Retail Financial Advice: Does One Size Fit All?*

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Abstract

Using unique data on Canadian households, we assess the impact of financial advisors on their clients' portfolios. We find that advisors induce their clients to take more risk, thereby raising expected returns. On the other hand, we find limited evidence of customization: advisors direct clients into similar portfolios independent of their clients' risk preferences and stage in the life cycle. An advisor's own portfolio is a good predictor of the client's portfolio even after controlling for the client's characteristics. This one-size-fits-all advice does not come cheap. The average client pays more than 2.7% each year in fees and thus gives up all of the equity premium gained through increased risk-taking.

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1 Introduction

The lifecycle asset allocation problem is complex. Choosing how to allocate savings across risky assets requires, among other things, an understanding of risk preferences, investment horizon, and the joint dynamics of asset returns and labor income. To help solve this problem, many households turn to investment advisors. In the United States more than half of households owning mutual funds made purchases through an investment professional (Investment Company Institute 2013). Likewise, nearly half of Canadian households report using financial advisors (The Investment Funds Institute of Canada 2012), and roughly 80% of the $876 billion in retail investment assets in Canada reside in advisor-directed accounts (Canadian Securities Administrators 2012).

Despite widespread use of financial advisors, relatively little is known about how advisors shape their clients' investment portfolios. Recent studies highlight underperformance and return chasing by advisor-directed investments and provide suggestive evidence that agency conflicts contribute to underperformance.[1] An opposing view is that financial advisors nevertheless add value by building portfolios suited to each investor's unique characteristics, an approach described as "interior decoration" by Bernstein (1992) and Campbell and Viceira (2002). In this paper, we use unique data on Canadian households to explore two dimensions through which advisors may add value: first, by inducing clients to take investment risk and, second, by tailoring investment risk to clients' particular circumstances as opposed to delivering one-size-fits-all portfolios.

Our analysis begins by using a regulatory shock to the supply of Canadian financial advisors to measure advisors' impact on risk-taking. Household survey data show a strong correlation between portfolio risk and use of an advisor in Canada—advised households allocate more of their portfolio to risky financial assets. However, these data also indicate substantial sample selection. Clients of advisors are more educated, wealthier, and earn higher salaries than their unadvised peers. Thus, the disparity in portfolio risk between advised and unadvised households likely provides a biased measure of advisors' impact, one that is confounded by unobserved differences in, for example, risk tolerance.

[1] A number of studies document underperformance of advisor-directed investments: brokered mutual funds underperform non-brokered funds (Bergstresser, Chalmers, and Tufano 2009; Christoffersen, Evans, and Musto 2013) and investors who pay for advice underperform lifecycle funds (Chalmers and Reuter 2013) and self-managed accounts (Hackethal, Haliassos, and Jappelli 2012). Brokers are also more likely to sell funds that earn them higher commissions (Christoffersen, Evans, and Musto 2013). Mullainathan, Noeth, and Schoar (2012) find in a field experiment that advisors encourage their clients to chase past returns and purchase actively managed mutual funds.

To resolve this selection problem, we study a 2001 regulatory change that imposed licensing, financial reporting and capital requirements on Canadian financial advisors operating outside of Quebec. This change provides a shock to the supply of financial advisors that is plausibly unrelated to demand for advice. Using a differences-in-differences model to compare affected households to those in Quebec, we find that the change reduced households' likelihood of using an advisor by roughly 10%. Exploiting this variation within an instrumental variables model, we estimate that financial advisors increase the marginal households' risky asset share by 30 percentage points, which exceeds the estimate from a least squares regression that controls for household characteristics. This finding suggests that advisors facilitate substantially greater financial market participation and risk-taking, perhaps by reducing households' uncertainty about future returns or by relieving households' anxiety when taking financial risk (Gennaioli, Shleifer, and Vishny 2014).

Next, we delve deeper into advisors' impact on risk-taking by examining the portfolios held by advised households. Using data furnished by four large Canadian financial institutions, we measure the extent to which advisors tailor their advice. The data include transaction-level records on over 10,000 financial advisors and these advisors' 800,000 clients, along with demographic information on both investors and advisors. Many of the investor attributes—such as risk tolerance, age, investment horizon, income, occupation, and financial knowledge—ought to be of first-order importance in determining the appropriate allocation to risky assets.

What determines cross-sectional variation in investors' exposure to risk? In neoclassical portfolio theory, differences in risk aversion account entirely for variation in risky shares (see Mossin (1968), Merton (1969), and Samuelson (1969)). In richer classes of models, many other factors also shape investors' optimal risk exposures. For example, according to most models, old investors and investors facing greater labor income risk should invest less in risky assets (see, for example, Bodie, Merton, and Samuelson (1992)). The recommendations implicit in lifecycle funds also embody such advice. These funds allocate nearly the entire portfolio to equities for young investors and then reduce this exposure as investors near retirement.

We test whether advisors adjust portfolios in response to such factors by studying variation in the proportion of equities in investors' portfolios ("risky share"). We find that advisors modify portfolios based on client characteristics, with a particular emphasis on clients' risk tolerance and point in the life cycle. As one would expect, more risk-tolerant clients hold riskier portfolios: the least risk tolerant allocate on average 40% of their portfolio to risky assets, while the most risk tolerant allocate 80%. The risky share also declines with age, peaking at 75% before age 40 and declining by 5 to 10 percentage points as retirement approaches. While risk-taking peaks at the same age as in a lifecycle fund, the risky share of advised clients otherwise differs substantially from the pattern in a lifecycle fund—younger clients take less risk and older clients take substantially more risk than they would in a lifecycle fund. Counter to theories of optimal portfolio allocation, we find slightly more risk-taking among clients that face greater labor income risk. Clients working in the financial sector, whose incomes are likely to move in tandem with stock returns, hold slightly more in equities than clients working in other sectors. Similarly, self-employed clients hold slightly more in equities despite receiving proprietary income that is more volatile and more strongly correlated with market returns than the labor income of their peers (Heaton and Lucas 2000).

The most striking finding from our analysis of portfolio allocations, however, is that clients' observable characteristics jointly explain only 13% of the cross-sectional variation in risky share. That is, although differences in risk tolerance and age translate into significant differences in average risky shares, a remarkable amount of variation in portfolio risk remains unexplained.

In contrast, we find that advisor fixed effects have substantial explanatory power. Advisor fixed effects more than double the model's adjusted R^2, from 13% to 32%, meaning that advisor fixed effects explain one and a half times as much variation in risky share as explained by the full set of client characteristics. Similarly, advisor fixed effects are pivotal in explaining home bias: client characteristics explain only 4% of variation in the share of risky assets invested in Canadian equity funds whereas advisor fixed effects explain nearly 28%. The advisor effects are economically large. Moving from the 25th to the 75th percentile in the advisor distribution corresponds to a 20-percentage point change in risky share and a 32-percentage point change in home bias. One interpretation of this finding is that, instead of customizing, advisors build very similar portfolios for all of their clients. Another interpretation is that matching between investors and advisors leads to common variation in portfolio allocations among investors of the same advisor; that is, advisor fixed effects stand in for omitted client characteristics that are common across investors of the same advisor.

We find little support for the latter hypothesis. Our data include investor identifiers that allow us to track investors who switch advisors. This feature allows us to implement a two-way fixed effects analysis, similar to research on managerial style (Bertrand and Schoar 2003). For this subset of investors (and their associated advisors) we estimate models with both advisor and investor fixed effects, the latter controlling flexibly for any unobserved persistent differences across investors and the former capturing the advisor-specific "style" in portfolio allocation. While investor fixed effects add explanatory power beyond observable investor characteristics, advisor fixed effects continue to be pivotal in explaining risky share and home bias. The joint set of advisor effects display similar statistical significance as the investor effects, and the model's adjusted R^2 increases substantially—from 30% to 45%—when advisor effects accompany investor effects.

If advisors do not base their advice on investor characteristics, then what explains variation in recommendations across advisors? We find that advisors may project their own preferences and beliefs onto their clients. A unique feature of our data is that we observe the portfolio allocations for advisors who maintain investment portfolios at their own firm (over half of advisors in our sample do so). For these advisors, we find that their own risk-taking and home bias are far and away the strongest predictor of risk-taking and home bias in their clients' portfolios even after controlling for advisor and client characteristics. The picture that emerges here is that no matter what a client looks like, the advisor views the client as sharing his preferences and beliefs.

