-and-mortar office. The common feature here is lack of face-to-face contact with a familiar bank branch employee. While Finnish investors do not use brokers to buy funds, some investors acquire funds through a voluntary pension plan or at the recommendation of free "independent" advisors.

Asset focus. Most but not all Finnish funds invest predominantly in the equity and bonds of foreign markets. General equity and bond funds concentrate in OECD markets with emphasis on Europe. Funds specializing in emerging markets' bonds and stocks are identified accordingly.

Tax treatment. Finnish mutual funds, like U.S. funds, do not pay tax on undistributed income, whether from interest or dividends, nor on capital gains realized by the fund. Investors are subject to taxation only for dividend distributions or for capital gains investors directly realize by selling fund shares that have appreciated.

Fund Alternatives. Mutual funds are the primary financial instruments Finns use to diversify outside of Finland. Indeed, only one Finnish domiciled closed-end fund and one exchange-traded fund existed during the period studied (both excluded from our sample). The prominence of retail networks, which market only domestic open-end funds, reflects how difficult and unpopular investing in foreign mutual funds or ETFs is.

B. Data Sources

Our analysis employs five distinct data sets, described below. An individual's unique identification number, similar to a social security number, links individuals across the data sets.

Finnish Armed Forces (FAF). The FAF provides data on intellectual ability. Around the time of induction into mandatory military duty in the Finnish armed forces, typically at ages 19 or 20, males in Finland take a battery of psychological tests. One portion consists of a 120-question intelligence test for which we have comprehensive data beginning January 1, 1982. Since financial investment is relatively rare among youth of military recruitment age, we typically observe investment behavior many years and sometimes decades after the

[14] Cremers et al. (2013) compares explicit and implicit indexing across countries. Finland's relatively small passive fund market, including one ETF (which, being closed-end, is not in our sample), may stem from the prevalence of retail distribution. Distribution methods influence the mix of actively and passively managed funds in the U.S. According to Del Guercio and Reuter (2014), passively managed funds account for less than 1.8% of the fund sales of U.S. brokers.

date of IQ assessment. The FAF test measures intellectual ability in three areas: mathematical ability, verbal ability, and logical reasoning. The FAF constructs a composite ability score from the results in these three areas. We use the composite ability score in our analysis, referring to it as "IQ". It is standardized to follow the stanine distribution: integers 1–9, approximating the normal distribution with each stanine representing one half of a standard deviation and 9 being the highest IQ. As noted in Grinblatt, Keloharju and Linnainmaa (2011), the FAF ability score significantly predicts life outcomes, such as income, wealth, and marital status.

Finnish Tax Administration (FTA). The FTA collects fund shareholder data from all directly held Finnish-domiciled open-end mutual funds in taxable accounts. Each individual's holdings are reported on a fund-by-fund basis. The filings we obtained, from holdings at end-of-years 2004–08, are highly reliable. The reliability stems both from enforceable statutory requirements, which penalizes funds for inaccurate, false, or incomplete reporting of their investors' holdings, and because the filings are submitted and stored in electronic format. We have no way to study Finnish investors' holdings of funds domiciled outside of Finland because the FTA does not collect these data. As noted above, foreign-domiciled funds are likely to represent a relatively small fraction of the Finnish mutual fund market. Moreover, because foreign-domiciled funds tend to have lower fees than Finnish-domiciled funds (as documented in Khorana, Servaes, and Tufano, 2008), they are likely to be more popular among investors for whom the cognitive costs of finding and accessing foreign funds are lower. Hence, the absence of lower-fee foreign-domiciled funds in the data only means that our results represent conservative assessments of IQ's role in fee sensitivity.

Euroclear Finland Registry. This data set contains the end-of-year values of the portfolios of all Finnish household investors in stocks registered to Euroclear Finland (all traded Finnish stocks plus foreign stocks traded on the Helsinki Exchanges). We use the Euroclear holdings to assess the market value of each investor's portfolio of individual stocks at the end of years 2004–08. Our wealth control at the end of each of these five years is the natural logarithm of the sum of the market values of the investor's stock portfolio and his FTA fund holdings.

Statistics Finland. Statistics Finland collects data from many government agencies, providing career and education information on the individuals we study. Their data are from a randomly drawn sequence of the population born after December 31, 1954 and before January 1, 1985 amounting to 5.8% of the IQ sample cohorts and 2.3% of the Finnish population (about 5.4 million). For each fund decision year (2004–08), we eliminate all subjects lacking IQ scores and those who hold no mutual funds.[16] The random sampling by Statistics Finland, combined with these filters, reduces the sample size to about 7,500 male subjects per year who hold funds. These data indicate whether the subject has a university degree, a degree in business or economics (offered at all levels of education), and whether he works in the finance profession at the end of each of the years

[16] Investors who hold funds only in some years are included in those investor-years in which they hold a fund.

2004–08. Although we control for education with degree dummies, IQ variation is unlikely to be explained by more precise controls that measure education quality. The Finnish school system is remarkably homogeneous and accessible. All education, including university education, is free and the quality of education is high and fairly uniform.

Mutual Fund Report, a monthly publication, details for our purposes fees, fund asset class (short-term bond, long-term general bond, long-term emerging markets bond, general equity, emerging markets equity, and balanced), distribution outlet (retail vs. non-retail), management's investment philosophy (actively managed or passive index fund), minimum investment size, and fund family (generating 22 dummies with every fund belonging to some family). We have all issues of the report over our sample period of December 2004–December 2008, as well as 41 additional issues allowing us to compute monthly fund returns from January 2002 to June 2009. Survivorship bias concerns do not apply to our analyses because the report covers all Finnish-domiciled funds and we study all funds from all reports. We exclude funds with incentive fees, hedge funds, miscellaneous funds, and any funds with fees that are not transparent from the report.

II. Empirical Results

A. Summary Data on Funds, Their Fees, and Their Investors

Table 1 presents end-of-2008 summary statistics from our sample of 335 Finnish mutual funds. For each fund category, it reports the number of funds and investors, the mean and standard deviation of fund management fees, aggregate assets under management, and (with each fund having equal weight) the average IQ of that category's investors.[17] Table 1's "AUM rows" show that the funds in our sample managed over 30 billion Euros in retail and institutional assets, with almost 40% concentrated in general equity, emerging markets equity, and balanced funds—an equity fraction comparable to the U.S. This fraction declined substantially after 2007 because of asset price declines and equity fund outflows in 2008 stemming from the world financial crisis. Despite the crisis, between the beginning and end of our sample period, 2004 to 2008, all categories witnessed net increases in the number of funds. The table's "fee rows" also indicate that balanced funds tend to have higher fees than a mix of general bond and equity funds that replicate the typical balanced fund's allocation of 60% in stocks and 40% in bonds. Except for balanced and emerging markets categories, funds distributed through a retail network tend to have higher fees. Emerging markets funds also tend to have higher fees, while passively managed (index) funds and funds requiring large minimum investment have lower fees. The "number of investors rows" in the table indicate that the three categories of pure fixed income funds are less popular than funds with equity investment; passively managed funds are far less popular than actively managed funds. These

[17] All numbers in the table, except those tied to IQ, come from Mutual Fund Report.

rows report sums of the number of investors in each fund in the category, measured at the end of 2008.[18] The "average IQ" rows in Table 1 indicate that high-IQ investors tend to avoid higher-fee fund categories: balanced, retail, actively managed funds, and funds that allow investment for less than 5,000 Euros.[19] Finally, the bottom of Table 1 provides the same summary statistics after dividing funds into below- and above-median fees funds. Funds with above-median fees tend to have investors with lower IQ.

Table 2 reports the distribution of IQ and of IQ-stratified fund ownership and wealth (Panel A), the averages of other key investor-specific attributes conditional on IQ (Panel B), the proportion of investor-fund observations for a specific fund type conditional on IQ (Panel C) and various education, career, and wealth attributes (Panel D), giving equal weight to each investor-fund pairing in the category. Panel A indicates that there are slightly fewer individuals in stanines 1–4 and slightly more in stanines 5–9 than in the theoretical stanine distribution. Bigger differences arise when we focus on mutual fund investors. They tend to be smarter than the theoretical distribution would predict because financial market participants have higher IQ scores. Panel B confirms that a high-IQ Finn is also more likely to have a university degree, a business or economics degree, and a career in the finance profession. The IQ-related fee pattern in Panel B reflects the preferences shown in Panel C: low-IQ investors' greater propensity to hold short-term bond funds, which have low fees, offsets their tendency to hold higher fee actively managed funds and funds distributed through a retail network. The propensity to hold funds with a large minimum investment size is also nearly monotonic in IQ stanine, perhaps because the greater wealth of high-IQ investors helps them meet the minimum investment requirements or because they are more cognizant that funds with large minimum investments tend to have lower advisory fees. Stanines 7, 8 and 9 are also less likely than others to hold balanced funds. Panel D indicates that investors with a university degree, a business degree, those in the finance profession, and those with above-median wealth exhibit a substantially greater propensity of holding a long-term general bond fund, a passively managed fund, or a fund with a minimum investment size, and a substantially lower propensity of holding a balanced fund or a retail fund.

