IQ and Mutual Fund Choice*

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Abstract

Using a comprehensive dataset of Finnish males, we study IQ's influence on mutual fund choice. High-IQ investors are less likely to own categories of funds that tend to charge higher fees—including balanced funds, actively managed funds, and funds marketed through a retail network. Moreover, within categories of funds stratified by asset class, investment philosophy, and distribution method, high-IQ investors prefer the lowest-fee funds, further reducing the fees incurred. IQ's effect on fee sensitivity controls for other investor attributes, including education and profession, and is robust to the addition of fund family dummies, alternative specifications, and analyses restricted to interesting subsamples of the data.

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Businesses often introduce features into products and pricing to obfuscate comparisons. Wireless telephone companies earn little profit from easily comparable monthly rates and subsidized equipment, but require lock-up periods. After the lock-up, they profit from ring-tone purchases, excess usage, and navigation software. Banks offer seemingly free accounts, but impose charges for statement printing, cancelled checks, or insufficiently frequent debit card use. Since January 2012, U.S. regulators, seemingly frustrated by the inconsistent inclusion of fees and taxes in posted fares, have required airlines to post all-inclusive fares.[1] However, consumers of airline travel still have to compare the costs and benefits of a bewildering number of services, including baggage, telephone bookings, travel plan changes, mileage awards, seat location, and even on-board use of a bathroom.

Theoretical models increasingly feature firms that optimize by making consumer product choice confusing.[2] 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 and difficult-to-solve consumer search problem.[3] Understanding which product features are important and how these features compare across competitors imposes significant cognitive costs on the consumer. Cognitive costs play a central role in models of consumption choice and contracting, such as those in Chetty, Looney, and Kroft (2007) and Tirole (2009). Models also now link cross-sectional differences in the cognitive cost of search to consumer demand elasticity, product choice, equilibrium pricing, and consumer welfare. For example, in Gabaix

[1] See "Airfares with less small print", New York Times, December 26, 2011.

[2] DellaVigna and Malmendier (2004) characterize the profit-maximizing contract for goods with immediate costs and delayed benefits, such as health club attendance. DellaVigna and Malmendier (2006) show that contractual design in the health club industry is consistent with suboptimal consumer behavior. Mullainathan, Schwartzstein, and Shleifer (2008) develop a model whereby objectively useless information influences individuals' choice of category, and document that many mutual fund ads include information on past performance in a bull market. In a bear market, however, ads rarely include references to performance, even for funds outperforming the market.

[3] See Diamond (1978) for a model of how firms earn rents from consumer search costs.

and Laibson's (2006) model, sophisticated consumers with high "consumer IQ" earn rents from those with "low consumer IQ."

In contrast to the impressive theoretical progress on consumer choice and cognitive ability, scarcely any empirical work studies cross-sectional variation in consumer cognitive ability and whether such variation generates "consumption mistakes." We study variation in intellectual ability (IQ) across consumers and analyze how IQ influences consumer choice in the mutual fund market, controlling for education and profession (which also influence price elasticity). We find that intelligent consumers are more price-sensitive about mutual fund fees.

The IQ data used to draw this conclusion come from a test specifically designed to measure intellectual ability. The test, administered to virtually every Finnish male who reaches military draft age, mimics the design of other well-known IQ tests, like the Wechsler Adult Intelligence Scale. It is also unique because of its timing—at the age of induction into military service (about 19 or 20), a time in life prior to any 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. Our data records are comprehensive; we have every score on the exam taken since 1982.

Mutual funds offer an ideal arena for understanding cross-sectional differences in consumer price elasticity and how cognitive costs (proxied by IQ score) influence the elasticity and the frequency of consumption mistakes. For one, it is easier to compare mutual funds than many other products or services, facilitating the econometrician's ability to identify the link between IQ and consumption mistakes. The key service rendered by mutual funds is an after-fee risk-return tradeoff. A large body of finance research concludes that higher mutual fund fees tend to reduce the risk-adjusted returns earned by fund investors.[4] In light of this literature, many researchers believe fees are informative about the extent to which an investor has overpaid for fund services.[5] Some consumers, barraged by recommendations, ratings, and information about ex-post performance, may make consumption mistakes, ignoring fees or think they are relatively minor contributors to the after-fee risk-return tradeoff. Even if fund attributes differ in dimensions like asset class, service speed, degree of "handholding," or quality of tax reports, the variation in these fund attributes is relatively easy to control for because the attribute is either observable (e.g., asset class) or likely to affect all funds within the same fund family in the same way (e.g., service speed, degree of handholding, or quality of tax reports).

The mutual fund industry may be the only industry where (at least in some countries) every consumer's demand is observable and can be linked with data on IQ and other important variables tied to cognitive frictions, like education and occupation. There also is widespread belief that cognitive costs are significant in the mutual fund industry, at least for some investors, possibly motivating regulation. In most developed countries, regulators require funds to disclose the expenses borne by their shareholders and in some jurisdictions can limit what they consider to be excessive fees.[6] While our study has no way to determine if the fees paid for fund services are fair, it does provide evidence on whether search costs significantly vary across consumers.

[4] See Blake, Elton, and Gruber (1993), Elton, Gruber, and Busse (1993) Malkiel (1995), Gruber (1996), Carhart (1997), Otten and Bams (2002), and Gil-Bazo and Ruiz-Verdú (2009).

[5] 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 Del Guercio and Reuter (2011), who show that actively managed funds do not underperform index funds within certain fund groups.

[6] 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.