Lastly, we examine the cost and investment performance of advised accounts. Including all management fees and front-end loads paid to advisors and mutual funds, we find that the average client pays an annual fee of nearly 2.7% of assets. Compared to lifecycle funds, which provide equity and bond investments without active management by the investor, advised portfolios thus pay an additional fee of 1.7% per year. We show that advisors do not add value through market timing or fund selection. The gross alphas are, if anything, negative when we benchmark advised portfolios against passive equity and bond portfolios. Investors' net underperformance therefore equals (or exceeds) the fees that they pay.

Given that advisors provide limited customization, the puzzle in this market is the high cost of advice.[2] Accounting for an equity premium of, say, 6% per year and our earlier finding that advisors raise their clients' allocation to risky assets by 30 percentage points, we estimate households gain

[2]Agency conflicts are one possible explanation for the high cost of advice (Inderst and Ottaviani 2009). Clients rarely pay direct compensation to advisors for their services. Rather, the advisor earns commissions from the investment funds in which his client invests, which raises the possibility that their investment recommendations are biased toward funds that pay larger commissions without better investment returns.

1.8% per year from using an advisor. After paying fees of 1.7% in excess of a lifecycle fund, however, the investor gives up nearly all of the incremental expected return. This finding is reminiscent of Berk and Green's (2004) competitive mutual fund industry, in which capital flows in and out mutual funds exactly to such an extent that even though managers have skill, in expectation none of that skill gets passed on to investors in the form of positive alphas. To be clear, advisors may still add value through broader financial planning. Advisors may, for example, help establish and meet retirement savings goals (Lusardi and Mitchell 2011), create tax-efficient asset allocations (Bergstresser and Poterba 2004; Amromin 2008), and reduce clients' anxiety (Gennaioli, Shleifer, and Vishny 2014).

Our analysis contributes three insights to the literature on financial advice. We document, first, that advisors increase their clients' exposure to equities. Advisors thus provide a concrete financial benefit—an increase in expected returns due to the equity premium—that matters for performance evaluation. An advised client's performance has to be compared against the portfolio that he would hold in the absence of the advisor. Second, we find little support for the view that advisors' value added resides in the customization of portfolios. Third, we find that advisors are nevertheless a major determinant of individual asset allocation. Understanding the intermediation process is therefore crucial for theories seeking to explain household portfolios. The fact that advisors' own risk taking influences how much risk their clients assume is particularly notable. Although it is reassuring that advisors are willing to hold the portfolio that they recommend, the portfolio that is suitable for the advisor may deviate substantially from what is best for the investor.

The rest of the paper proceeds as follows. Section 2 uses survey data to investigate advisors' effect on their clients' risk-taking. Sections 3 and 4 describe our administrative data on client accounts, and present analysis of risk-taking, investment performance and the cost of advice. Section 5 uses an extended sample to evaluate the robustness of our results. Section 6 concludes.

2 The Effect of Financial Advisors on Risk-taking: Evidence from Survey Data

In this section we use the Canadian Financial Monitor (CFM) survey of households to evaluate the impact of financial advisors on their clients' risk-taking. Ipsos-Reid, a survey and market research firm, designed the CFM survey and collected the data through monthly interviews of approximately 1,000 households per month between January 1999 and June 2013. In addition to providing a wealth of demographic information, each interview measures households' asset holdings, including checking and savings accounts, stocks, bonds and mutual funds (by asset class). Most importantly for our analysis, the survey also collects information on the use of financial advisors.

Table 1 displays descriptive statistics for Canadian households, stratified by use of a financial advisor. Advised households are on average younger (46.3 vs. 47.9), less likely to be retired (11.9% vs. 17.2%), and more likely to have either a college or graduate degree (54.1% vs. 41.9%). From a financial standpoint, advised household also have higher average incomes (CND $58,700 vs. 44,600), more financial assets (CND $91,700 vs. 46,200) and are more likely to own a home (72.9% vs. 63.1%). Last, households that use financial advisors invest more in equity (32.8% vs. 20.1% of financial assets) and fixed-income products (29.9% vs. 22.8%) and hold less in checking, savings and money market accounts (37.3% vs. 57.0%).

These summary statistics indicate that advised households shift their portfolio allocation away from cash to riskier equity and fixed-income assets. However, given the substantial differences in other characteristics such as income and wealth, it is unclear whether these differences arise due to client preferences or advisor input. Risk-taking in financial markets may depend on the same (unobserved) household characteristics that influence the demand for advice.

We address this identification issue by using a regulatory change in the early 2000s that reduced the supply of financial advisors. Specifically, as of February 2001 mutual fund dealers and their agents, such as financial advisors, were required to register with the Mutual Fund Dealers Association of Canada (MFDA) and follow the rules and regulations of the MFDA. The introduction of this registration requirement meant that dealers who wished to remain in business were now subject to more stringent regulatory standards, including minimum capital levels as well as audit and financial reporting requirements. For the underlying advisors, the registration requirement also mandated securities training and established a basic standard of conduct.[3] The draft rules and bylaws were originally posted for comment on June 16, 2000. An overview of public comments given by dealers and advisors reveals particular concern about the compliance costs associated

[3]The standard of conduct is quite broad, prescribing that advisors "deal fairly, honestly and in good faith" with clients, "observe high standards of ethics" in their business transactions and not engage in conduct detrimental to the public interest (Canadian Securities Administrators 2012).

with financial reporting and capital costs created by the minimum capital standards (Mutual Fund Dealers Association 2000). These changes appeared to reduce the supply of advisors, and in that way constitute a shock to households' use of advisors that is unrelated to their demand for advisory services. Importantly, the regulatory change did not apply to dealers and advisors in the province of Quebec, allowing us to use Quebec residents as a comparison group that was not affected by the registration requirement.

We assess the impact of the registration requirement through the following differences-in-differences model:

$$y_{ipt} = \alpha + \beta \text{Register}_p \times \text{Post}_t + \gamma \text{Register}_p + \delta \text{Post}_t + \boldsymbol{\theta X}_{it} + \varepsilon_{ipt}, \tag{1}$$

in which subscripts i, p, and t index households, provinces, and months between January 1999 and January 2004, respectively. The variable Post_t is an indicator that takes the value of one for dates after June 2000, when the registration requirement was announced and draft rules were published for comment. Register_p is an indicator variable that takes the value of one for households located in provinces that faced the registration requirement. The coefficient β on the interaction of Register_p and Post_t measures the impact of the registration requirement over time. The vector $\boldsymbol{X}_{it}$ contains household-level controls for income, home ownership, education, age, and retirement status.[4] In some versions of the model we include province and month fixed effects to control more flexibly for differences over time and across provinces. To estimate the model we use weighted least squares, incorporating survey weights from the CFM to provide regression estimates that reflect a nationally representative sample. We cluster the observations by province in calculating Huber-White standard errors.

First, we estimate the impact of the registration requirement on households' use of financial advisors. Table 2 Panel A reports the regression estimates from three models in which the dependent variable is an indicator for whether the household uses a financial advisor. The baseline probability of using an advisor prior to the registration requirement is 43%. The estimates in the three models,

[4] Ipsos-Reid codes household income as a categorical variable, and we use indicator variables that represent these categories as controls. We control flexibly for the age of the head of household with indicator variables for 16 five-year age bins covering ages 20 to 100. We code education based on the maximum level of education of the head of household and spouse, and include indicators for each of four categories: high school diploma or less, some college, college degree, and graduate degree.

which differ in terms of the inclusion of household controls and fixed effects, suggest that the registration requirement had a statistically and economically significant effect on the use of financial advisors. The point estimates place the marginal effect between -4.3 and -3.9, translating into a proportional decrease of roughly 10%. In each case, the coefficient is statistically significant at the 1% level.[5] In the first model, which excludes household controls, the coefficient on the registration-requirement indicator is positive and significant at the 5% level. This estimate indicates that before the law change residents of Quebec are less likely to use advisors than their counterparts in other provinces. Differences in income and demographics, however, explain this disparity in its entirety; the coefficient on Register_p is very close to zero once we add household-level controls to the model. This evidence helps support our premise that, after controlling for observable differences, Quebec residents can serve as a baseline from which to measure the change in advisor usage. The substantial increase in R^2 induced by the inclusion of these controls shows that income, home ownership, education, age, and retirement status substantially correlate with the demand for advisory services. The estimated coefficient on the Post_t indicator of -3.1 indicates a decline in the use of advisors across all provinces following June 2000. One possible explanation for this trend is the poor performance of Canadian stocks during that period (nearly a 20% decline).