B. Multivariate Results

Table 1 and Panel C of Table 2 indicated that high-IQ investors tend to concentrate in fund types with

[18] Here, an investor who holds *k* distinct funds in the category is counted *k* times because Mutual Fund Report, the provider of most of Table 1's data, aggregates data for each fund; the vendor does not possess the personal identification number we use for much of our analysis. Thus, some of the investors counted by Table 1 lack data on IQ or some control variable and do not appear in many analyses.

[19] In contrast to the rest of Table 1, the investors in Table 1's IQ rows and in all subsequent tables are necessarily males. The distinction arises from the requirement that investors in these rows have an IQ score.

lower fees. These findings are intriguing, but rely only on the simple bivariate relationship between IQ and choice of fund type. Because IQ correlates—like wealth, education, and profession—are also likely to influence fund choice, proper analysis of IQ's role in fund selection requires controls for these contributing effects. This consideration motivates study of fund selection with multivariate logit regression, controlling for education (2 variables), finance career, and wealth. Including wealth has the added benefit of ruling out wealth-related differences in access to services as the source of a spurious IQ-fee relationship.

We first focus on the choice of fund type without separate regard for abnormally large or small fund fees within the fund category. For this portion of the study, the unit of observation consists of each pairing of an investor with one of his fund holdings in a year. With this data structure, an investor who owns M mutual funds in a year has M observations for that year. The second part studies how fund type, abnormal fund fees within the fund category, and investor characteristics interact to identify desirable and undesirable funds. The unit of data here consists of every fund-investor-year triplet. Data organized in the latter fashion have a much larger set of observations because funds that are not held by an investor contribute to the sample size. For example, if the number of funds in a given year is N, and the number of funds held by an investor is M, the investor, along with every other investor, appears N times for that year.[20]

In the logit regressions that follow, the IQ score coded as an integer from 1 to 9 is rescaled with a linear transformation to vary from –1 to 1. This rescaling facilitates interpretation of the IQ and IQ interaction coefficients without affecting test statistics. The coefficient on rescaled IQ represents the effect of being a stanine-9 rather than a stanine-5 investor, or a stanine-5 rather than a stanine-1 investor. In the second part of our analysis, which allows IQ to interact with fees, the transformation allows the reader to add or subtract the interaction coefficient to understand how much more (or less) sensitive stanine-9 and stanine-1 investors are to fees compared to stanine-5 investors. The four-stanine difference embodied by the IQ interaction terms corresponds to a 30-IQ point change using a standard IQ test. We also facilitate interpretation of some of the non-interaction coefficients by demeaning the measures of all investor attributes. For example, we measure logged wealth in excess of average logged wealth.

B.1. The Choice of Asset Class, Distribution Channel, and Investment Philosophy

Table 3 analyzes the joint role of five investor attributes, including IQ, in selecting ten particular categories of fund. Its rows present logit coefficients and marginal effects along with logit coefficient fund-clustered test statistics for a single fund category. The marginal effects and reference probabilities are evaluated at the average values of the continuous regressors and at zero for binary regressors. The first seven categories are

[20] All significance tests in both types of logit regressions use fund-clustered standard errors.

associated with the asset class the fund invests in; the remaining three identify whether the fund is distributed via a retail network, whether it is passively managed, and whether it requires a sizable minimum investment.

Each regression estimates the probability of owning funds in a category as a function of IQ, holding a university degree, having a degree in business or economics, working in the finance profession, and wealth (the logged sum of mutual fund and individual stock wealth). We also include (unreported) calendar-year fixed effects in each of the ten regressions. Two of the asset class regressions indicate how investor attributes influence demand for balanced funds; one of the two is for a subset of investors with fund holdings that contain both stocks and bonds.

Table 3 uses each of the five year's holding-investor pairings for data organization: The dependent variable is "1" only if the fund held by the investor that year belongs to the listed category associated with the regression row. For nine of Table 3's ten regressions, the reported sample sizes are identical. For the "Balanced fund, bond and equity exposure" row, we throw out observations associated with any investor who does not own (i) at least one balanced fund (alone or in combination with any other funds) or (ii) at least one general equity and one general long-term bond fund (referred to as a "home-made balanced fund"). The latter specification tests whether substitution between balanced funds and homemade balanced funds is related to IQ.

Table 3's regression coefficients indicate whether investors of differing IQ, education, profession, and wealth select funds from each of the ten categories. Among the more striking findings is that high-IQ investors are reluctant to hold balanced funds. The marginal effect for IQ in this regression suggests that a four-stanine shift in IQ (exactly 30 IQ points on a standardized test) decreases the probability of balanced fund ownership by 0.024 other things equal.[21]

Do high-IQ investors shun balanced funds because they perceive balanced funds' services to be overpriced? Recall from Table 1 that balanced funds charge 43 basis points more per year than a 60-40 mix of equity and bond funds. The significantly negative IQ coefficients in Table 3's two balanced fund regressions are consistent with high-IQ investors recognizing that a homemade balanced fund generates lower fees than an otherwise identical balanced fund. The IQ (–0.035), university (–0.036), and business (–0.019) marginal effects for substituting a homemade balanced fund for a balanced fund (in the "Balanced fund, bond and equity exposure" row) suggest that a university education is roughly equivalent to about 31 more IQ points, while a business education has the same effect as about 16 more IQ points.

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[21] This is a large number. Recall, from Table 1, that a fund holder's unconditional probability of holding a balanced fund is 0.183 (322,075 divided by the sum of the numbers in the same row). Moreover, Table 3's reference probability for holding a balanced fund is 0.170. These two benchmarks imply that the 0.024 marginal decrease is approximately 13% and 14% of the 0.183 and 0.170 unconditional and reference probabilities, respectively.

The bottom rows of Table 3 present three regressions that analyze the choice of retail versus non-retail funds, actively managed versus passively managed funds, and funds with large minimum investments sizes versus those without such restrictions. The “Retail funds” regression’s negative IQ, education, and finance professional coefficients and “Passively managed” and “Minimum investment” regressions’ analogous positive coefficients suggest that more sophisticated investors tend to embrace non-retail funds, passively managed funds and funds requiring large minimum investments. Table 1 indicated that these types of fund categories are likely to have lower fees. However, all three regressions have effects that are significant only for IQ. Business education plays no significant role in avoiding retail funds, university education plays no significant role in preferring funds with minimum investment sizes, and being in the finance profession has no significant bearing on whether one favors passively managed funds.

Table 3’s marginal effects also offer some guidance on the relative and absolute importance of each investor attribute in the choice of fund distribution type, investment philosophy, and required minimum investment. For example, the “retail fund” row’s first four marginal effects (–0.059, –0.046, –0.009, and –0.020) indicate that the influence of a four-stanine (or 30 IQ-point) change in IQ on avoidance of high-fee retail funds is more than 25% larger than the effect from obtaining a university degree, and several times larger than the effect of either having a business degree or being a finance professional. In absolute terms, a one-point increase in IQ shrinks the probability of holding a retail fund (relative to the .898 reference probability) by a factor of 0.22%.[22] The 0.010 and 0.004 IQ coefficients in the passively managed and minimum investment marginal effect rows correspond to a single IQ point increase scaling up the probability that a fund held is passively managed or has a 5,000 Euro minimum by factors of 1.85% and 0.83%, respectively.[23]

B.2. High-IQ Investors Avoid High-Fee Funds Other Things Equal

In contrast to Table 3, which only uses information about funds held, Table 4 uses data points on the funds an investor holds and does not hold to fit its regression. This shift in observation unit (to data points that are elements of a fund-investor-year matrix) dramatically increases the sample size, to about 7 million observations. Adding pairings of funds not held with each investor allows inclusion of a fee regressor, along with other fund attributes, as determinants of fund choice.

[22] 0.22% is 1/30 the ratio of the magnitude of the marginal effect to the reference probability, 0.059/0.898.

[23] The results above assume a linear IQ specification. Using individual IQ stanines as dummy variables leads to similar results. The aversion of high-IQ investors to balanced funds, retail funds, and actively managed funds is nearly monotonic in IQ and differences in this aversion across the IQ spectrum tend to be statistically significant.