Our study also represents an alternative way to assess the finance literature's prescriptive conclusion, presented as longstanding "folk wisdom," which suggests that it is a mistake to invest in high-fee funds. The smart-investor preference for low-fee funds corroborates the folk wisdom, particularly if one believes the observed behavior has some likelihood of arising from independent validation. This would mean smart investors are doing their own homework or extrapolating from their own experience (as opposed to parroting others' recommendations).

Using unique individual-level data from Finland on fund holdings and IQ, our study shows that investors with high IQ tend to avoid high-fee funds in two ways. First, they avoid categories of funds that tend to charge higher fees. These categories include actively managed funds, balanced funds, and funds distributed through a retail network. We also find that high-IQ investors, controlling for other investor characteristics, avoid high-fee funds even after holding fund asset class, distribution channel, investment philosophy (active vs. passive), and minimum investment requirement (above vs. below 5,000 Euros) 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, or minimum investment. For example, within the class of actively managed equity funds without large minimums, constrained even further to a single fund family, 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 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.

Controls used to study the marginal influence of IQ on price elasticity include the investor's wealth, education (university or business), and profession (here, working in the financial services industry) and two sets of fund attribute controls. The basic set of fund controls include dummy variables for the asset class primarily held by the fund, the fund's method of distribution, its investment philosophy, and its minimum investment requirement. The more elaborate set of fund attribute controls add fund family dummies. To the extent that additional service differences are captured by fund family dummies, the interactions between the fund family dummies and investor attributes capture the differential appeal of these service differences to investors of differing education, profession, and IQ. The influence of IQ on the sensitivity to fund fees remains highly significant when we control for fund family. In all of our specifications, IQ's influence over fee sensitivity is economically large, and of a magnitude comparable to that of significant education variables.

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, evidence presented in this paper suggests that high-IQ investors would have no significant preference for passively managed funds if these funds charged the same fees as actively managed funds in the same asset class; only the fee difference leads high-IQ investors to gravitate towards the passively managed funds.

Our results are highly robust. We generate nearly identical findings with additional controls for educational field of concentration, urban residency, employment in a large firm, or the tendency of measured IQ to increase over time (i.e. the "Flynn effect"). IQ's influence on fee sensitivity does not diminish when analyzed separately for each year, or for the wealthiest investors. Its influence is eliminated by business education, suggesting that financial literacy may play a useful role in reducing the IQ advantage in financial markets. Finally, alternative ways of estimating coefficients (the linear probability model), clustering standard errors, and measuring wealth differently generate qualitatively similar results.

Our paper builds on three strands of empirical literature. The first, which studies the role of fees and expenses in fund selection, arrives at conflicting conclusions. Barber, Odean, and Zheng (2005) contend that investors are sensitive to loads but not 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 et al. (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. None of these studies uses real IQ data representative of a broad population or relate IQ to real-world investment choice.

The second strand, exemplified by Grinblatt, Keloharju, and Linnainmaa (2011, 2012), studies IQ's role in stock market decisions. It shows that high-IQ investors are more likely to participate in the stock market and earn high returns and Sharpe ratios. It also concludes that smart investors are more likely to be diversified, time the market, provide liquidity, incur low trading costs, and engage in share purchases that predict the returns of individual stocks. They are less likely to exhibit wealth destroying behavioral biases. These studies are silent on the role IQ plays in generating price sensitivity to offerings of financial products.

The final strand links various measures of financial literacy and cognitive skill to the use of financial services. 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 (2011) 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. 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 strand of the literature.

The paper is organized as follows: Section I describes the institutional setting, the data, and provides summary statistics. Section II presents multiple regression results. Section III concludes the paper by interpreting the regression results.

I. Institutional Setting, Data, and Summary Statistics

A. The Finnish Mutual Fund Market

The market for mutual funds in Finland differs from the U.S. market in size, advisory fees, distribution, asset focus, and tax treatment.

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. Distribution fees, like the 12b-1 fees charged by U.S. funds, are part of the management advisory fee rather than being allocated to the expense ratio portion that is separate from the management fee. Management fees, which tend to be modestly higher than expense ratios in the U.S., account for over 90% of Finnish advisory firm revenue.[7] 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—usually below 1% for equity and balanced funds, and 0.5% for bond funds. Because loads are one-time events, are relatively small, and do not vary much across Finnish funds, 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 its bank's financial products, which include a single family of funds.[8] We refer to the funds distributed by banks

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

[8] Some banks or asset management houses also sell more specialized products (e.g., North America or Japan funds) produced by foreign subcontractors under their own brands. Only one bank with a relatively small retail network sells mutual fund products of its domestic competitors.

with extensive branch outlets as "retail funds" and refer to all other funds as non-retail funds. The retail funds come with advice on how to invest and a great deal of handholding. Retail fund sales are concentrated; the three largest banks account for about two-thirds of the market. A retail network generally does not distribute index funds, which are far less popular in Finland than in the U.S.[9] There also are many smaller asset management houses or other players in the market, such as one major Swedish bank, Handelsbanken, but its funds lack the wide distribution network of the banks that offer what we refer to as retail funds. While investors do not use brokers to buy funds, some investors acquire fund shares through a voluntary pension insurance plan or at the recommendation of free "independent" advisors.[10]

Asset focus. Most but not all Finnish funds invest predominantly in the equity and bonds of foreign markets. The general equity and bond funds concentrate in OECD markets, with emphasis on Europe. Some funds specializing in emerging markets' stocks or bonds 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 when they receive dividend distributions from the funds or when they realize capital gains by selling shares in the fund. However, in contrast to the U.S., Finnish mutual funds are not compelled to distribute interest, dividend, or capital gains income. Indeed, Finnish mutual funds have tranches that reinvest these sources of income in the fund rather than

[9] Finland's relatively small aggregate investment in passive funds, including one ETF (which, being a closed-end fund, is not in our sample) may stem from the prevalence of retail distribution. Distribution method influences the mix of actively managed and passively managed funds in the U.S. as well. For example, Del Guercio and Reuter (2011) observe that few U.S. passively managed funds are distributed through brokers. Moreover, among U.S. funds directly distributed to investors, they discern no significant difference in the risk-adjusted returns to investors of actively managed and passively managed funds.