Using the variation documented above, we estimate financial advisors' impact on households' risk-taking in a two-stage least squares model:

$$\begin{aligned} \text{Use Advisor}_{ipt} &= \alpha_1 + \beta_1 \text{Register}_p \times \text{Post}_t + \boldsymbol{\eta}_{1p} + \boldsymbol{\Psi}_{1t} + \boldsymbol{\theta}_1 \boldsymbol{X}_{it} + \varepsilon_{1ipt}, & (2) \\ y_{ipt} &= \alpha_2 + \beta_2 \widehat{\text{Use Advisor}}_{ipt} + \boldsymbol{\eta}_{2p} + \boldsymbol{\Psi}_{2t} + \boldsymbol{\theta}_2 \boldsymbol{X}_{it} + \varepsilon_{2ipt}. & (3) \end{aligned}$$

Each regression includes both household-level controls as well as province and month fixed effects. The first stage provides an estimate of each household's predicted probability of using an advisor ($\widehat{\text{Use Advisor}}_{ipt}$), allowing for variation due to the $\text{Register}_p \times \text{Post}_t$ instrumental variable. The second stage uses this predicted probability to provide an estimate of advisors' impact on risk-taking.

[5] Clustering with relatively few groups (Canada has 10 provinces) provides noisy estimates of standard errors and may lead to overstating the statistical significance of regression coefficients. When we correct for this potential issue by using the wild cluster bootstrap procedure proposed by Cameron, Gelbach, and Miller (2008), we estimate similar—in fact, slightly tighter—confidence intervals around the point estimate for β.

The estimates from this analysis, which are displayed in Table 2 Panel B, show that financial advisors increase risk-taking. A household's likelihood of owning any risky assets (stocks and equity mutual funds) increases by 59 percentage points. The proportion of equities in the portfolio increases by 30 percentage points. In each case the IV estimate exceeds the OLS estimate, which suggests a downward bias in the OLS estimate, perhaps because individuals who are comfortable holding risky assets are less likely to solicit an advisor's input.

As a placebo test we also examine the correlation between household income and the use of an advisor. OLS analysis reveals that high-income households are significantly more likely to use financial advisors: the OLS coefficient in the regression of log income on Use Advisor$_{ipt}$ is economically large and statistically significant. Since there is no obvious channel through which financial advisors causally influence household earnings, this correlation likely stems from differences in demand for advice. Once we instrument for use of an advisor with the registration requirement, we indeed find no significant relationship between log-income and households' use of financial advisors. This finding provides further comfort that the registration requirement leads to changes in the supply of advisors while leaving demand-side factors unchanged.

3 Analysis of Portfolio Customization in Mutual Fund Dealer Data

3.1 Description of the data

In the balance of the paper we use detailed, transaction-level data to measure the extent to which advisors shape their clients' portfolios and to measure the costs of financial advice.

Four Canadian financial advisory firms—known as Mutual Fund Dealers (MFDs)—supplied the data for our study. This class of non-bank financial advisors accounts for the majority of advised assets in Canada—$390 billion, or 55%. Advisors within these firms are licensed to sell mutual funds and precluded from selling individual securities and derivatives. Advisors make recommendations and execute trades on clients' behalf but cannot engage in discretionary trading.

Three firms provided a full history of client transactions over a 14-year period, from January 1999 to June 2012, along with detailed information on clients and advisors. The sample includes

5,920 advisors and 581,044 investors. The total value of assets under advice (AUA) in our sample is \$18.9 billion as of June 2012, representing 6% of the mutual fund dealer sector. We also obtained data from a fourth mutual fund dealer. The resulting four-firm sample is substantially larger, with over 10,000 advisors and 11% coverage of mutual fund dealers. Because these data cover a shorter time period and lack some variables of interest, we use the three-dealer sample in our main tests and reserve the extended sample for Section 5's robustness tests.

Table 3 provides the key summary statistics for the main sample. The investor characteristics displayed in Panel A show that our data cover a broad cross-section of investors. Men and women are equally represented in the data. The median investor is 51 years old, has one account and, as of the end of the sample period, has been with his current advisor for 3 years. Retirement savings or income accounts, which receive favorable tax treatment comparable to 401(k) plans in the U.S., are most prevalent (66% of accounts), followed by unrestricted general-purpose accounts (24% of accounts) and education savings accounts (5% of accounts). The median account size is CND \$27,330 and is invested in 3 mutual funds. Account values are right-skewed, with the average value of CND \$68,140 substantially exceeding the median value.

The data also contain information on clients' occupations. For the purposes of this study we identify two occupations, finance professional and self-employed, that theoretical models and empirical work have highlighted as important determinants of portfolio choice. Just over 1% of clients are employed in the financial advisory and investments industry, and 5% of clients are self-employed.

We assess advisor's influence over portfolio choice by examining the risky share and home bias of client portfolios. Risky share is the fraction of the portfolio invested in equity and home bias is the fraction of the equity invested in Canadian companies.[6] For the median investor in our sample, the risky share is 70% and the home bias is 64%. Between the bottom and top deciles risky share varies from 47% to 100% and home bias varies from 0% to 100%.

Panel A also describes investors' responses to questions about their investment horizon, risk tolerance, financial knowledge, net worth, and income. Financial advisors collect this information

[6]We assume that an all-equity fund invests 100% in equities; a balanced fund invests 50% in equities; and a fixed-income fund invests nothing in equities. We compute each investor's risky share and home bias by taking the value-weighted average of the funds the investor holds. We set the home-bias measure to missing when an investor has no equity exposure.

through “Know Your Client” forms at the start of the advisor-client relationship. Consistent with the retirement focus of most accounts, the vast majority of investors report a long investment horizon—68% of clients indicate a 6 to 9 year horizon and another 23% indicate a horizon of ten or more years. The majority of clients (52%) report “moderate” risk tolerance and a substantial fraction indicates higher risk tolerance (32%). The remaining 17% report risk tolerance that ranges from “very low” to “low to moderate.”[7] Clients report having little financial knowledge: 43% of investors report “low,” 51% report “moderate” and only 6% report “high” financial knowledge.[8] Incomes are modest: 71% of investors report an annual salary of less than \$70k, and only 13% of investors earn more than \$100k per year. Net worth, on the other hand, is somewhat higher: more than three-quarters of investors report a net worth of \$100k or more.

Table 3 Panel B shows summary statistics for the advisors in our sample. The age distribution of advisors looks similar to that of investors. The median advisor is 52 years old and has been with the current firm for 4 years. The number of clients and total assets under advice vary markedly within the sample. The median advisor has 24 clients, while advisors in the bottom decile have just one client and those in the top decile have over 200 clients. The median advisor has \$916,880 in assets under advice, and advisors in the bottom and top deciles manage under \$5,064 and more than \$14.6 million, respectively.

3.2 Portfolio choice, investor attributes, and advisor fixed effects

Our analysis begins with regressions that explain cross-sectional variation in investors’ portfolios with investor attributes and advisor fixed effects. From the underlying account records we create panel data with one observation per year (as of year-end) for each investor. We estimate regressions of the form,

$$y_{iat} = \boldsymbol{\mu}_a + \boldsymbol{\mu}_t + \boldsymbol{\theta X}_{it} + \varepsilon_{iat}, \tag{4}$$

[7] A short description accompanies each risk tolerance category. The descriptions characterize how an investor in that category feels about the risk-return trade-off and lists some investments suitable for those preferences. The “low to moderate” category, for example, describes an investor who wants to limit the potential losses and volatility of the portfolio while ensuring that the growth of the portfolio keeps up with inflation. The description then lists bond funds, asset allocation funds, and balanced funds as examples of suitable investments.