Table 4 reports logit and marginal effects coefficients from a single logit regression (despite its appearance as an array) to assess whether *fees per se* (measured as logged percentage fee in excess of the average logged percentage fee across observations) influence fund choice, separate from fee correlates like asset class, distribution channel, and investment philosophy. The regression thus jointly estimates fund preferences over a set of attributes in Table 4's rows (linked to risk and service) for someone with a given vector of investor characteristics given in the Table 4's columns. The dependent variable is one when the investor owns the fund that year. We use logged percentage fee as the fee regressor to facilitate the aggregation of funds with differing attributes (particularly asset classes) within the same regression. Funds with different attributes tend to have different fee levels and different variation in fees across funds. For example, being 20 basis points higher than another fund may be far more salient for a passively managed bond fund than for an actively managed emerging markets equity fund. Alternatively, it approximately implies that a passively managed bond fund charging 10% (or 2.6 basis points) more than the average passively managed bond fund's fee of 26 basis points is as "excessive" as an actively managed emerging markets equity fund charging 10% (or 26 basis points) more than the 260 basis points average fee of its category.

The five columns on the right report the regression's "interaction coefficients," describing how investor characteristics, particularly IQ, alter their row's main effect coefficient in the leftmost column.[24] For example, the fee row indicates how IQ, university education, business education, having a finance career, and wealth alter the sensitivity of fund choice to the fee regressor. Including asset class, distribution channel, investment philosophy, and minimum investment dummies as regressors ensures that the fee component associated with the fund category (asset class, retail vs. non-retail, active vs. passive, large minimum vs. no large minimum) does not influence the fee coefficient; only the fee's idiosyncratic variation within the category matters. The regression also includes (unreported) calendar year fixed effects.

The IQ column coefficients assess how stanine-9 or (if subtracting) stanine-1 investors react to fund attributes in comparison to stanine 5. One of the paper's central results comes from the fee coefficient in this column. The logit coefficients and marginal effects for the IQ-fee interaction, –0.26 and –0.0017, respectively, are highly significant. Thus, high-IQ investors shun high-fee funds, other things equal. The other four investor characteristics have negative fee interaction coefficients, but the coefficients are significant only for the two education dummies. The significance of these education-fee interaction coefficients will not survive more extensive controls for fund service, as we will see shortly.

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[24] We are well aware of Ai and Norton's (2003) critique of interaction effects in logit models. Because the linear probability model yields similar results and significant logit coefficients are almost always associated with marginal effects of similar significance and sign, we do not believe the critique is valid here.

The remaining coefficients of the IQ column show that high IQ influences preferences towards some of the other fund attributes. Holding fees constant, high-IQ investors have stronger preferences for equity and emerging markets equity funds than short-term general bond funds. It also appears that they would like balanced funds, but only if their fees are the same as the other classes of funds. Apparently, high-IQ investors shun balanced funds in Table 3 only because balanced funds have higher fees. We can make similar statements about other investor attributes. The columns to the right of IQ in Table 4 reflect the fund-attribute preferences generated by the non-IQ investor characteristics: education, profession, and wealth. For example, educated investors seem to have a relatively greater preference for the higher risk categories of funds, other things equal, including fees, just like high-IQ investors.

B.3. Robustness: Additional Proxies for Omitted Service Attributes

Table 4 makes the striking observation that fees matter more to high-IQ and educated individuals, controlling for asset class and a trio of fund service attributes. However, service has many dimensions that may not be captured by these controls. Anyone familiar with the U.S. mutual fund market knows that fund families differ in the quality of their advice, service speed, software for executing transactions or monitoring portfolio value, and quality of tax reports. Service hours and number of walk-in branches also vary widely. These service differences are likely to influence the attractiveness of a particular fund family.

IQ and other investor attributes, like wealth, could also influence how attractive the services offered by mutual funds are. For example, as Alexander, Jones, and Nigro (1997) demonstrate, investors self-select into different distribution channels based on their overall level of financial literacy. A low-IQ investor may place greater value on a telephone or personal contact with an investment advisor and be more averse to funds that restrict access to investors facile with a computer and an Internet connection. A high-IQ investor may show greater appreciation for the specialized software of a particular fund family. A wealthy investor may appreciate a fund family's tax and estate planning resources more than a less wealthy investor.

Motivated by the observation that funds operating within the same family share similar services, that fund families attract different clienteles, and that these clienteles stratify by different levels of service, Table 5 adds 132 additional regressors as service controls. These regressors consist of 22 fund family dummies and their interactions with each of the five investor attributes in Table 4's regression. As the fund family dummies are perfectly collinear with the retail network dummy, we omit the latter variable from the analysis. For brevity, we do not report the coefficients on the 132 fund family variables in the table.

Table 5's fee interaction coefficients thus represent fee preferences that are orthogonal to observable asset class, passive-fund, and minimum investment dummies, as well as any unobservable variable tied to the fund family itself. If the services provided by a fund do not vary across the fund family, this regression effectively controls for the attractiveness of a fund's unobservable services. These fund family dummies represent effective controls even if the attractiveness of the services varies across investors. Table 5's implementation of fund family fixed effects thus offer powerful controls for omitted variables that might explain a relationship between fees and IQ, or between fees and other investor attributes.

Table 5 shows that the interaction between fees and IQ remains highly significant (the *z*-statistic increases from –2.64 in Table 4 to –3.46 in Table 5), suggesting that high-IQ investors shun high-fee funds, even within the same fund family, asset class, management philosophy (passive vs. active), and minimum investment requirement. The primary difference from Table 4 is that the fee interaction with having a university or business degree no longer has a significant influence on aversion to fund fees once we control for fund family.

The marginal coefficients from Tables 4 and 5 tell a similar story. Indeed, comparing the IQ columns from these panels shows very similar coefficient vectors. IQ's interaction coefficients with fund attributes are scarcely influenced at all by the inclusion of the fund family dummies. This suggests that observable fund characteristics adequately capture the service dimensions that have differing appeal across the IQ spectrum.

B.4. Other Robustness Checks

IQ's inverse relationship with mutual fund fees survives many other model specifications and estimation techniques. Each of Table 6's eight columns contains logit or OLS coefficients from alternatives to Table 4's regression. For brevity, each column reports only on the fee-related interaction coefficients from its regression, but includes Table 4's full set of fund attributes and interactions with investor attributes.

More extensive education controls. If IQ is correlated with one's field of study, Table 4's IQ-driven price elasticity may simply proxy for smart investors' proclivity to choose fields of study that make them financially more literate. Table 6's Specification 1 assesses this conjecture, supplementing Table 4's education regressors with dummy variables for eight fields of study. The –0.22 IQ-fee interaction coefficient in the column, which has a significant *z*-statistic of –2.34, is similar to Table 4's coefficient of –0.26. The fee-business education interaction remains significantly negative; business education is the only type of education that is associated with statistically significantly lower fees at the 5% level. Having a degree in educational science or agriculture and forestry generates a significantly positive fee interaction coefficient.

Other specifications. Table 6 also shows that high IQ elevates price sensitivity using OLS estimation (Specification 2), an alternative wealth regressor that uses wealth in funds only rather than wealth in both stocks and funds (Specification 3), controls for whether the investor resides in one of the five largest cities and corresponding interactions of the large-city dummy with fund attributes (Specification 4),[25] controls for whether the investor works for a large company (Specification 5),[26] an IQ score adjusted for investor age to avoid the Flynn (1984) effect (Specification 6),[27] controls for one-year past returns and their interaction with investor characteristics (Specification 7),[28] and a less parsimonious specification for IQ (Specification 8). This last specification has a coefficient pattern that motivates IQ's functional form in prior tables. Finally, our results (not reported for brevity) are also robust to alternative minimum investment controls (2,500 and 10,000 Euro), standard errors clustered at the investor level or with conservative two-way logit clustering,[29] the exclusion of investors in IQ stanine 1 and 9 investors from Table 4's regression, and regressions run separately for each year of the sample period.

B.5. Fee Interaction Coefficients and Investor Characteristics

Table 7 employs four separate regressions to study whether any of Table 4's fee-related logit interaction coefficients vary with investor characteristics. Its first two columns report the IQ, business education, finance profession, and wealth-related fee-sensitivity coefficients for investors without and with a university education. These coefficients appear in both columns but are inferred from a single regression that replaces eight of Table 4's regressors with eight pairs of regressors—derived by multiplying each of the four fee-related interaction regressors and four investor main effect regressors by a pair of complementary dummy variables. The dummies represent whether one has (right column dummy) or lacks (left column dummy) a university degree. Other column pairs are implemented analogously. For all column pairs, the regression's title defines the dummy pair that multiplies the eight regressors. Despite two columns for each regression, Table 7 reports only its fee-

[25] The similarity between the IQ-fee coefficient in Table 4 and in Specification 4 suggests that location-based access to or preference for low-fee funds cannot explain IQ's influence on fee sensitivity in Table 4.

[26] IQ may spuriously correlate with fees if large firms hire more intelligent employees and offer pension plan choices with lower fees (Bikker and De Dreu, 2009), provided that the fund choices mimic the offerings of one's employer. Specification 5's significant IQ-fee interaction indicates that the professional investment counseling or other communication that is more readily available at large firms cannot explain IQ's effect on the fee paid.

[27] Specification 6's replacement of IQ with "residual IQ," computed from regressing IQ on dummies for the year in which an investor's IQ is assessed, scarcely alters Table 4's results. This regression effectively orthogonalizes IQ and investor age—implying also that age cannot account for IQ's fee effect.