[10] This type of advisor (as opposed to the management advisory firm) makes money by negotiating volume discounts with the funds (including an exemption from the front-load fee), pocketing the difference. In practice, the volume discounts often generate little incentive for the advisers to recommend the funds, so they tend to advise clients to buy *more expensive* products (e.g., nontransparent insurance products) that offer the advisor fatter margins.

distribute them to fund investors. The vast majority of Finnish investors prefer these tax-advantaged tranches. Their existence implies that Finland's relatively unpopular index funds lack the same relative tax advantage that U.S. index funds possess. Likewise, balanced funds, which are more popular in Finland than in the U.S., lack U.S. balanced funds' tax disadvantage from rebalancing. During the period studied, our sample of Finnish investors paid a flat 28% rate (in 2004, a flat 29% rate) on their capital income. (See Grinblatt and Keloharju (2004) for a more exhaustive description of personal taxation in Finland.)

Alternative diversification vehicles. In contrast to the U.S., Finnish mutual funds were largely the "only game in town" for Finnish investors who wanted a single diversified investment vehicle during our sample period. The prominence of retail networks, which market only domestic open-end funds, reflects the fact that investing in foreign mutual funds or ETFs was more difficult and unpopular. Moreover, there was only one Finnish closed-end fund (excluded from our sample), and no Finnish-domiciled exchange-traded funds during the period studied.

B. Data Sources

We obtain data from five sources, described below. To link individuals across the data sets, we employ a personal identification number unique to an individual, similar to a U.S. social security number.

Finnish Tax Administration (FTA). The FTA collects fund shareholder data from all directly held Finnish-domiciled open-end mutual funds in taxable accounts.[11] Each individual's

[11] Finland has a generous defined-benefit pension system, which is jointly financed by employers and employee contributions, much like the social security system in the U.S. In addition, some companies augment the pensions with supplemental pensions that tend to offer defined benefits. When the supplemental pension comes from a defined contribution plan, choice tends to be limited to a few funds. Thus, the influence employees have on the choice of funds in pension plans ranges from highly limited (defined contribution supplemental plans) to nonexistent (defined benefit plans). Tax authorities lack data on individuals' fund holdings in any of these plans.

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 penalize inaccurate, false, or incomplete reporting, 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.

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 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.

Statistics Finland. Statistics Finland, which collects data from many government agencies, provides career and education information for the subjects in our sample. The data they collect is from a randomly drawn sequence of the population born after December 31, 1954 and before January 1, 1985. The sample consists of about 5.8% of the 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.[12] 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 2004–08. Although we control 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.

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

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 six additional issues allowing us to compute monthly fund returns from January 2005 to June 2009. Because we analyze all funds from all reports and the report covers all Finnish-domiciled funds, survivorship bias concerns do not apply to our study. We exclude funds with incentive fees, hedge funds, miscellaneous funds, and any funds with fees that are not transparent from the report.

C. 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, the mean and standard deviation of the fees charged by management, aggregate assets under management, number of investors holding funds in the category, and average IQ of those who invest in that category. All numbers in the table, except for average IQ, come from the Mutual Fund Report.

Table 1 indicates that the funds in our sample managed over 30 billion Euros in 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 also indicates 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 funds and the relatively small emerging markets fund categories, funds distributed through a retail network tend to have higher fees. The higher fees for balanced funds and retail funds are consistent with the findings of Korkeamäki and Smythe (2004). Emerging markets funds also tend to have higher fees, while passively managed (index) funds and funds that require 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 rows report sums of the number of investors in each fund in the category, measured at the end of 2008. Hence, an investor who holds two funds in the category is counted twice, although most investors hold only one fund. This double counting is necessary because the data for Table 1 come from Mutual Fund Report, which provides aggregate data for each fund and does not contain the personal identification number used for later analysis. Thus, many of the investors counted by Table 1 are not in our sample because we lack data on IQ or some control variable for them.

D. Summary Data on IQ

The "average IQ" rows in Table 1 indicate that the average investor in balanced funds and in retail funds tends to possess lower IQ than other investors, and that the IQs of those in passively managed funds and funds with at least a 5,000 Euro minimum investment tend to be higher. Thus, high-IQ investors tend to concentrate in the lower-fee fund categories. 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.

Table 2 reports the distribution of the IQ variable (Panels A), the averages of other key investor-specific attributes conditional on IQ (Panel B), along with the proportion of fund investors holding a specific fund type conditional on IQ (Panel C) and various education, career, and wealth attributes (Panel D). 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 quite a bit smarter than the theoretical distribution would predict, consistent with Grinblatt, Keloharju, and Linnainmaa's (2011) finding that 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. Panel C suggests that high-IQ fund investors are more likely to hold passively managed funds and less likely to hold short-term bond 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 high-IQ investors 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.