[8] A short description similar to those provided for risk-tolerance categories accompanies each category of financial knowledge. The “low” category, for example, describes an investor who has some investing experience but does not follow financial markets and does not understand the basic characteristics of various types of investments.

in which the dependent variable is either the risky share or home bias of investor i of advisor a in year t. Each specification includes year fixed effects to absorb common variation in portfolios caused, for example, by changes in stock prices. The vector $\boldsymbol{X}_{it}$ includes investor attributes such as risk tolerance, investment horizon, and age. The advisor fixed effects $\boldsymbol{\mu}_a$ capture common variation in portfolios among investors of the same advisor. We exclude $\boldsymbol{\mu}_a$ in some specifications to gauge the explanatory power of investor attributes alone. We exclude from the analysis clients who are advisors themselves—we describe and utilize this information in Section 3.5. We estimate the model using OLS, with standards errors clustered by advisor to account for arbitrary correlations in errors over time and between investors who share an advisor.

Table 4 Panel A reports the regression estimates for investors' risky shares. The intercept of this regression, 37.9%, is the average risky share in December 1999 of an investor who is in the lowest (omitted) category for every variable. Risk tolerance stands out in the first regression for its statistical and economic significance in explaining cross-sectional variation in risky shares. The risky share increases monotonically with risk tolerance. Relative to the excluded "very low" category, those with low-to-moderate risk tolerance invest 16.7 percentage points more in equities, while those with moderate risk tolerance invest 30.8 percentage points more in equities. At the top of the range, investors with high risk tolerance hold nearly 40 percentage points more in equities.

Many other regressors are also statistically highly significant with signs typical to the literature. The age profile, for example, is mildly hump-shaped, with investors between ages 35 and 39 having the highest risky shares.[9] Figure 1 illustrates the age and risk tolerance profiles in the data. The thick line shows, for reference, the age profile used in Fidelity's Canadian target-date funds. These target-date funds invest 85% in equities for investors up to the 35-year mark and then reduce the equity exposure approximately linearly so that it falls to 40% at the expected retirement date of 65. The risky-share profiles of advised investors differ considerably from target-date allocations. All investors, independent of their risk tolerance, assume less equity exposure relative to the target-date benchmark when they are young and more when they are old.

[9]Guiso, Haliassos, and Jappelli (2002) note that although in most countries the age profile for the ownership of risky assets is strongly hump-shaped, the share of risky assets *conditional* on participation is relatively flat. Poterba and Samwick (2001) and Ameriks and Zeldes (2004) analyze the age and cohort effects in detail using U.S. data. Fagereng, Gottlieb, and Guiso (2013) examine the interaction between the participation and portfolio-share decisions using Norwegian microdata.

The remaining regressors in Table 4 show that women's risky shares—controlling for other demographics such as risk tolerance—are on average 1.3 percentage points below those of men. Investors with longer investment horizons assume roughly 6 percentage points more equity risk than those with short horizons. Investors who report higher levels of financial knowledge have between 2 and 3 percentage points higher risky shares than low-knowledge investors. After accounting for all other investor attributes, income and wealth contribute only modestly in explaining cross-sectional variation in risky shares: the risky share is essentially unchanged across income categories and increases only slightly with wealth.[10] Investors in finance-related and entrepreneurial occupations hold slightly higher shares of equities conditional on other characteristics. This finding runs counter to the typical implication of portfolio theory that investors whose labor income varies in tandem with stock returns should take less investment risk.[11]

The most striking fact about the first regression is that all the regressors in the model—there are 33 variables in the model in all excluding the year fixed effects—jointly explain just over one-eighth of the cross-sectional variation in risky shares. That is, although differences in risk tolerance translate to significant differences in *average* risky shares, the model's R^2 is just 13.1%. A remarkable amount of variation remains unexplained. Our model's explanatory power is comparable to or even higher than other estimates in the literature. Calvet and Sodini (2014), for example, regress risky shares on investor attributes and year fixed effects using Swedish data and find an adjusted R^2 of 11.5%. This comparability suggests, first, that the low explanatory power of investor attributes is not sample-specific and, second, that measurement errors—Calvet and Sodini (2014) use administrative data—do not depress the R^2 measure.

The explanatory power of investor attributes is even lower in Panel B's home-bias regressions. The same set of regressors yields an adjusted R^2 of just 3.6% and, although some coefficients are statistically significant in isolation, no clear age or investment-horizon patterns are apparent in the data. The strongest finding is that the most risk-tolerant investors allocate 17 percentage points less of their risky assets to Canadian equity funds. The lack of explanatory power in this regression is perhaps unsurprising. Unlike the optimal risky share, the optimal mix of domestic and

[10] Wachter and Yogo (2010) show that portfolio shares increase in wealth in a lifecycle model with basic and luxury consumption goods, and find this positive correlation present also in the Survey of Consumer Finances data.

[11] The finding that individuals in the finance industry hold more equities is, however, consistent with evidence from Christiansen, Joensen, and Rangvid (2008) and Grinblatt, Keloharju, and Linnainmaa (2011).

international equities should be largely invariant to investor characteristics.[12] Any cross-sectional variation in home bias probably emanates from differences in beliefs, transaction costs, or other frictions.

The second regression model within each panel of Table 4 modifies the first by adding advisor fixed effects. The results reveal remarkably powerful advisor effects. The adjusted R^2 in Panel A more than doubles from 13.1% to 31.6% as we add the advisor fixed effects. In Panel B's home-bias regression the adjusted R^2 increases from 3.6% to 27.9%! These findings indicate substantial systematic variation in portfolios among clients of the same advisor.

Figure 2 plots the distributions of the advisor fixed effects from these regressions. These distributions illustrate that, in addition to being statistically very important in explaining cross-sectional variation in portfolio choices, the advisor fixed effects are economically important. Moving from the 25th percentile to the 75th percentile of the advisor distribution corresponds to a 20-percentage point change in risky share and a 32-percentage point change in home bias. To put these results into perspective, we predict the same 20-percentage point change in risky share for a three-level increase in risk tolerance from "low to moderate" to "high" (see column 2 of Table 4). It is important to emphasize that the fixed-effect estimates are orthogonal to the investor attributes of column 2. That is, they measure differences in risky share and home bias after accounting for differences in investor attributes such as age, gender, and risk tolerance.

3.3 Interpreting advisor fixed effects

How should we interpret our finding that advisor fixed effects explain cross-sectional variation in portfolio choices? We can delineate two potential explanations. First, advisors may have idiosyncratic "tastes" in portfolio allocation. These tastes may reflect advisors' personal beliefs—for example, "equities are relatively safe in the long run and offer a very attractive return-to-risk trade-off"—or they may arise from agency conflicts—some advisors may respond more to financial incentives by recommending higher-commission equity funds over cheaper fixed-income funds. Second, advisor fixed effects may *appear* to be important because of matching between advisors and investors. If investors match with advisors who share their beliefs and preferences, then advisor

[12] In a model in which labor income correlates with asset returns, the optimal mix of domestic and international equities would vary in the cross-section of investors if there is variation in how labor income correlates with returns on domestic and international equities. Section 3.4 addresses the role of *any* omitted variable such as this correlation.

fixed effects will capture common variation in portfolio choices induced by shared beliefs rather than advisors' common influence across clients.

We test directly for the importance of omitted investor attributes in section 3.4. Before describing that analysis, however, we first observe that the results in Table 4 cast some doubt on the matching explanation. First, we measure and control for a number of important attributes. If some investor attributes are to explain differences in equity allocation, we would expect risk tolerance, investment horizon, financial knowledge, age, and wealth to be at the top of the list. Nevertheless, these variables jointly explain just one-eighth of the variation in risk shares and less than 4% of the variation in home bias. Although these results do not rule out the possibility of important omitted variables that drive both the portfolio choice and the investor-advisor match, they substantially narrow down the set of potential variables that could be at work.