[28] For brevity, Specification 7 only reports the (negligible) coefficient for the IQ-past return interaction. The IQ-fee coefficient remains the same as in Table 4. Similar results are found with a 6-month past return regressor.

[29] See Cameron, Gelbach, and Miller (2011).

related interaction coefficients for brevity.

In addition to pairs of logit coefficients and z-statistics testing whether the individual coefficients are zero, the p-values in the bottom half of Table 7 test whether each pair of coefficients is identical. Note that most coefficient pairs do not significantly differ from one another. Table 7 exhibits a couple of significant coefficient differences and one case of near significance (at the 5 per cent level). The most highly significant difference stems from IQ's effect on fee sensitivity for those with and without a business education (p-value = 0.01). Here, the IQ-fee coefficient is significantly negative (z = –2.93) for those lacking a business education and positive, but insignificant (z = 0.92), for those with a business education. This finding raises the intriguing possibility that financial literacy, proxied by a business degree, may substitute for high IQ when comparing prices. Also the other significant or nearly significant differences are for the business degree-fee interaction coefficient. Here, a business degree's effect on fee sensitivity may be mitigated either by being in the top wealth decile or by working in the finance profession (p-value = 0.03 and 0.07, respectively). Finally, Table 7 shows IQ's significant influence on the fee sensitivity (z = –2.17) of the wealthiest investor decile (median wealth > 70,000 Euros), motivating study of IQ-related wealth lost to high fees.

B.6. How Big is the Fee Difference Associated with IQ?

Using each investor-fund-year observation as a data point, we now regress the fund fees on IQ and control variables. We use the logarithm of fund fees as the dependent variable to facilitate comparisons across asset classes, as in Table 4, which lends a percentage change interpretation to our coefficients. Table 8 presents the coefficients for eight specifications, each with calendar year fixed effects and t-statistics based on fund-clustered robust standard errors. Asset class dummies are included in all specifications, but their coefficients are omitted from the table for brevity. The first four specifications treat IQ as a linear variable while the remaining specifications use IQ stanine dummies. The specifications also vary in the controls for fund and investor characteristics. Specifications 4 and 8 contain the full set of controls for fund and investor characteristics, while the other specifications omit (non-asset class) fund attributes or (non-IQ) investor attributes, or both sets of attributes as regressors.

The first four columns of Table 8 indicate that a 4-stanine increase in IQ generates a 0.9−4.5 per cent reduction in fees depending on the specification. The difference in fees between stanines 1 and 9 is twice the coefficient: 9.0% lower fees with only asset class controls (Specification 1) and 1.7% lower fees with the full set of fund controls (Specification 4).[30] Although not reported formally, adding fund family dummies to specifications 4 and 8 leads to qualitatively similar IQ coefficients. The more granular IQ stanine specifications (5−8) indicate that the highest-IQ stanine pays from 9.9% lower fees (with only asset class controls) to 3.9% lower fees (with all controls). As can be seen in Table 8, or in Figure 1's plot, the IQ stanine coefficients in Specifications 5−8 are fairly monotonic. The lack of significance on some of the IQ stanine coefficients is not surprising in light of all the controls and the granular level at which IQ is measured. Nevertheless, in each of Specifications 5−8, stanine-9 investors exhibit significantly less tolerance for high fees than stanine-1 investors.[31]

How large are these fee reductions? Using continuous compounding for simplicity, we expect one Euro invested in a fund with a fee of f and assets with expected annualized returns of r to be worth $e^{(r-f)T}$ after T years. Hence, a fee that is x percent smaller than f generates a terminal expected value of $e^{(r - f(1 - x/100))T}$ after T years, which is $e^{(fx/100)T} e^{(r-f)T}$, or approximately $e^{(r-f)T} + (fx/100)T\, e^{(r-f)T}$. Thus, 40 years of 5% lower fees, when fees are normally 100 basis points, raises wealth by about 2%. For a 40-year annuity, the wealth effect is about half of that amount, or 1%.[32]

[30] Fees represent a greater fraction of total taxable wealth or financial wealth for the two lowest IQ stanines than for any other IQ stanine. Therefore, if anything, low-IQ investors suffer relatively more from high fees than high-IQ investors.

[31] Beside IQ, having a business degree is the only investor attribute in Table 8 that significantly influences fees in the two specifications (4 and 8) containing the full set of controls. In Specification 8, the 1.6% reduction in fees from a business degree is roughly 40% of the stanine 9 coefficient, suggesting a business degree is worth 24 IQ points. While other specifications lead to a larger IQ equivalent of a business degree, we do not want to overinterpret them because fund family fixed effects render the business degree coefficients (but not IQ) far smaller and insignificant.

[32] We also developed a "back of the envelope" calculation of the aggregate fee reduction from IQ, derived from the four right columns of Table 8 and the fund wealth percentages in Table 2 Panel A. Using these percentages as weights, the weighted average of the coefficients for the stanine 2−9 dummy variables ranges from −7.6% (Specification 5) to −3.9% (Specification 8). Multiplying this weighted average fee reduction by the approximately 300 million Euro product of Table 1's asset-class specific fees of Finnish funds and the total assets under management in Finnish mutual funds yields 12−23 million Euros. This range is the annual reduction in aggregate fees from investors being smarter than the lowest stanine. Recognize here that the U.S. fund market is more than two hundred times larger.

III. Summary and Conclusion

Fees are not perfectly transparent to mutual fund investors and we believe it takes some sophistication, generated by native ability or education, to understand their ramifications. Barraged by recommendations, ratings, and information about ex-post performance, some investors—plausibly those with less cognitive ability—may make mistakes, ignoring fees. Using data from Finland, including measurement of individual investor IQ and fund holdings, we find that high-IQ investors tend to own low-fee funds. Their gravitation to low-fee funds partly reflects a tilt towards asset classes, distribution outlets, and passive vs. active management philosophies that tend to have low fees. However, controlling for observable fund attributes and unobserved fund attributes proxied for by fund family dummies—as well their interaction with five investor attributes—high-IQ investors still prefer low-fee funds. While IQ influences the fees of the fund's investors when they lack a business degree, IQ has no effect on fees if one has a business degree. This points to financial literacy as a way for all to enjoy some of the financial benefits of having a high IQ. Of the non-IQ investor attributes—having a university or business degree, working in the finance profession, and wealth—only the business degree dummy has this type of effect. Separate from IQ, these other investor characteristics are also sometimes related to the tendency to hold a low-fee fund, depending on specification.

Intellectual ability, education, and career-related expertise are also likely to play a broader role in consumer demand elasticity. We focused on price elasticity in the mutual fund market because the underlying product in this market is a relatively simple pre-fee risk-return investment trade-off—which many believe is the same for all funds. This feature, along with data availability, makes the mutual fund industry ideal for studying the drivers of consumer price elasticity.

The possibility that high-fee funds do not fully compensate investors for their higher fees may be of interest to regulators. Policy makers often express concerns that mutual funds overcharge for services, pointing to the fact that mutual fund fees vary widely, even among funds with identical investment objectives. This perspective stems from a "cognitive friction" story. According to the story, low-IQ investors, being either bad judges of value or less able to discern the price charged, receive nothing extra in exchange for the higher fees. What complicates this inference, however, is that a significant IQ-fee correlation could also arise from IQ's stratification of preferences—here, for unobserved costly services. This "clientele equilibrium" story implies that investors of low intellectual ability place greater value on the services higher-fee funds provide.

Our evidence lends support to both stories. Quite plausibly, the low-IQ preference for higher-priced retail funds in Tables 3 (without fee controls) and 4 (with fee controls) reflects rational recognition of a greater need for costly handholding and other services retail distribution provides. The resulting clientele equilibrium allocates the costly services of retail funds to those who value them most—the low-stanine groups. We also find evidence consistent with the cognitive friction story: Table 5's fund family fixed effects regression, which contains effective controls for service differences, not only exhibits a significant IQ-fee interaction component, but one of similar magnitude to Table 4's regression. Our results thus appear to be driven by some high-IQ investors avoiding funds with the most egregious fees.

Regressions of fees on IQ and controls also indicate a statistically significant effect on fees. For a horizon of 40 years, a large IQ advantage has a single-digit percentage effect on retirement wealth. An analogy may help the reader draw her own judgment about the import of these magnitudes. If one saves by placing 20% of wages into a mutual fund earning 8% annually and has equal wages over 40 years, 1% more wealth (a figure described earlier) is offset by not saving for retirement over the last two and half years of work and consuming the 20% savings instead. Moreover, high IQ generally means one will be university educated, wealthier, and have a greater tendency to be business educated or work in the finance profession. These other factors also contribute to lower fees and IQ's fee effect more than doubles if we do not control for other investor characteristics.