II. Multivariate Results

Table 1 and Panel C of Table 2 indicated that high-IQ investors tend to concentrate in certain types of funds. Within asset classes, high-IQ shareholders are more prevalent in fund types with lower fees: the non-retail, passively managed, and minimum investment funds. They also tend to avoid balanced funds, which have fees similar to equity funds but far higher than bond funds. 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. Motivated by this consideration, this section studies 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. All significance tests use fund-clustered standard errors.

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.

In the regressions that follow, IQ score, coded by the Finnish Armed Forces as an integer from 1 to 9, is rescaled with a linear transformation to vary from –1 to 1. This rescaling, which has no effect on test statistics, facilitates the interpretation of the IQ and IQ interaction coefficients. The coefficient on the rescaled IQ variable represents the effect of being a stanine-9 rather than a stanine-5 (median IQ) 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 represents a change of exactly 30 IQ points 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.

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

Table 3 analyzes the role jointly played by five investor attributes, including IQ, in selecting ten particular categories of fund. It presents logit coefficients and marginal effects along with logit coefficient fund-clustered test statistics (which negligibly differ from the marginal effects test statistics) for ten logit regressions, each appearing in separate rows. The marginal effects and reference probability are evaluated at the average values of the continuous regressors and at zero for binary regressors. The first seven categories are 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 economics or business, 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.

The coefficients from Table 3's regressions effectively summarize whether investors of differing IQ, education, profession, and wealth select funds from each of the ten categories. One of the more striking inferences 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 owning a balanced fund by 0.024 other things equal. To assess the economic relevance of the 0.024 coefficient, recall the investor-fund row in Table 1's "All funds" section. Here, Table 1 suggested that a mutual fund holder's unconditional probability of holding a balanced fund is 0.183 (322,075, seen in Table 1's rightmost column, 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 effect magnitude is approximately 13% and 14% of the 0.183 and 0.170 unconditional and reference probabilities, respectively.[13] As –0.024 represents the effect of a four-stanine (or 30-point) increase in IQ, a one-point increase in IQ decreases the probability of holding a fund by 1/30 of this amount, 0.0008 (about ½% of the unconditional and reference probabilities).

Do high-IQ investors shun balanced funds because they perceive balanced funds' services to be overpriced? Recall from Table 1 that among the three most popular fund classes—general bond, equity, and balanced funds—the balanced fund class exhibits the highest fees given the asset mix they typically have. On average, they 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 equivalent to about 31 more IQ points, while a business education has the same effect as about 16 more IQ points. These calculations, like others in the paper that scale nonlinear marginal effects, necessarily represent rough approximations.

[13] The reference probability is the predicted likelihood of holding a fund, computed (like the marginal effects) at the means of regressors, except for dummies that characterize fund attributes, which are calculated at zero. Both reference probabilities and marginal effects would differ, due to nonlinearities, at other regressor values.

Table 3's short-term bond fund rows indicate that high-IQ investors are less willing to hold short-term bond funds. It is possible that high-IQ investors are better at finding profitable alternatives to short-term bond funds that charge 37 basis points for a low-yield financial instrument. Bank CDs come to mind. High-IQ and business-educated investors also exhibit a relative preference for emerging markets equity funds in Table 3. Such a preference could arise from IQ being correlated with an omitted variable like risk tolerance (Frederick, 2005 and Dohmen, Falk, Huffman, and Sunde, 2010) or a better understanding of diversification and the risk-reward tradeoff (Grinblatt, Keloharju, and Linnainmaa, 2011).

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-points) 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%.[14] 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.[15]

B. 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.

Table 4 reports logit and marginal effects coefficients from a single logit regression 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. In this regression, the dependent variable is one when the investor owns the fund that year. We use logged percentage fee as the fee

[14] 0.22% being 1/30 the ratio of the magnitude of the marginal effect to the reference probability, 0.059/0.898.

[15] The results above assume a linear IQ specification. Using individual IQ stanines as dummy variables leads to similar results. High-IQ investor aversion 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.

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.

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.[16] 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 with fee, but the coefficients are significant only for the two education

[16] 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.

dummies. The significance of these education-fee interaction coefficients will not survive more extensive controls for fund service, as we will see shortly.

To illustrate the economic magnitude of Table 4's –0.0017 IQ-fee marginal effects coefficient, consider a fund that doubles its fee, thus increasing the logged fee by ln(2). The interaction coefficient represents the shift in fee sensitivity between a stanine-5 and a stanine-9 investor. Doubling the fee reduces the stanine-9 investor's holding propensity by 0.0012 (=.ln(2) × 0.0017) more than it reduces the stanine-5 investor's probability of holding the same fund, thus decreasing an investor's propensity to hold a fund by 0.56% for each one-point increase in IQ.

The IQ column asset class coefficients measure IQ-related preferences relative to the omitted asset class category—short-term bonds. The relative preferences expressed by the IQ column's asset class coefficients hold fees constant. Thus, they cannot be compared to IQ coefficients from Table 3, as the latter regressions lack controls for fees. Table 4's asset class coefficients measure whether there is an IQ-related (or for other columns, wealth-, education-, or profession-related) preference for the asset class over short-term bonds that is separate from preferences about distribution channel and management philosophy. Table 4 also studies the influence of distribution channel and investment philosophy, controlling for fees and other fund categorizations.