Second, when we include advisor fixed effects, moving from the first regression to the second in Table 4, we estimate similar coefficients on the investor attributes. Figure 3 illustrates this point by plotting the marginal effects associated with the age and risk-tolerance categories with and without advisor fixed effects. The marginal effects are nearly identical. When we add advisor fixed effects we also estimate the coefficients on investor attributes with more precision. The increase in precision implies little collinearity between investor attributes and advisor fixed effects. If investors and advisors are matched by shared attributes that determine portfolio allocations, these attributes must be largely unrelated to age, gender, risk tolerance, and financial knowledge. If the matching relates, at least in part, to the variables included in the model, then the advisor fixed effects—perfect proxies for the shared link—would kill the statistical significance of the imperfect empirical proxy such as age or gender. This argument is intuitive if we think of running the regression in two stages. Suppose that we first "clean" the data by regressing risky share only on advisor fixed effects. Column 2's estimates show that if we now collect the residuals from such a first-stage regression and run them against investor attributes, many attributes are statistically more significant in the residual data relative to the raw data. That is, the variation in risky shares that emanates from advisor fixed effects is mostly noise when studied from the vantage point of investor attributes.

Third, the last two regressions in Table 4 show that advisor fixed effects are equally important whether an advisor serves a diverse or an homogeneous group of clients. We divide advisors into high- and low-dispersion groups based on the estimated client-base heterogeneity. We measure heterogeneity each year by recording the predicted values from the first column's regression and then computing within-advisor variances of these predicted values. Advisors in the low-dispersion group have homogeneous client bases, that is, the first column's model predicts these investors to make very similar portfolio allocations. Advisors in the high-dispersion group, by contrast, have more heterogeneous client bases. If advisor fixed effects increase the adjusted R^2 through omitted variables, we would expect these fixed effects to play a far smaller role in the sample of high-dispersion advisors—by definition, a single advisor's characteristics cannot match (many of) those of his clients when the clients constitute a diverse group of individuals. In the data, however, the overall explanatory power of the model is largely insensitive to this grouping. Moreover, advisor fixed effects increase the adjusted R^2 by roughly the same amount independent of whether advisors' clienteles are homogenous or heterogenous.

3.4 Controlling for unobserved attributes using investor fixed effects

In the analysis that follows, we use a subset of the data to control for unobserved heterogeneity among investors and thereby disentangle investor effects from advisor effects. We adapt the prior regression model by replacing the investor attributes with investor fixed effects, and estimate panel regressions of the form,

$$y_{iat} = \boldsymbol{\mu}_i + \boldsymbol{\mu}_a + \boldsymbol{\mu}_t + \varepsilon_{iat}, \tag{5}$$

in which y_{iat} is investor i's risky share or home bias in year t and $\boldsymbol{\mu}_i$, $\boldsymbol{\mu}_a$, and $\boldsymbol{\mu}_t$ represent investor, advisor, and year fixed effects. To identify separate investor and advisor fixed effects, we must observe portfolio choices for investors who use multiple advisors during the sample period.[13]

We construct the sample for estimating regression (5) by first identifying investors who change advisors at least once during the sample period. To exclude cases in which a client initiates the switch because of a change in preferences, we focus on the subset of switches caused by advisors' disappearances due to retirement, death, or withdrawal from the advisory business. We infer these disappearances by recording an investor's move from advisor A to advisor B only if advisor A stops advising *all* of his or her clients within one year of the date of the move. After identifying investors

[13] Bertrand and Schoar (2003), for example, employ this estimation strategy to separate managerial style from firm effects. Abowd, Kramarz, and Margolis (1999) and Graham, Li, and Qiu (2012) extend this estimation strategy to draw inferences also about "non-movers'" fixed effects in studies that separate firm and employee effects on wages and disentangle the roles that firm and manager effects play in executive compensation.

who complete at least one move, we create a list of all advisors who are ever associated with these investors. Instead of studying *portfolio*-level risky share and home bias within this sample—as we did in Table 4—we study the average risky share and home bias for new investments made while paired with the current advisor. Portfolio-level measures will persist if advisors do not reset net clients' portfolios overnight. An investor, for example, may be locked into some investments through back-end loads on redemptions within seven years of purchase. Focusing instead on the new investments allows us to measure cleanly the current advisor's input to the portfolio.

The first two columns in Table 5 replicate the regressions from Table 4 using this alternative sample. The coefficient patterns are similar, which reassures us that this subset of investors does not differ from the main sample. The decrease in sample size, of course, reduces the precision of the slope estimates. Investor attributes explain similar amounts of cross-sectional variation in risky share and home bias as they do in the main sample—the adjusted R^2s are now 8.9% and 3.5% compared to 13.1% and 3.6%. As in Table 4, the model's explanatory power increases substantially when we include advisor fixed effects.

Table 5's rightmost regression replaces *observable* investor attributes with investor fixed effects. Although investor age varies over the sample period, the model omits age because it is not possible to identify year, investor, and age effects without additional restrictions. Intuitively, investor fixed effects reveal—among all other things!—each investor's birth year, and the birth year together with the year fixed effects recovers age.[14] In the risky-share regression, the explanatory power of the model increases from 35.1% to 47.5% as we swap observable investor attributes for investor fixed effects.

Although investor fixed effects add explanatory power over and above investor attributes, they do not meaningfully "crowd out" the advisor fixed effects. The estimates in the last column of Table 5 show that advisor fixed effects remain strong predictors of risky share. Adding the advisor effects to the model raises the adjusted R^2 substantially, from 31.3% with investor fixed effects alone to 47.5% with both sets of fixed effects. Investor fixed effects provide roughly the same incremental explanatory power; the adjusted R^2 increases from 30.3% with advisor fixed effects alone to 47.5% with both sets of fixed effects. Second, the F-statistics reported in Table 5 show

[14] Ameriks and Zeldes (2004) discuss the importance of the problem of (unrestricted) identification of age, time, and cohort effects.

that both sets of fixed effects are highly statistically significant. These statistics for the advisor and investor fixed effects are $F(471, 1519)$- and $F(1823, 1519)$-distributed in Panel A.[15] A back-of-the-envelope "translation" of these statistics into t-values illustrates their magnitudes relative to the other regressors. If we compute the p-values associated with these statistics—which are both in the $p < 10^{-20}$ range in Panel A—and then recover these percentiles from the normal distribution, the advisor and investor fixed effects are significant with "t-values" of 11.50 and 12.52, respectively.

The home-bias regressions in Panel B yield a similar picture. The adjusted R^2 of the model increases from 30.0% to 45.9% when we include advisor fixed effects in addition to investor fixed effects. The two sets of fixed effects also exhibit similar statistical significance. The F-values associated with the advisor and investor fixed effects in the last column's full model translate to (pseudo) t-values of 10.95 and 12.15. The one notable difference between the risky-share and home-bias regressions is that while observable investor characteristics explain little of the cross-sectional variation in home bias, a model with investor fixed effects explains approximately a quarter of this variation. This result suggests that investors indeed have subjective views on the optimal allocation of domestic-versus-international equity, but that these views are unrelated to attributes such as age, gender, and risk tolerance.

3.5 Explaining advisor fixed effects using advisor attributes

We documented in sections 3.2 and 3.4 the importance of advisors' input in explaining portfolio allocations and in Figure 2 the remarkable dispersion in recommendations across advisors. We now ask why advisors differ so much in their recommendations.

Our dealer data contain a unique dimension for studying the determinants of advisor's recommendations. First, the basic data include advisor demographics such as gender and age. Second, and more importantly, most investors and advisors in the data are also associated with encrypted personal insurance numbers, similar to social security numbers in the United States. These identifiers are useful because many advisors also maintain an account at their own firm and therefore appear in the data also as clients—which is why we excluded these advisor-investors from the previous sections' tests. This link allows us to observe many advisors' personal portfolios and to test

[15] The first argument in the first distribution, 471, is the number of advisor fixed effects that we can identify by exploiting investors making suitable moves from one advisor to another.

whether the personal portfolio explains the "abnormal tilt" (that is, the advisor fixed effect) seen in the portfolios of his or her clients.