The fact that high IQ reduces the basis points paid in fees by at most single digits probably reflects IQ's inability to perfectly segregate investors into low- and high-fee funds. This imperfection is not surprising. Every IQ test assesses true intelligence with error and even true intelligence is not a perfect measure of the ability or willingness to make price comparisons. A "single-digit IQ effect" may also reflect fund fees that are fairly competitive for the services provided. There probably are funds, at the edges, that charge high fees for what they deliver to investors. We don't know the reasons they charge higher fees, and while they attract more low- than high-IQ investors, they do not attract many investors. The small investor base of these funds dampens the IQ slope coefficient of best fit for all observations. Buttressing this more innocuous view of the high-fee funds is that—at least for Finland—little evidence exists that the higher fees compromise risk-adjusted returns and we lack information about the underlying costs of providing fund services. The latter two facts prevent us from offering the strong scientific conclusion that Finland's high-fee funds overcharge for their services.

What seems to be evident, however, is that some high-IQ consumers of fund services find less expensive workarounds for the services others pay dearly for, like the asset allocation of balanced funds and the handholding of retail distribution networks. Moreover, when we control for services, high IQ tends to enhance the ability to evaluate the exchange of services for money and find the best bargain. We believe that this IQ-related acuity at evaluating economic exchange extends to other industries. Incorporating this feature into models of the consumption decision can only help economic thought rest on a more intelligent foundation.

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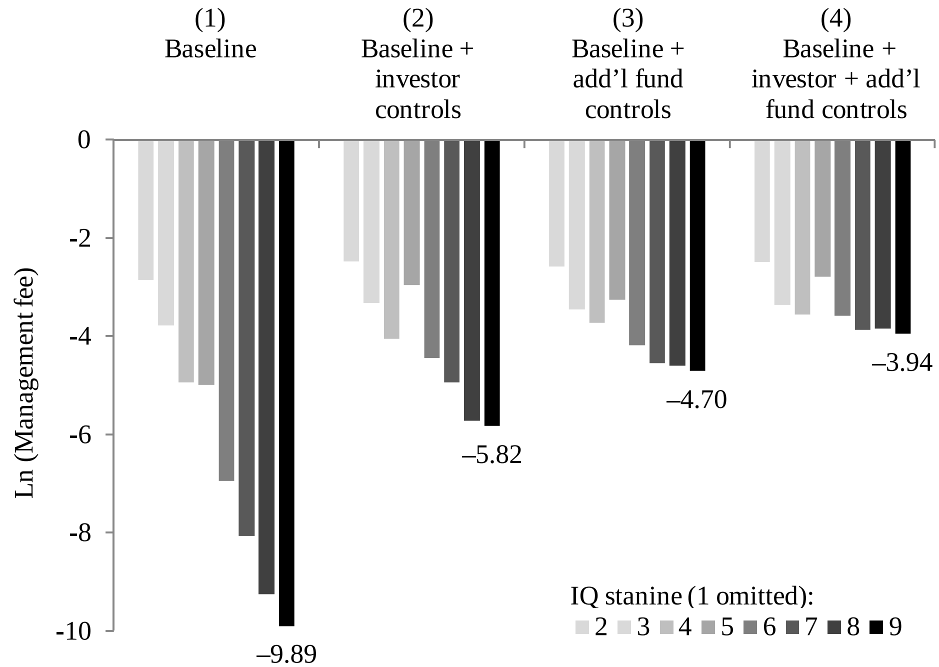

Figure 1. Fund fees and IQ

The graph plots the OLS regression coefficient of the investor's IQ stanine from columns 5−8 of Table 8. The regression's dependent variable, ln(management fee), is measured in logged basis points to facilitate comparisons across asset classes. The bars can thus be interpreted as (approximately) the percent decrease in fees paid by investors from IQ stanine 2 (light grey) to 9 (black) compared to the omitted category of stanine 1, controlling for the investor and fund characteristics listed at the top of each graph. Dummy variables for asset classes (plots 1−4), retail funds, passively managed funds, and minimum investment funds (plots 3−4) adjust the fees for variation related to fund characteristics. Plots 2 and 4 include controls for investor attributes.

Table 1

Descriptive statistics on funds

For each asset class, and for various categories of funds, Table 1 lists 2008 values of the number of funds, average fee, standard deviation of the fee, aggregate assets under management (AUM), and number of investors in all funds in the category along with their average IQ. Each Finnish-domiciled mutual fund in the category at the end of 2008 is a data point. Closed-end funds (including ETFs), hedge funds, and any funds with performance-related fee components or nontransparent fees are excluded from the sample. Long-term bond funds include intermediate- and long-term bond funds. Retail funds are funds run and distributed by fund families affiliated with commercial banks. Minimum investment funds have an investment threshold equal to or larger than 5,000 euros.

	Pure asset classes					Balanced funds
	Short-term bond	Long-term general bond	Long-term emerging market bond	General equity	Emerging markets equity	
All funds						
Number of funds	32	61	8	153	42	39
Average fee, bp	37.4	61.1	98.8	146.7	259.9	155.7
Sd of fee, bp	13.2	26.9	30.0	56.1	55.1	44.8
AUM, mill. Euros	9,018	10,580	249	7,268	1,456	2,788
Number of investor-funds	191,051	89,157	2,912	749,939	405,905	322,075
Average investor IQ	6.51	6.76	6.86	6.59	6.66	6.22
Retail funds						
Number of funds	21	42	4	81	28	29
Average fee, bp	39.6	64.3	92.5	162.1	237.7	155.7
Sd of fee, bp	14.1	28.7	25.0	46.3	46.8	41.7
AUM, mill. Euros	6,981	8,877	197	5,352	1,160	2,404
Number of investor-funds	179,646	79,772	1,861	705,029	386,546	309,790
Average investor IQ	6.19	6.58	6.47	6.28	6.29	5.95
Non-retail funds						
Number of funds	11	19	4	72	14	10
Average fee, bp	33.0	54.2	105.0	129.1	304.3	155.8
Sd of fee, bp	10.3	21.3	37.0	61.2	42.9	55.3
AUM, mill. Euros	2,036	1,703	52	1,916	296	385
Number of investor-funds	11,405	9,385	1,051	44,910	19,359	12,285
Average investor IQ	7.04	7.21	7.06	6.98	7.36	6.87
Actively managed funds						
Number of funds	32	54	8	138	42	39
Average fee, bp	37.4	65.6	98.8	157.2	259.9	155.7
Sd of fee, bp	13.2	25.0	30.0	48.3	55.1	44.8
AUM, mill. Euros	9,018	9,607	249	6,668	1,456	2,788
Number of investor-funds	191,051	88,097	2,912	736,297	405,905	322,075
Average investor IQ	6.51	6.71	6.86	6.51	6.66	6.22
Passively managed funds						
Number of funds		7		15		
Average fee, bp		26.1		50.8		
Sd of fee, bp		9.6		19.4		
AUM, mill. Euros		973		599		
Number of investor-funds		1,060		13,642		
Average investor IQ		7.10		7.17		

Table 1 continued

	Pure asset classes					Balanced funds
	Short-term bond	Long-term general bond	Long-term emerging market bond	General equity	Emerging markets equity	
Funds with no minimum investment						
Number of funds	20	44	8	116	39	34
Average fee, bp	42.4	68.9	98.8	163.7	261.9	156.4
Sd of fee, bp	13.0	25.3	30.0	49.4	56.3	47.4
AUM, mill. euros	5,378	8,479	249	6,090	1,392	2,568
Number of investor-funds	179,025	86,545	2,912	743,373	405,670	288,222
Average investor IQ	6.41	6.64	6.86	6.49	6.56	6.23
Funds with minimum investment						
Number of funds	12	17		37	3	5
Average fee, bp	29.0	40.9		91.9	233.3	151.0
Sd of fee, bp	8.6	19.7		38.8	28.9	22.1
AUM, mill. euros	3,640	2,101		1,177	64	221
Number of investor-funds	12,026	2,612		6,566	235	33,853
Average investor IQ	6.74	7.18		7.06	8.50	6.00
Funds with above median fees						
Number of funds	16	30	4	76	21	19
Average fee, bp	48.1	81.6	117.5	189.6	306.4	191.9
Sd of fee, bp	8.3	20.3	31.0	24.5	23.5	10.8
AUM, mill. euros	5,048	4,594	92	3,337	490	1,700
Number of investor-funds	168,215	45,675	1,955	518,250	63,074	236,508
Average investor IQ	6.50	6.71	6.39	6.41	6.71	5.91
Funds with below median fees						
Number of funds	16	31	4	77	21	20
Average fee, bp	26.6	41.3	80.0	104.0	213.3	121.3
Sd of fee, bp	6.7	15.0	14.1	44.4	33.4	36.6
AUM, mill. euros	3,970	5,985	157	3,931	966	1,088
Number of investor-funds	22,836	43,482	957	231,689	342,831	85,567
Average investor IQ	6.53	6.82	7.33	6.76	6.61	6.51