The five positive asset class coefficients in Table 4's IQ column indicate that as IQ increases, the investor is less likely to be holding a short-term bond fund in lieu of some other fund asset class. For example, the significant balanced fund coefficient in the IQ column suggests that high-IQ investors exhibit a relative preference for balanced over short-term bond funds, other things equal. The balanced fund IQ coefficient is also larger than (but does not differ significantly from) the long-term general bond fund IQ coefficient. Thus, high-IQ investors show a slight preference for balanced funds over long-term general bond funds, other things equal. The IQ-related substitution of homemade balanced funds for balanced funds in Table 3 must therefore arise from high-IQ investors' greater fee sensitivity combined with the tendency of balanced funds to charge higher fees. Table 4's IQ column also indicates that smart investors place relatively lower value on retail bank funds' services. However, there are no significant IQ-related preferences for active over passive management or for funds with high minimums, other things (including fees) equal. (Being university-degreed is the only investor characteristic with a significant influence on Table 4's passive vs. active fund choice and being business-degreed is the only investor characteristic associated with a preference for funds with large minimums.)

The main-effects (leftmost) column indicates that there are significant differences in the "baseline" investor's preferences for funds within certain asset classes, a preference for retail funds, and aversion to funds with significant minimum investment requirements. The coefficients here largely reflect the relative prevalence of various fund types, which has been documented in Table 1. The corresponding main-effects row suggests that wealthier investors tend to invest in more funds. The coefficients in the main-effects column represent an investor with average values of the investor attributes and (except for the fee coefficient) hold fees constant. Similarly, coefficients in the main-effects row apply only to non-retail actively managed short-term bond funds with average logged percentage fees, and must thus be interpreted with caution.

C. Robustness: Additional Proxies for Omitted Service Attributes

Table 4 makes the striking observation that fees matter more to high-IQ and educated individuals, as well as finance professionals, 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 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.[17] 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

[17] Del Guercio and Reuter (2011) find that for U.S. funds, the choice of distribution channel operates almost exclusively at the fund family level.

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 represents a powerful way to control 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.

D. Other Robustness Checks

The prior section demonstrated that IQ's inverse relationship with mutual fund fees survives the addition of fund family fixed effects. Here, additional robustness checks show that the inverse relationship is apparent with many other model specifications and estimation techniques. Table 6 shows that high IQ elevates price sensitivity even with an alternative functional form for IQ, OLS estimation, finer education regressors, an alternative wealth regressor, controls for whether the investor resides in one of the five largest cities or works for a large company, and an IQ score adjusted to control for investor age and avoid the "Flynn effect." The IQ-fee interaction coefficient also remains negative and significant with a different clustering assumption, alternative thresholds for minimum investment, and regressions run separately for each calendar year. We describe the results in more detail below.

Table 6 contains seven columns, each representing logit or OLS coefficients from alternatives to Table 4's regression. Table 6's seven regressions each contain Table 4's full set of fund attributes and interactions with investor attributes. For brevity, each column reports only on the fee-related interaction coefficients from its regression. Hence, for comparison purposes, each column of Table 6 is comparable to the fee row in Table 4.

Alternative functional form for IQ. Table 6's first column replaces Table 4's linear IQ metric with dummies for being in stanines 1–3 and stanines 7–9, leaving the middle stanines 4–6 as the omitted category. It interacts both the low- and high- cognitive ability dummies with the fund attributes. (Finer IQ partitions are impractical because of the low number of investors in the extreme stanines.) The coefficient for the low-IQ group is 0.19 *(z*-value 1.33) while that for the high-IQ bin is –0.17 (*z*-value –2.30). The similar magnitudes, which represent sensitivity to fees compared to the average IQ group, suggest that IQ is monotonically and approximately linearly related to avoidance of high-fee funds.

OLS estimation. Table 4 estimates coefficients with logit regression. Table 6's second column, which uses the same specification and clustering assumptions as Table 4, estimates its coefficients with a linear probability model. The OLS IQ-fee interaction coefficient of –0.0011 (with a significant *t*-statistic of –2.15) is about two-thirds the size of the marginal effect from its logit cousin (–0.0017). However, the two coefficients are not directly comparable because the logit marginal effect is nonlinear and estimated only at one set of regressor values.

More extensive education controls. Inadequate education controls could artificially inflate IQ's importance in Table 4. For example, those educated in the social sciences might be more financially literate than those educated in agriculture and forestry. If IQ is correlated with one's field of study, IQ is still a driver of price elasticity, but perhaps only by steering investors into courses that tend to make them financially more literate. To assess whether this interesting alternative hypothesis has merit, Table 6's third column supplements Table 4's education regressors—employing all remaining education controls collected by Statistics Finland. Specifically, it adds dummy variables for general education and degrees in educational science, social sciences, natural sciences, technology and engineering, agriculture and forestry, health and welfare, and services. 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, while having a degree in educational science or agriculture and forestry generates a significantly positive fee interaction coefficient.

Alternative wealth measure. Column 4 of Table 6 assesses whether an alternative wealth control would affect our findings. Instead of using wealth measured from investment in stocks and funds, Column 4's wealth control consists of logged euros invested only in mutual funds. The alternative wealth metric does not materially alter Table 4's results. For example, the IQ-fee coefficients are identical to the second decimal place.