To set the stage for this analysis, Figure 4 demonstrates the variation in advisors' personal risky shares as a function of advisor age and risk tolerance. Panel A shows that, unlike non-advisor clients, advisors' personal risky shares do not vary systematically as a function of age. Panel B indicates that more risk-tolerant advisors take more equity risk. The estimates for the lowest two risk-tolerance categories are very noisy because fewer than 1 percent of advisors report low or very-low risk tolerance. Advisor's gender also matters. In (untabulated) regressions of advisor risky share on age and gender, we find that female advisors have on average 3.4 percentage points lower risky share (t-value = -3.51). In analogous home-bias regressions women invest 5.8 percentage points (t-value = 4.08) more in Canadian equities.

Table 6 examines the extent to which advisor age and gender explain cross-sectional variation in Table 4's estimates of advisor fixed effects. Because we extract these fixed effects from regressions that control for investor age and gender (among other investor attributes), no patterns can arise here because investors and advisors match by age and gender; that is, the advisor fixed effects are orthogonal to observable investor attributes. The unit of observation in Table 6's regressions is an advisor. In the first regression, for example, we have the requisite data—the fixed effect from the risky-share regression and advisor age and gender—for 3,605 advisors. We define advisor's age in these regressions as the advisor's average age during his or her presence in the data.

The estimates in the first column suggest that older advisors direct their clients into substantially riskier portfolios than younger advisors. The omitted age category contains the very youngest advisors, and the point estimates in Table 6 indicate that advisors of age 60 or older, near or beyond retirement age, allocate an additional ten percentage points of clients' portfolios to risky assets. These differences are highly statistically significant. This age result is in contrast with the finding that clients' risky shares are hump-shaped as a function of their own age as well as with the finding that advisors' own average risky share is flat with respect to advisor age. Gender, by contrast, is unrelated to the advisor-driven heterogeneity in risky shares.

The second regression in Table 6 adds the advisor's own risk tolerance to the model. The omitted category combines the three lowest risk-tolerance categories because the first two are so infrequent in the data. Here, the model estimates indicate that more risk-tolerant advisors allocate roughly 5 percentage points more of their clients' assets to equities.

The third regression in Table 6 adds as a regressor the advisor's own average risky share. The positive and highly significant slope estimate of 24.5 (t-value = 15.57) indicates that advisors' own preferences and beliefs bleed over to their clients' portfolios. An additional 10 percentage points of risky share in the advisor's portfolio corresponds to a 2.5 percentage point increase in the client's risky share. The model now explains 14.9% of the cross-sectional variation in advisors' risky-share fixed effects. An advisor with a higher personal risky share gives his or her clients higher risky shares, *controlling* for investor attributes (and advisor age and gender). The advisor-age effect, however, is unrelated to the shared-preferences effect. In the fourth regression, which controls for the advisor's risky share, the age coefficients increase in magnitude and statistical significance. There must thus be a reason other than heterogeneity in advisors' own beliefs or preferences about the risk-return tradeoff that induce them to give their clients' riskier portfolios. Conflicts of interest and advisors' career concerns provide one explanation. Older advisors may be more willing to give their clients riskier portfolios because, first, equity products are associated with higher commissions and, second, advisors close to retirement worry less about their reputation.

The home-bias regressions of Table 6 yield a similar picture. In the first regression, older advisors give their clients more international portfolios. This effect arises fully from the difference between the very youngest advisors (the omitted category) and all other advisors. Gender also plays a role. The "abnormal" share of domestic equity is 2.2 percentage points (t-value = 2.27) higher among female advisors.

The last two columns show that advisors' own home bias correlates significantly with the home-bias fixed effect. The slope on this variable is 33.13 (t-value = 22.97) and the full regression explains more than one-fifth of the variation in advisor fixed effects. In contrast to risky-share regressions, the slopes on the age and gender variables attenuate when we control for advisor home bias. Gender, for example, turns insignificant. This result is consistent with the earlier result that female advisors display more home bias also in their personal portfolios. The attenuation here shows that once we control directly for the heterogeneity in home bias that advisors display in their own portfolios, advisor age and gender have no reliable association with the home-bias fixed effect.

4 Do Advisors' Investment Recommendations Add Value?

We assess the cost of advisors' services by comparing clients' investment performance to passive investment benchmarks. The analysis proceeds in two stages. First, we assess advisors' skill in fund selection, asset allocation and market timing by comparing gross investment returns to a variety of passive investment benchmarks. Second, we repeat the same analysis using net returns to account for fees paid for advice and fund management.

4.1 Client performance gross of fees

We construct a monthly time-series of gross returns for each advisor by computing the return on the aggregate portfolio held by the advisor's clients. In measuring gross returns we add back to each client's monthly account balance all fees paid on mutual fund investments, including management expense ratios and front-end loads. We examine risk-adjusted returns with a series of models that adjust for common equity and bond market risk factors. We begin with the CAPM and then move to the Fama and French (1993) three-factor model by adding size and value factors. The third model adds the momentum factor and two bond factors to account for clients' non-equity allocations. As equity factors, we use the Canadian market return and the North American size, value and momentum portfolios constructed by Ken French. As fixed-income factors, we use the excess return for long-term Canadian Treasuries relative to 90-day Canadian Treasuries and the excess return for Canadian high-yield corporate bonds relative to long-term Canadian Treasuries. The returns on the long-term Treasuries and high-yield corporate bonds are computed from Bank of America Merrill Lynch's 10+ Year Canada and Canada High Yield indexes.

Table 7 presents the performance results. The columns labeled "gross" present the gross alpha estimates for the aggregate advised portfolio. We aggregate across advisors using three separate methods: "average dollar" represents the performance of the average advised dollar, weighting each advisor by assets under advice; "average advisor" represents the performance of the average advisor, weighting each advisor equally; and "average client" represents the performance of the average advisor, weighting each advisor by the number of clients. Advisor portfolios earn annualized gross alphas that are small and statistically indistinguishable from zero. In the CAPM, the average dollar's alpha is 10 basis points; the average advisor's alpha is −16 basis points; and the average client's alpha is 4 basis points. However, because the average client holds 31% in fixed-income products (Table 3), a failure to control for returns on this segment of the market can overstate client performance. The gross-alpha estimates decline when we add controls for size and value (the three-factor model) and decline further when we add momentum and the fixed-income factors (the six-factor model). For the six-factor model, the gross-alpha estimates range from −80 basis points to −95 basis points. These estimates, while negative, are not statistically distinguishable from zero.

Though the average advisor shows no evidence of skill, we find some evidence that the best performing advisors produce positive risk-adjusted returns before subtracting fees. The bottom part of Table 7 reports the distributions of t-values for alphas estimated from 4,821 advisor-specific performance regressions. We estimate these regressions for each advisor who is in the sample for at least 12 months. The t-value distributions are asymmetric with the length of the positive tail exceeding that of the negative tail. The 5th and 95th percentiles of the t-value distribution from the CAPM, for example, are −1.42 and 3.32. Some—but not all—of this asymmetry is due to some advisors allocating more to fixed-income products: the 5th and 95th percentiles from the six-factor model are −1.91 and 2.42. Although not as pronounced, this asymmetry suggests that some advisors may deliver positive abnormal returns before adjusting for fund expense ratios and front-end loads.

Because alpha estimates reflect both luck and skill, we would expect to observe some "significant" t-values just by chance even if all true alphas zero. The distributions of t-values in Table 7's column "Ref." provide a benchmark against which to compare the actual t-value distributions in gauging advisors' skill. We construct these distributions using Fama and French's (2010) bootstrapping methodology. This methodology recovers the distribution of t-values one would expect to observe under the null hypothesis that all deviations from zero alphas represent luck. The innovation with this methodology is that it resamples *months* from the data with replacement to preserve the properties of the data-generating process.[16] The reference distributions indicate that the right tails of the t-value distribution represent meaningful deviations from the null hypothesis. In every specification the right tail of the t-value distribution extends farther than that of the ref-

[16] The full details of the Fama and French (2010) bootstrapping procedure are as follows: (1) estimate each fund's alpha using all available data; (2) set funds' full-sample alphas to zero by subtracting estimated alphas from monthly funds returns; (3) resample months from the panel with replacement to preserve the covariance structure of fund returns and factors; (4) re-estimate alphas of all funds using the resampled data; and (5) go back to step 3 and repeat the simulation procedure 100,000 times.

erence distribution. In the six-factor model, for example, the 95th percentile of the t-values (2.42) is close to the 99th percentile of the reference distribution (2.57). A non-trivial number of advisors thus delivered positive abnormal gross returns vis-à-vis this asset pricing model during the sample period. These performance estimates, however, do not account for the fees that advisors charge their clients.