Table 2

IQ, investor, and fund variables

Panel A's first three rows report the theoretical IQ stanine distribution and its empirical equivalents for both the full sample and the sample of mutual fund holders. Its last three rows report the number and proportion of individuals in each stanine who have some fund holdings, respectively, and the relative fund wealth held by each IQ stanine. Mutual fund holdings exclude closed-end funds (including ETFs), hedge funds, and any funds with performance-related fee components or non-transparent fees. The full sample randomly selects Finns who are born between 1955 and 1984. Panel B summarizes investor attributes in the total sample of mutual fund holders. Each investor at the end of each year 2004–08 is the unit of observation. Financial wealth is the value of all fund and stock holdings at the end of a year. Fund fees in euros multiply the value of fund holdings with their fees. Fund fees in basis points equal the value-weighted average fee of an investor's fund portfolio. Highest education is the proportion of investors whose highest degree is basic, vocational, high school, or university. Business degree refers to having earned a degree in business or economics. Finance professionals work in the finance industry. Panel C and D calculate the proportion of investor-fund observations in each asset class and in each fund type for groups of investors stratified by IQ (Panel C), as well as education, profession, and wealth (Panel D). "ST" refers to short-term, "LT" to long-term, and "Em. market" to Emerging market. Minimum investment funds have an investment threshold equal to or larger than 5,000 euros.

Panel A: IQ distribution

	IQ stanine									
	1	2	3	4	5	6	7	8	9	*N*
Theoretical IQ distribution	4.0%	7.0%	12.0%	17.0%	20.0%	17.0%	12.0%	7.0%	4.0%	
Full sample IQ distribution	2.5%	6.0%	7.4%	16.9%	22.3%	16.8%	15.0%	7.1%	6.1%	34,490
Fund holder IQ distribution	1.2%	3.6%	5.4%	12.5%	21.0%	18.1%	18.1%	10.4%	9.6%	7,454
Number of fund holders	91	270	403	935	1,568	1,346	1,351	772	718	7,454
% who hold funds	10.4%	13.1%	15.9%	16.0%	20.4%	23.2%	26.2%	31.7%	34.3%	
Fund wealth distribution by IQ	0.4%	2.0%	3.0%	7.8%	14.7%	13.1%	20.4%	12.8%	25.7%	

Panel B: IQ stratified averages of investor attributes

	IQ stanine									
	1	2	3	4	5	6	7	8	9	All investors
Financial wealth, euros	4,430	8,077	12,037	12,357	12,830	16,641	23,168	22,998	218,907	37,073
Number of funds	1.4	1.6	1.6	1.7	1.9	2.0	2.1	2.3	2.6	2.0
Fund fees, euros	36.6	59.4	69.4	68.8	88.1	87.7	126.4	143.6	281.4	115.9
Fund fees, bp	113.4	104.1	122.6	108.6	124.5	118.9	110.8	114.9	104.0	112.6
Highest level of education										
Basic	28.2%	25.3%	17.9%	13.0%	7.3%	5.5%	5.3%	3.1%	3.5%	7.8%
Vocational	65.8%	65.9%	72.1%	67.7%	58.3%	41.7%	31.0%	21.4%	11.5%	43.7%
High school	1.7%	3.5%	2.6%	7.0%	8.9%	13.9%	14.2%	18.5%	16.4%	11.8%
University	4.4%	5.3%	7.4%	12.3%	25.5%	38.9%	49.5%	57.0%	68.5%	36.7%
Business degree	4.0%	4.3%	6.4%	7.5%	13.5%	14.9%	14.6%	15.2%	11.7%	12.5%
Finance professional	0.0%	2.0%	1.5%	1.8%	3.8%	4.3%	4.1%	4.9%	5.5%	3.8%

Panel C: Share of investor-fund observations in asset classes and fund types stratified by IQ										
	IQ stanine									
	1	2	3	4	5	6	7	8	9	All investors
Asset classes										
ST bond	21.3%	14.1%	15.0%	13.4%	11.3%	9.2%	10.4%	9.2%	9.2%	10.7%
LT general bond	3.2%	5.5%	4.9%	3.6%	4.1%	5.0%	5.6%	5.3%	6.6%	5.0%
LT em. market bond	0.0%	0.0%	0.0%	0.2%	0.2%	0.3%	0.3%	0.2%	0.4%	0.3%
General equity	36.2%	35.7%	36.3%	40.7%	40.8%	42.5%	42.1%	43.6%	43.0%	41.6%
Em. market equity	21.3%	19.6%	22.7%	21.8%	25.4%	25.8%	26.3%	28.3%	26.4%	25.5%
Balanced	18.1%	25.1%	21.1%	20.3%	18.2%	17.2%	15.3%	13.3%	14.4%	16.9%
Fund types										
Retail	97.9%	97.3%	97.7%	95.8%	90.8%	90.7%	87.3%	83.9%	75.1%	88.2%
Passively managed	0.0%	0.7%	0.0%	0.7%	1.6%	2.7%	3.6%	5.1%	5.3%	2.9%
Minimum investment	0.0%	0.3%	0.7%	1.4%	1.2%	1.6%	2.4%	2.2%	2.9%	1.8%

Panel D: Share of investor-fund observations in asset classes and fund types stratified by investor attributes								
	University degree		Business degree		Finance professional		Above median wealth	
	Yes	No	Yes	No	Yes	No	Yes	No
Asset classes								
ST bond	9.7%	11.6%	11.1%	10.7%	15.3%	10.5%	12.2%	9.7%
LT general bond	6.5%	3.8%	6.3%	4.8%	9.4%	4.8%	7.3%	3.3%
LT em. market bond	0.3%	0.3%	0.3%	0.3%	0.7%	0.3%	0.5%	0.1%
General equity	42.9%	40.6%	42.1%	41.5%	40.2%	41.7%	41.6%	41.6%
Em. market equity	26.6%	24.6%	28.0%	25.0%	27.3%	25.4%	25.7%	25.3%
Balanced	14.0%	19.1%	12.2%	17.6%	7.2%	17.3%	12.7%	20.0%
Fund types								
Retail	81.8%	93.3%	83.9%	88.9%	76.0%	88.8%	80.3%	94.3%
Passively managed	5.4%	1.0%	5.2%	2.5%	6.8%	2.7%	4.7%	1.6%
Minimum investment	2.5%	1.2%	3.9%	1.5%	7.4%	1.5%	3.2%	0.8%

Table 3

Choice of asset class and fund type

This table reports logit coefficients, their associated *z*-values in parentheses, and marginal effects above the *z*-values from logit regressions that explain investor *i*'s decision to hold a fund in an asset class or of a service type at the end of year *t*, where *t* ranges from 2004 to 2008. Marginal effects are calculated at the means of regressors, except for dummies that characterize investor attributes, which are calculated at zero. Standard errors used to compute test statistics are clustered at the fund level and are robust to heteroskedasticity. The regressions are estimated over investor-holdings-year observations. The dependent variable is one if the fund held by the investor that year belongs to the category in each row. Balanced fund regressions are run separately for all investors and investors who hold a balanced fund or at least a pair of general equity and long-term bond funds (the latter containing both intermediate- and long-term bond funds). Independent variables, which are demeaned, are the IQ stanine rescaled to vary from –1 to 1, dummies for having a university or a business degree and working in the finance industry, and logged wealth (in Euros) held in mutual funds and individual stocks at the end of year *t*. All regressions include unreported dummies for the five calendar years of observation, 2004–08.

Dependent variable: The fund an investor holds is...	Independent variables					Summary statistics:
	IQ score	University degree	Business degree	Finance professional	Ln (Wealth)	Pseudo-R^2 Ref. prob. *N*
	–0.337	–0.074	0.006	0.167	0.036	0.006
Short-term bond	–0.037	–0.008	0.001	0.018	0.004	0.127
	(–3.07)	(–0.72)	(0.07)	(0.60)	(0.63)	49,219
	0.059	0.268	0.032	0.030	0.191	0.024
Long-term general bond	0.002	0.011	0.001	0.001	0.008	0.042
	(0.59)	(2.86)	(0.28)	(0.12)	(3.55)	49,219
	0.210	–0.241	–0.169	0.533	0.462	0.087
Long-term emerging market bond	0.000	–0.001	0.000	0.001	0.001	0.002
	(1.26)	(–1.13)	(–0.46)	(0.70)	(3.40)	49,219
	0.105	0.045	0.005	–0.072	–0.009	0.007
General equity	0.026	0.011	0.001	–0.018	–0.002	0.438
	(1.49)	(0.82)	(0.08)	(–0.61)	(–0.33)	49,219
	0.192	0.027	0.130	0.151	0.065	0.018
Emerging markets equity	0.033	0.005	0.022	0.026	0.011	0.221
	(2.51)	(0.53)	(2.23)	(1.23)	(2.32)	49,219
	–0.171	–0.123	–0.219	–0.306	–0.144	0.022
Balanced fund, all investors	–0.024	–0.017	–0.030	–0.042	–0.020	0.170
	(–2.41)	(–1.85)	(–3.40)	(–2.38)	(–3.69)	49,219
	–0.183	–0.190	–0.101	–0.355	–0.440	0.126
Balanced fund, bond and equity exposure	–0.035	–0.036	–0.019	–0.067	–0.083	0.341
	(–2.59)	(–2.59)	(–1.34)	(–2.43)	(–9.55)	24,469
	–0.710	–0.562	–0.111	–0.244	–0.408	0.133
Retail fund	–0.059	–0.046	–0.009	–0.020	–0.034	0.898
	(–10.71)	(–6.00)	(–1.37)	(–2.34)	(–13.79)	49,219
	0.586	1.183	0.578	0.215	0.157	0.087
Passively managed fund	0.010	0.020	0.010	0.004	0.003	0.018
	(6.13)	(5.59)	(8.55)	(1.22)	(3.93)	49,219
	0.288	0.180	0.448	1.039	0.500	0.138
Minimum investment fund	0.004	0.003	0.007	0.015	0.007	0.016
	(2.82)	(1.55)	(3.11)	(2.15)	(5.18)	49,219