Controlling for urban residence. Could low-IQ investors' relatively greater tendency to select high-fee funds in Table 4 be due to limited choice associated with IQ demographics? Recall that retail funds distributed by banks predominate in Finland. Higher-IQ Finns, likely to be relatively more concentrated in the large cities, have more banks to choose from. Table 5, which uses fund family dummies, largely refutes this demographic explanation for the IQ-fee relationship because the magnitude of its IQ-fee coefficient is modestly larger than Table 4's coefficient. However, there is also the possibility that communication is more effective in large cities. Table 6's fifth column illustrates that the IQ-fee relationship remains virtually unchanged when Table 4's regression controls for being in a big city. It adds a dummy for whether one resides in a top-5 urban area (and corresponding interactions with the eight fund attribute variables). The alternative specification yields an IQ-fee logit coefficient of –0.24 with a significant z-statistic of –2.41 (the corresponding coefficient and z-value in Table 4 are –0.24 and –2.64, respectively). The urban-fee interaction coefficient is negative but not significant. This robustness check, (as well as Table 5's coefficient pattern compared to Table 4), suggests that location-based access to or preference for low-fee funds cannot explain Table 4's conclusion that IQ influences fee sensitivity.

Controlling for employment in a large firm. IQ may spuriously correlate with fees if investors select funds that mimic the offerings of their employers' pension plans. In particular, large firms may hire more intelligent employees and offer pension plan choices with lower fees (Bikker and De Dreu, 2009). These considerations motivate the sixth column of Table 6, which adds a dummy for whether one works in a large firm to Table 4's specification. The inclusion of this dummy variable does not eliminate the effect of IQ on fee sensitivity: to the contrary, the logit interaction coefficient here, –0.42, is more than 50 per cent larger than the corresponding coefficient from Table 4, which lacks the large employer control. This finding also suggests that the professional investment counseling or other communication that is more readily available at large firms cannot explain Table 4's IQ-fee result.

Flynn effect and the role of investor age. Table 6's rightmost column adjusts IQ for Flynn's (1984) effect—the tendency of measured IQ to rise in a repeatedly tested population over time. It replaces IQ in Table 4 by "residual IQ," computed from regressing IQ on dummies for the year in which an investor's IQ is assessed. Measuring IQ in this fashion scarcely alters our results. As an example, the IQ-fee coefficient changes from –0.26 in Table 4 to –0.25 here. Since, for most subjects, IQ is assessed at a similar age, this regression effectively orthogonalizes measured IQ and investor age—and thus controls for the effect of the investor's age on the IQ-fee relationship.

Clustering and minimum investment assumptions plus separate regressions by year. A few other robustness results deserve mention, but are not included in Table 6 for brevity. First, Table 4's *z*-statistic with fund clustering, –2.64, would be a significant –2.46 if computed from standard errors clustered at the investor level. Second, when a dummy control using a 2,500 Euro or a 10,000 Euro minimum replaces Tables 4's 5,000 Euro minimum, the IQ-fee logit interaction coefficient is –0.26 (the same as Table 4, but with a *z*-value –2.56) and –0.23 (*z*-value –2.29), respectively. Finally, Table 4's regression, run separately for each year of the 2004–2008 sample period, show a similar IQ effect on fee elasticity for each year. The five IQ-fee interaction coefficients range from –0.26 (year 2005) to –0.29 (year 2007). All coefficients are significant, with *t*-statistics ranging from –2.01 (year 2005) to –2.27 (year 2004). In sum, the IQ-fee relationship is quite robust.

E. Fee Interaction Coefficients and Investor Characteristics

Table 7 analyzes fee sensitivities that are generated by IQ and the other four investor attributes, and whether these fee sensitivities differ for investors with different attributes. Using four separate regressions, each extending Table 4's specification, it addresses questions like whether the IQ-fee interaction coefficient varies with education, profession, or wealth. More generally, each regression studies whether any of Table 4's fee-related logit interaction coefficients depend on a specific investor characteristic given in the regression's title.

For example, Table 7's university degree columns report the IQ, business education, finance profession, and wealth-related fee-sensitivity coefficients for investors without and with a university education. These coefficients, portrayed in Table 7's first pair of columns, are inferred from a single regression. The latter regression 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[18] by a pair of complementary dummy variables. The first dummy represents having a university degree and the second (one minus the first dummy) represents not having a university degree.

For all column pairs, the regression's title—university degree, business degree, finance professional, or top wealth decile—defines the dummy pair that multiplies the eight regressors. Despite two columns for each regression, each regression has many more regressors than space allows. Table 7 reports only fee-related interaction coefficients. As with Table 6, each of the four column pairs in Table 7 corresponds to the interaction coefficients in Table 4's fee row.

In addition to reporting the logit coefficient pairs 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 of these coefficient pairs do not significantly differ from one another, suggesting that Table 4's fee-related interaction coefficients are relatively stable across investors with different characteristics.

[18] We exclude the two redundant university regressors to avoid perfect multicollinearity.

Of particular interest among the insignificant coefficient differences is IQ's influence on fees among wealthy (top decile) and non-wealthy investors. The median mutual fund wealth of Table 7's high-wealth group (the column on the far right) exceeds 70,000 Euros. Because IQ significantly influences fee sensitivity, even for wealthy investors (z = –2.17), substantial amounts of wealth may be lost to high fees. This result also indicates that access to low-fee funds from being wealthy, separate from our minimum fee control, does not explain Table 4's significant IQ-fee interaction coefficient.

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 of difference = 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, eliminates any advantage at comparing prices conveyed by high IQ.

The other significant or nearly significant coefficient differences are for the business degree-fee interaction coefficient. Table 7's wealth and profession regressions indicate that a business degree's effect on fee sensitivity (p-value of differences = 0.03 and 0.07, respectively) may be mitigated either by being in the top wealth decile or by working in the finance profession. For the latter two investor categories, a business degree has no significant effect on fee sensitivity (z = –0.50 for the wealthy and –0.36 for finance professionals, respectively); for the complementary groups, a business degree significantly elevates fee sensitivity (z = –3.40 for the less wealthy and z = –3.60 for those not in the finance profession).