4.2 Client performance net of fees

The gross-return computations suggest that the average investment advisor is not able (or does not attempt) to profit by timing the market or selecting securities. As a consequence, the fees that advisors charge result in negative net alphas for the average advisor. These fees are substantial. The average advised dollar pays 2.67% in fees, and the 5th and 95th percentiles in the distribution of advisors are 2.04% and 4.71%. These fees emanate from mutual funds' management expense ratios, which include sales commissions paid to advisors, and from loads that clients pay when purchasing front end-load funds. An important note is that our fee calculations ignore back-end load payments. Although investors pay deferred-sales charges when they sell back-end load funds "too early"—typically within seven years of the purchase—advisors *could* reimburse their clients for some of these penalties. Because we lack data on such reimbursements, we conservatively omit all back-end loads from our fee computations. The net alphas we report here thus represent upper bounds on investors' realized alphas.

The net alphas reported in Table 7 are significantly negative. In the CAPM the average advised dollar earns an annualized alpha of -2.45% (t-value $= -2.28$), and this estimate falls to -3.34% (t-value $= -3.22$) as we move to the six-factor model that accounts for clients' bond-market exposures. The t-value distributions shift markedly to the left. Although in the CAPM and the three-factor model the right tails of the actual t-value distributions extend farther out than the simulated distributions, in the six-factor model even the 99th percentile of the actual distribution falls short of the simulated distribution.[17] The row "% Skilled" provides further perspective. We follow

[17] We report only one set of reference distributions that we compute from advisors' net returns. Although the reference distributions computed from advisors' gross returns are different, in practice these differences are very small. The reason is that time-series variation in fees is almost uncorrelated with the asset pricing factors, and so the gross alpha estimate on average is almost the same as the net-alpha estimate plus fee. Because the Fama-French procedure sets full-sample estimated alphas to zero, it thus does not make a significant difference whether it is the gross or net returns that we "demean" by running the asset-pricing regressions.

Fama and French (2010) and recover from the simulations the percentile at which the actual t-value exceeds that percentile's simulated t-value in at least half of the simulations—that is, at this percentile luck alone would produce this large a t-value at most half the time. The estimate of skilled advisors is then 100% minus this percentile. Even in the CAPM and three-factor models that fold returns earned by non-equity holdings into alphas, the estimated fractions of advisors whose investment advice covers the costs they impose on their clients are 6.4% and 11.0%. In the six-factor model the estimated fraction of skilled advisors is zero.

The costs of advice are economically significant. Consider, for example, the average advised dollar's annual net alpha of -3.34% in the six-factor model. This alpha reflects the fees that advisors charge—2.67% for the average advisor—and the underperformance of the advised portfolio on a before-fees basis. Investors could earn a *gross* alpha of 0% by investing in index funds, and then the question is how expensive such funds are relative to the costs borne by the advised investors. We compare to lifecycle funds because they are the simplest vehicle for retirement-oriented investors to gain equity and fixed-income exposure. Although cheaper index funds were available to investors, the benefit of lifecycle funds is that they require no active trading by the client. The average management expense ratio on Fidelity Clearpath funds—the largest target-date funds by assets—was 1.02% during the sample period. Our estimates then imply that the average advised dollar incurs an extra cost of $3.34\% - 1.02\% = 2.22\%$ per year. The cost of advice is slightly larger for the other two methods of aggregation. The average advisor's clients pay $3.80\% - 1.02\% = 2.72\%$ per year and the average client pays 2.46%.[18]

5 Robustness within Extended Sample of Dealer Data

We assess the robustness of our key findings within a substantially larger sample that includes data from a fourth dealer firm. To avoid disclosing firm-specific information about the anonymous data provider, we analyze an "extended sample" that pools the data of all four firms. The extended

[18] We could regress the return difference $r_{it} - r_{it}^{\text{lifecycle}}$—in which r_{it} is the actual rate of return of earned by an advised investor and $r_{it}^{\text{lifecycle}}$ is the return on a retirement-date matched lifecycle fund—against the asset pricing models used in Table 7 to quantify how much investors give up on the margin when they move one dollar from a lifecycle fund to an advisor. Such regressions yield a more pessimistic view of advisors because the lifecycle funds earn positive *net* alphas during the sample period, and so the implied cost of advice exceeds the negative net alphas reported in Table 7. Because it seems reasonable to assume that the long-run gross alphas on lifecycle funds are close to 0%, we impose this assumption when carrying out the loss computations.

sample covers a shorter time period than the main sample—January 2001 through December 2010 compared to January 1999 through June 2012—and lacks two variables that we use in the main analysis. Front-end load payments are not included in the extended sample, nor are the personal identifiers needed to match advisors to their own portfolios.

The first two panels of Table 8 summarize the extended sample and provide a comparison to the main sample. The extended sample includes 814,000 investors, 40% more than the main sample. Investors' mean and median account values are somewhat lower in the extended sample, but the average portfolio allocations—roughly 70% to risky assets and just under 60% to Canadian equity—are almost the same as in the main sample. The extended sample covers over 10,000 advisors, 4,000 more than the main sample. The size of the median advisor's business is similar in both samples, whether measured in number of clients or in assets under advice.

The third panel of Table 8, labeled "Advisor Influence," reports the adjusted R^2 for models explaining clients' portfolio allocations. The results within the extended sample confirm our earlier findings. In the extended-sample analysis of risky share, advisor fixed effects roughly double the model's explanatory power to 31.4% from 16% in a specification with investor characteristics alone. Similarly, for the sample of clients that switch advisors, advisor fixed effects increase the adjusted R^2 from 32% with investor fixed effects to 47% with both investor and advisor fixed effects. Advisors' influence on home bias is even more striking. In the extended-sample analysis, advisor fixed effects raise the cross-sectional model's explanatory power ten-fold from 2.3% to 22.4% and the two-way fixed effect model's explanatory power almost two-fold from 23.1% to 41.1%.

The final panel of Table 8 reports the gross and net alpha estimates within the extended sample. The six-factor gross alpha is -1.28% per year, lower than in the main sample but still statistically indistinguishable from zero. After subtracting fees—in this case, management expense fees, but not front-end loads—we estimate a six-factor net alpha of -3.61% per year.

Overall, the extended sample analysis confirms our key findings that advisors exert considerable influence over clients' portfolio allocations and that clients' portfolios substantially underperform passive benchmarks after deducting fees.

6 Conclusions

Most households rely on recommendations from financial advisors when investing their money. Nonetheless, relatively little is known about advisors' influence over their clients' portfolios. Using data on Canadian financial advisors and their clients, we show that financial advisors have a substantial impact. We present three key findings. First, advisors encourage increased risk-taking among their clients. Exploiting a regulatory change that reduced the supply of advisors, we estimate that taking on a financial advisor leads to an increase of roughly 30 percentage points in the share of risky assets held by the client. Second, advisors do relatively little to customize their advice on risk-taking. In total, a broad set of investor characteristics including risk tolerance and the point in the lifecycle explain only 13% of the variation in risky share across clients. Third, advisor *fixed effects* explain an additional 20% of the variation in risky share and predict remarkably large differences in risk-taking: moving from an advisor at the 25th percentile to an advisor at the 75th percentile equates to a 20-percentage point increase in risky asset share. We also find that the amount of risk an advisor takes in his or her own portfolio strongly predicts the risk taken by his or her clients. Differences in advisors' beliefs and preferences thus contribute to the advisor-specific effects.