Table 4

Single logit regression of fund choice

This table reports logit coefficients, their associated *z*-values in parentheses, and marginal effects above the *z*-values from a single logit regression that explains investor *i*'s decision to own fund *j* at the end of year *t*, where *t* ranges from 2004 to 2008. The regression's estimates are displayed in an array. Marginal effects are calculated at the means of regressors, except for dummies that characterize fund attributes, which are calculated at zero. Standard errors used to compute test statistics are clustered at the fund level and are robust to heteroskedasticity. The regression includes main effects for each fund and investor attribute and the interaction of each fund attribute with each investor attribute. Fund variables are the management fee, six dummy variables for asset classes (short-term bond funds omitted) and three dummy variables—for funds that are run and distributed by a retail bank, for passively managed funds, and for funds with a 5,000 Euro minimum investment threshold. Long-term bond funds include intermediate- and long-term bond funds. Management fee is measured in logged basis points to facilitate comparisons across asset classes. The main effects of fund attributes are reported in column 1. The first row of columns 2 through 6 reports the main effects of investor attributes. The IQ score from 1 to 9 is rescaled to vary from –1 to 1 and ln(Wealth) is investor *i*'s logged Euros held in mutual funds and individual stocks at the end of year *t*. Investor attributes and logged fee are demeaned. The remaining rows in columns 2 through 5 report the coefficients on interactions of the investor attribute in the column and the fund attribute in the row. The regression includes unreported dummy variables for the five calendar years of observation, 2004–08. Funds with non-transparent fees and missing information on the underlying asset class are excluded from the sample.

Dependent variable	Ownership dummy					
Specification	Logit					
	Main effects of fund attributes	Main effects and interactions				
		IQ	University degree	Business degree	Finance professional	Ln (Wealth)
	1	2	3	4	5	6
Main effects of investor characteristics		0.14	0.19	–0.30	–0.23	0.46
		0.0009	0.0013	–0.0020	–0.0015	0.0031
		(1.05)	(1.47)	(–2.48)	(–0.68)	(9.35)
Ln (Management fee)	0.41	**–0.26**	–0.31	–0.36	–0.45	–0.01
	0.0028	**–0.0017**	–0.0021	–0.0024	–0.0030	–0.0001
	(1.56)	**(–2.64)**	(–2.52)	(–3.69)	(–1.47)	(–0.43)
Long-term general bond fund	–1.93	0.46	0.44	0.15	0.08	0.14
	–0.0130	0.0031	0.0030	0.0010	0.0005	0.0009
	(–4.51)	(3.27)	(3.15)	(1.04)	(0.24)	(2.19)
Long-term emerging market bond fund	–2.14	0.56	–0.01	0.18	0.72	0.35
	–0.0144	0.0038	–0.0001	0.0012	0.0049	0.0024
	(–4.34)	(2.78)	(–0.08)	(0.51)	(0.92)	(4.53)
General equity fund	–1.14	0.69	0.45	0.43	0.44	–0.02
	–0.0077	0.0047	0.0030	0.0029	0.0029	–0.0001
	(–2.10)	(4.35)	(2.55)	(3.05)	(1.05)	(–0.29)
Emerging market equity fund	–0.56	0.86	0.57	0.70	0.80	0.05
	–0.0038	0.0058	0.0038	0.0047	0.0054	0.0003
	(–0.86)	(4.36)	(2.66)	(3.76)	(1.50)	(0.74)
Balanced fund	–0.91	0.50	0.36	0.28	0.26	–0.12
	–0.0061	0.0034	0.0024	0.0019	0.0017	–0.0008
	(–1.68)	(3.11)	(1.96)	(1.85)	(0.64)	(–1.89)
Retail fund	1.37	–0.61	–0.50	0.01	–0.08	–0.32
	0.0093	–0.0041	–0.0034	0.0001	–0.0005	–0.0021
	(9.95)	(–9.09)	(–6.36)	(0.15)	(–0.63)	(-14.47)
Passively managed fund	0.15	–0.09	0.70	0.10	–0.47	–0.07
	0.0010	–0.0006	0.0047	0.0007	–0.0032	–0.0005
	(0.33)	(–0.61)	(3.15)	(0.84)	(–1.03)	(–1.18)
Minimum investment fund	–2.19	0.07	–0.07	0.31	0.75	0.34
	–0.0148	0.0005	–0.0005	0.0021	0.0051	0.0023
	(–8.29)	(0.61)	(–0.42)	(2.20)	(1.90)	(5.11)
Pseudo-R^2	0.101					
Reference probability	0.007					
Number of observations	7,183,674					

Table 5

Controlling for omitted services

This table adds 22 fund family dummies and their interactions with all investor attributes to Table 4's regression. Fund family dummies and fund family dummy interactions are not reported for brevity. The table reports logit coefficients, their associated *z*-values in parentheses, and marginal effects above the *z*-values from a logit regression that explains investor *i*'s decision to own fund *j* at the end of year *t*, where *t* ranges from 2004 to 2008. See Table 4's legend for more details on the regression specification.

Dependent variable	Ownership dummy					
Specification	Logit					
	Main effects of fund attributes	Main effects and interactions				
		IQ	University degree	Business degree	Finance professional	Ln (Wealth)
	1	2	3	4	5	6
Main effects of investor characteristics		–0.38	0.004	–0.09	0.02	0.26
		–0.0026	0.00003	–0.0006	0.0001	0.0018
		(–2.56)	(0.04)	(–0.82)	(0.06)	(6.47)
Ln (Management fee)	0.49	**–0.34**	–0.03	–0.12	–0.29	–0.03
	0.0033	**–0.0023**	–0.0002	–0.0008	–0.0020	–0.0002
	(2.17)	**(–3.46)**	(–0.29)	(–1.06)	(–0.89)	(–1.05)
Long-term general bond fund	–2.17	0.50	0.36	0.08	0.14	0.14
	–0.0146	0.0034	0.0024	0.0005	0.0009	0.0009
	(–5.69)	(3.95)	(2.86)	(0.59)	(0.47)	(2.49)
Long-term emerging market bond fund	–2.55	0.57	–0.09	0.10	1.09	0.34
	–0.0171	0.0038	–0.0006	0.0007	0.0073	0.0023
	(–6.39)	(3.16)	(–0.47)	(0.30)	(1.62)	(5.62)
General equity fund	–1.48	0.81	0.14	0.18	0.33	0.01
	–0.0099	0.0054	0.0009	0.0012	0.0022	0.0001
	(–3.04)	(5.50)	(0.93)	(1.14)	(0.88)	(0.20)
Emerging market equity fund	–0.84	0.87	0.12	0.38	0.68	0.02
	–0.0056	0.0058	0.0008	0.0025	0.0045	0.0001
	(–1.53)	(5.14)	(0.70)	(2.03)	(1.37)	(0.35)
Balanced fund	–1.33	0.62	0.07	0.05	0.39	–0.08
	–0.0089	0.0041	0.0005	0.0003	0.0026	–0.0006
	(–2.75)	(4.21)	(0.45)	(0.27)	(1.00)	(–1.53)
Passively managed fund	0.32	–0.16	0.08	0.01	–0.13	–0.13
	0.0021	–0.0011	0.0005	0.0001	–0.0009	–0.0009
	(1.17)	(–1.24)	(0.39)	(0.11)	(–0.33)	(–3.03)
Minimum investment fund	–2.29	0.09	0.17	0.42	1.01	0.38
	–0.0154	0.0006	0.0011	0.0028	0.0068	0.0026
	(–8.02)	(0.77)	(1.11)	(2.76)	(2.64)	(5.12)
Pseudo-R^2	0.132					
Reference probability	0.007					
Number of observations	7,183,674					