The coefficient pattern for other pairs of fee-investor attribute interactions, while rarely showing significant differences, largely is consistent with the more sophisticated of the pair classification as having less sensitivity to fees. At the very least, it seems clear that these investor attributes do not reinforce each other's effect on price elasticity.

III. Summary and Conclusion

Using remarkable data from Finland, including measurement of individual investor IQ, we find that high-IQ investors tend to own low-fee funds. Their gravitation to low-fee funds partly reflects a preference for asset classes, distribution outlets, and passive vs. active management philosophies that tend to have low fees. However, controlling for these fund attributes, high-IQ investors still prefer low-fee funds. We also control for service differences by adding 22 fund family dummies, but these fund family fixed effects scarcely alter the IQ-fee relationship.

Our study of IQ's role in fund selection focuses on its incremental effect, holding four other investor characteristics constant. These other characteristics—having a university or business degree, working in the finance profession, and wealth—are sometimes related to the tendency to hold a low-fee fund, controlling for observable fund attributes, depending on specification. However, the joint effect of these four investor attributes does not eliminate the IQ-fee relationship, irrespective of specification. The influence of IQ on fee elasticity is quite strong in light of all the controls and the fact that for many investors, it represents an exam score taken years, and sometimes decades, prior to the observed behavior.

While the paper's results are highly robust to alternative specifications, we would be remiss if we censor all mention of heretofore unmentioned analyses lacking significance. First, conditional on owning the fund, the size of a holding is not significantly influenced by the interaction between IQ and fee ($t = -1.48$). Thus, while IQ explains whether an investor tends to own low-fee funds, it does not explain investment size conditional on owning the fund.

Second, high-IQ investors' fund flows are no less sensitive to performance in the past 6 or 12 months than low-IQ investors' fund flows. We analyze this issue by regressing investor buy decisions[19] on Table 4's regressors and either IQ×6 month past return or IQ×12 month past return. Significant coefficients on one of the latter two variables indicate IQ-related fund flow sensitivity to fund past performance. The z-values for the IQ×past return control are 0.57 and 1.64, respectively.

Third, high-IQ investors' funds do not earn significantly greater net-of-fee returns or risk-adjusted returns than low-IQ investors' funds over the 54 months for which we have returns data (January 2005 to June 2009). The insignificant performance difference is not surprising given the power of the test and plausible magnitudes for fee differences. For example, the standard error of the monthly return differences between the stanine 1 and 9 portfolios is 0.093%. However, with only 54 monthly observations, two standard error significance requires an annualized average return difference above 220 basis points (2×0.093%×12)), which is larger than any conceivable IQ-related fee difference. Accordingly, the two standard error threshold is four times larger than the observed 55 basis point spread between the annualized returns of the stanine 1 and 9 portfolios over our sample period.

Our empirical results suggest that intellectual ability, education, and career-related financial expertise play a role in consumer demand elasticity. Because the underlying fund product is a relatively simple risk-return investment trade-off—which many believe is the same

[19] A pair of an investor and a fund is considered a year t "buy" if the fund is held by the investor at the end of year t, but not at the end of year $t-1$.

for all funds—mutual funds are an ideal industry for studying the drivers of consumer price elasticity. Despite the narrow industry focus, price is a common attribute in the exchange of money for goods and services. Thus, IQ's documented influence over price elasticity for mutual funds should generalize to other products.

It is probably easier to compare mutual funds than products whose demand critically depends on attributes other than price. Since IQ represents a metric that helps the consumer assess quality as well as price, it may play an even more important role in the demand for other products. However, the added complexity of such products also makes it much more difficult for the econometrician to verify that IQ influences price elasticity because of the greater challenge of finding adequate controls. For example, medical services may vary along many dimensions—skill of the doctor at diagnosing and treating many different disease categories, hospital one can be admitted to, waiting time when seeking medical help, bedside manner, etc. Some of these are unique to the provider. Similarly, the utility obtained from a fashionable line of clothing or cosmetics may differ along dimensions that are unique to the provider.

Besides the implications for consumer models, the study may also 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.[20] 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 some funds charge. However, a significant IQ-fee correlation could also arise from IQ's stratification of preferences—here, for

[20] See Elton, Gruber, and Busse (2004) and Hortaçsu and Syverson (2004) for documentation of such wide variation in fees.

unobserved costly services. This "clientele equilibrium" story implies that investors of low intellectual ability place greater value on the services higher-fee funds provide.

There is evidence to support 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 it most—the low-stanine groups. We also find evidence consistent with the cognitive frictions 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.