Table 6

Additional robustness checks

This table analyzes the robustness of Table 4's fee-related coefficients. The table reports the fee-related interaction coefficients and their associated *t*- or *z*-values, in parentheses, from one OLS and seven logit regressions that explain investor *i*'s decision to own fund *j* at the end of year *t*, where *t* ranges from 2004 to 2008. For each of the eight regressions, coefficients for regressors that interact investor and fund attributes besides fees, as well as main effects coefficients are not reported for brevity. Table 4's legend provides more detail on regression specification. Column 1's regression is identical to Table 4's, except that it adds eight dummies for field of education (humanities and arts omitted) and their interactions with fund attributes. Column 2's regression is identical to Table 4's specification, except that the linear probability model is used to estimate coefficients in lieu of the logit specification. Column 3's regression replaces Table 4's wealth variable with logged wealth invested in mutual funds. Columns 4 and 5 add dummies for an investor living in one of the five largest cities and working for a firm that ranks in the top decile based on number of employees decile, respectively. Column 6 replaces the IQ variable with residuals from regressing IQ on dummies for the year the investor took the IQ test. Column 7 adds controls for a fund's past 12-month return and its interactions with investor characteristics, but, for brevity, reports the coefficient only for the IQ-past return interaction regressor. Column 8 has the same specification as Table 4, except that three IQ dummies replace IQ.

Robustness check	Extended education controls	Linear probability model	Fund wealth control	Urban resident control	Large firm employee control	Age control	12-month return control	IQ dummies
	1	2	3	4	5	6	7	8
IQ	–0.22	–0.0011	–0.26	–0.24	–0.42	–0.25	–0.25	
	(–2.34)	(–2.15)	(–2.63)	(–2.41)	(–3.15)	(–2.61)	(–2.30)	
IQ = [1,3]								0.19
								(1.33)
IQ = [7,9]								–0.17
								(–2.30)
University degree	–0.30	–0.0015	–0.31	–0.29	–0.08	–0.31	–0.36	–0.35
	(–2.12)	(–2.62)	(–2.57)	(–2.48)	(–0.62)	(–2.58)	(–2.47)	(–3.68)
Business degree	–0.36	–0.0020	–0.36	–0.35	–0.46	–0.36	–0.38	–0.35
	(–2.22)	(–3.79)	(–3.71)	(–3.61)	(–3.91)	(–3.70)	(–3.71)	(–3.68)
Finance professional	–0.41	–0.0029	–0.45	–0.43	0.07	–0.45	–0.51	–0.45
	(–1.36)	(–1.53)	(–1.47)	(–1.40)	(0.20)	(–1.46)	(–1.66)	(–1.49)
Ln (Wealth)	–0.01	0.0002	0.00	–0.01	0.01	–0.01	–0.02	–0.32
	(–0.37)	(0.83)	(–0.12)	(–0.29)	(0.19)	(–0.46)	(–0.62)	(–2.65)
General education	–0.05							
	(–0.35)							
Educational science	0.82							
	(2.53)							
Social sciences	–0.02							
	(–0.11)							
Natural sciences	–0.26							
	(–1.67)							
Engineering	0.10							
	(0.84)							
Agriculture and forestry	0.47							
	(2.00)							
Health and welfare	0.14							
	(0.75)							
Services	0.30							
	(1.60)							
Urban resident				–0.14				
				(–1.42)				
Large firm employee					–0.26			
					(–2.19)			
Interaction of IQ and 12-month return							0.01	
							(0.99)	
Pseudo-R^2 / Adjusted R^2	0.101	0.006	0.102	0.103	0.101	0.104	0.101	0.109
Number of observations	7,183,674	7,183,674	7,183,674	7,183,674	7,183,674	3,348,190	7,183,674	6,884,939

Table 7

Fee interactions by investor attributes

This table analyzes whether Table 4's fee-related coefficients differ for investors with various binary attributes. The table reports the fee-related interaction coefficients and their associated *z*-values, in parentheses, from four logit regressions that explain investor *i*'s decision to own fund *j* at the end of year *t*, where *t* ranges from 2004 to 2008. For each of the four regressions, coefficients for regressors that interact investor and fund attributes besides fees, as well as main effects coefficients, are not reported for brevity. Table 4's legend provides more detail on regression specification. Each of the four regressions has the same specification as Table 4, except that fee interactions and investor main effects are allowed to vary with one of four binary investor attributes. In the bottom half of the table, *p*-values indicate whether coefficient pairs significantly differ from each other.

Fee interaction	Investor attributes							
	University degree		Business degree		Finance professional		Wealth in top decile	
	No	Yes	No	Yes	No	Yes	No	Yes
	1		2		3		4	
IQ	–0.21	–0.14	–0.29	0.12	–0.26	–0.09	–0.24	–0.21
	(–2.08)	(–2.42)	(–2.93)	(0.92)	(–2.67)	(–0.65)	(–2.42)	(–2.17)
University degree			–0.29	–0.08	–0.30	–0.10	–0.24	–0.27
			(–2.46)	(–0.79)	(–2.47)	(–0.83)	(–1.98)	(–3.47)
Business degree	–0.31	–0.07			–0.34	–0.05	–0.34	–0.04
	(–2.86)	(–0.77)			(–3.60)	(–0.36)	(–3.40)	(–0.50)
Finance professional	–0.37	–0.08	–0.40	–0.04			–0.44	0.04
	(–1.00)	(–0.56)	(–1.25)	(–0.36)			(–1.28)	(0.25)
p-value for difference between 'No' and 'Yes'								
IQ	0.61		0.01		0.30		0.19	
University degree			0.15		0.28		0.84	
Business degree	0.15				0.07		0.03	
Finance professional	0.56		0.35				0.30	
Pseudo-R^2	0.101		0.101		0.101		0.101	
Number of observations	7,183,674		7,183,674		7,183,674		7,183,674	

Table 8

OLS regressions of fund fees on IQ and control variables

The OLS regressions in this table explain the management fee of an investor's holding in a year with investor characteristics. Management fees are measured in logged basis points to facilitate comparisons across asset classes. IQ enters linearly in columns 1−4 whereas columns 5−8 include dummies for each IQ stanine (1 omitted). Unreported dummy variables for the five calendar years of observation and six asset classes (all columns), as well as for retail funds, passively managed funds, and minimum investment funds (columns 3−4, 7−8) adjust the fees for variation related to fund characteristics. The *t*-values, reported in parentheses below the coefficients, are based on standard errors clustered at the fund level and robust to heteroskedasticity.

Dependent variable	Ln (Management fee)							
Specification	Linear IQ				IQ stanine dummies			
	Asset class dummies		+ retail, passively managed, and minimum investment dummies		Asset class dummies		+ retail, passively managed, and minimum investment dummies	
	No investor controls	Investor controls	No investor controls	Investor controls	No investor controls	Investor controls	No investor controls	Investor controls
	1	2	3	4	5	6	7	8
IQ	–4.48	–2.19	–1.29	–0.86				
	(–3.13)	(–2.99)	(–2.65)	(–2.26)				
IQ = 2					–2.85	–2.47	–2.58	–2.49
					(–1.64)	(–1.40)	(–1.55)	(–1.49)
IQ = 3					–3.78	–3.32	–3.45	–3.36
					(–1.97)	(–1.72)	(–1.89)	(–1.83)
IQ = 4					–4.94	–4.05	–3.73	–3.56
					(–2.49)	(–2.05)	(–1.98)	(–1.88)
IQ = 5					–4.99	–2.95	–3.26	–2.79
					(–2.75)	(–1.68)	(–1.99)	(–1.68)
IQ = 6					–6.94	–4.44	–4.17	–3.58
					(–3.66)	(–2.58)	(–2.59)	(–2.24)
IQ = 7					–8.07	–4.94	–4.55	–3.87
					(–3.55)	(–2.58)	(–2.52)	(–2.18)
IQ = 8					–9.25	–5.72	–4.59	–3.83
					(–3.78)	(–3.10)	(–2.80)	(–2.37)
IQ = 9					–9.89	–5.82	–4.70	–3.94
					(–3.55)	(–2.80)	(–2.41)	(–2.07)
University degree		–3.49		–1.13		–3.50		–1.14
		(–2.71)		(–1.80)		(–2.73)		(–1.82)
Business degree		–3.91		–1.59		–3.93		–1.60
		(–4.10)		(–2.42)		(–4.13)		(–2.43)
Finance professional		–5.28		–2.59		–5.35		–2.63
		(–1.68)		(–1.24)		(–1.70)		(–1.26)
Ln (Wealth)		–0.55		0.11		–0.55		0.11
		(–2.04)		(0.78)		(–2.08)		(0.75)
Adjusted R^2	0.747	0.750	0.846	0.847	0.747	0.750	0.846	0.847
Number of observations	49,219	49,219	49,219	49,219	49,219	49,219	49,219	49,219