Despite this evidence, we lack data on the underlying cost of providing fund services, which prevent us from determining whether funds are overcharging for their services. What seems to be evident, however, is that high-IQ consumers of fund services are relatively better off. They find less expensive workarounds for the services others pay dearly for, finding alternatives to balanced funds and the handholding of retail distribution networks. Even more importantly, they seem to be less confused about pricing, making better choices when evaluating the exchange of services for money. 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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Table 1

Descriptive statistics on funds

For each asset class, Table 1 lists 2008 values of the number of funds, average fee, standard deviation of the fee within the category, 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	5.88	6.42	6.76	6.24	6.29	5.89
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	5.72	6.31	6.78	6.09	6.18	5.83
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	7.00	6.99	6.73	7.12	7.18	6.98
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	5.88	6.41	6.76	6.16	6.29	5.89
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		6.59		7.26		

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	5.81	6.39	6.76	6.22	6.28	5.89
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	6.76	7.00		6.86	8.33	6.00

Table 2

IQ, investor, and fund variables

Panel A reports the theoretical stanine distribution and its empirical equivalents for both the full sample and the sample of mutual fund holders. The full sample randomly selects Finns who are born between 1955 and 1984. The percent of fund holders is the proportion of individuals who have some fund holdings in each stanine. 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. 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
% fund holders in IQ stanine	10.4%	13.1%	15.9%	16.0%	20.4%	23.2%	26.2%	31.7%	34.3%	21.6%

Panel B: IQ stratified averages of investor attributes										
	IQ stanine									
	1	2	3	4	5	6	7	8	9	Total
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
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: Portfolio weights in asset classes and fund types stratified by IQ										
	IQ stanine									
	1	2	3	4	5	6	7	8	9	Total
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: Portfolio weights 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 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 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
Short-term bond	–0.337	–0.074	0.006	0.167	0.036	0.006
	–0.037	–0.008	0.001	0.018	0.004	0.127
	(–3.07)	(–0.72)	(0.07)	(0.60)	(0.63)	49,219
Long-term general bond	0.059	0.268	0.032	0.030	0.191	0.024
	0.002	0.011	0.001	0.001	0.008	0.042
	(0.59)	(2.86)	(0.28)	(0.12)	(3.55)	49,219
Long-term emerging market bond	0.210	–0.241	–0.169	0.533	0.462	0.087
	0.000	–0.001	0.000	0.001	0.001	0.002
	(1.26)	(–1.13)	(–0.46)	(0.70)	(3.40)	49,219
General equity	0.105	0.045	0.005	–0.072	–0.009	0.007
	0.026	0.011	0.001	–0.018	–0.002	0.438
	(1.49)	(0.82)	(0.08)	(–0.61)	(–0.33)	49,219
Emerging markets equity	0.192	0.027	0.130	0.151	0.065	0.018
	0.033	0.005	0.022	0.026	0.011	0.221
	(2.51)	(0.53)	(2.23)	(1.23)	(2.32)	49,219
Balanced fund, all investors	–0.171	–0.123	–0.219	–0.306	–0.144	0.022
	–0.024	–0.017	–0.030	–0.042	–0.020	0.170
	(–2.41)	(–1.85)	(–3.40)	(–2.38)	(–3.69)	49,219
Balanced fund, bond and equity exposure	–0.183	–0.190	–0.101	–0.355	–0.440	0.126
	–0.035	–0.036	–0.019	–0.067	–0.083	0.341
	(–2.59)	(–2.59)	(–1.34)	(–2.43)	(–9.55)	24,469
Retail fund	–0.710	–0.562	–0.111	–0.244	–0.408	0.133
	–0.059	–0.046	–0.009	–0.020	–0.034	0.898
	(-10.71)	(–6.00)	(–1.37)	(–2.34)	(-13.79)	49,219
Passively managed fund	0.586	1.183	0.578	0.215	0.157	0.087
	0.010	0.020	0.010	0.004	0.003	0.018
	(6.13)	(5.59)	(8.55)	(1.22)	(3.93)	49,219
Minimum investment fund	0.288	0.180	0.448	1.039	0.500	0.138
	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

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 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. 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 the logged percentage fee of the fund. 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)
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

Table 5 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)
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

Table 6 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 six 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 seven 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 has the same specification as Table 4, except that three IQ dummies replace IQ. 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 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 4's regression replaces Table 4's wealth variable with logged wealth invested in mutual funds. Columns 5 and 6 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 7 replaces the IQ variable with residuals from regressing IQ on dummies for the year the investor took the IQ test.

Robustness check	IQ dummies	Linear probability model	Extended education controls	Fund wealth control	Urban resident control	Large firm employee control	Age control
	Interactions of investor attributes with management fee						
	1	2	3	4	5	6	7
IQ = [1,3]	0.19						
	(1.33)						
IQ = [7,9]	–0.17						
	(–2.30)						
IQ		–0.0011	–0.22	–0.26	–0.24	–0.42	–0.25
		(–2.15)	(–2.34)	(–2.63)	(–2.41)	(–3.15)	(–2.61)
University degree	–0.35	–0.0015	–0.30	–0.31	–0.29	–0.08	–0.31
	(–3.68)	(–2.62)	(–2.12)	(–2.57)	(–2.48)	(–0.62)	(–2.58)
Business degree	–0.35	–0.0020	–0.36	–0.36	–0.35	–0.46	–0.36
	(–3.68)	(–3.79)	(–2.22)	(–3.71)	(–3.61)	(–3.91)	(–3.70)
Finance professional	–0.45	–0.0029	–0.41	–0.45	–0.43	0.07	–0.45
	(–1.49)	(–1.53)	(–1.36)	(–1.47)	(–1.40)	(0.20)	(–1.46)
Ln (Wealth)	–0.32	0.0002	–0.01	0.00	–0.01	0.01	–0.01
	(–2.65)	(0.83)	(–0.37)	(–0.12)	(–0.29)	(0.19)	(–0.46)
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)	
Adjusted R^2 / Pseudo-R^2	0.101	0.006	0.102	0.103	0.101	0.104	0.101
Number of observations	7,183,674	7,183,674	7,183,674	7,183,674	7,183,674	3,348,190	7,183,674

Table 7

Fee interactions by investor attributes

Table 7 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	