Given the lack of customization and the fact that advisor fixed effects—which are, in essence, one-time draws of luck—have an economically significant impact on clients' portfolios, the puzzle then is that this one-size-fits-all advice does not come cheap. We find that investors pay on average 2.7% of assets per year for advice—or 1.7% in excess of lifecycle funds. If the equity premium is 6 percent, the 30-percentage point increase in risky share *caused* by advisors translates into $0.30 \times 6.0\% = 1.8\%$ higher expected return on investors' total portfolios. But for the average investor it is the advisor and mutual funds who capture all of these additional returns. Advised investors also pay an implicit cost: they hold riskier portfolios without being compensated with higher net returns. We conclude that, for the average investor, investment advice alone does not justify the fees paid to advisors.

Given households' strong revealed preference for using financial advisors, it is likely that they receive other benefits beyond investment advice. Our results, however, impose constraints on the set of plausible benefits. The benefits cannot be of one-time nature because investors pay the fee continually as they remain advised. Such benefits may come in the form of financial planning, including advice on saving for college and retirement, tax planning and estate planning. It is also possible that financial advisors add value by mitigating psychological costs rather than providing financial benefit; that is, reducing anxiety (Gennaioli, Shleifer, and Vishny 2014) or eliciting feelings of trust (Guiso, Sapienza, and Zingales 2008) rather than improving investment performance. Exploring the importance of these benefits is an important topic for future work.

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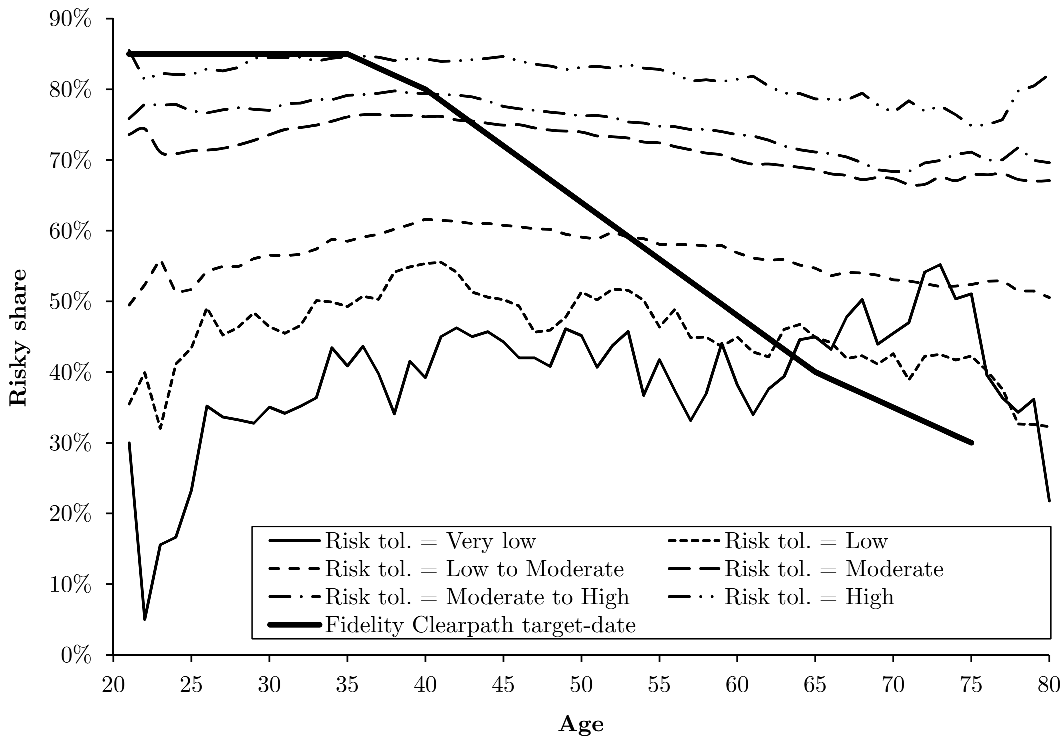

Figure 1: **Advised investors' average risky share as a function of age and risk tolerance.** This figure plots advised investors' average risky shares separately for the six risk-tolerance categories as a function of age. Solid line plots the risky share of Fidelity Clearpath target-date funds.

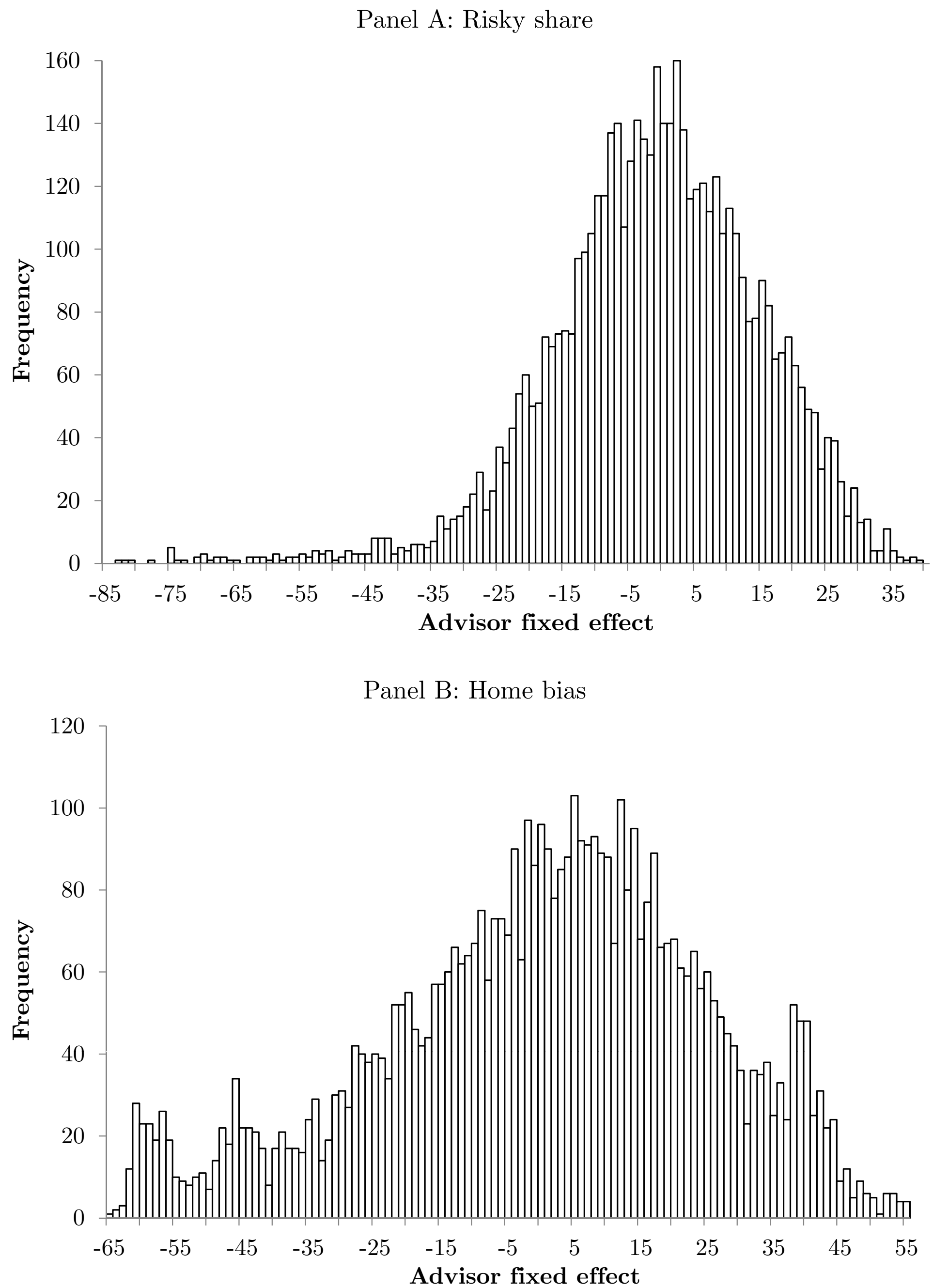

Figure 2: **Distributions of advisor fixed effects in risky-share and home-bias regressions.** This figure plots the distributions of advisor fixed effects from Table 4's regressions (2) and (4) in which the dependent variable is the risky share (Panel A) or home bias (Panel B) and the regressors consist of investor characteristics, advisor fixed effects, and year fixed effects.

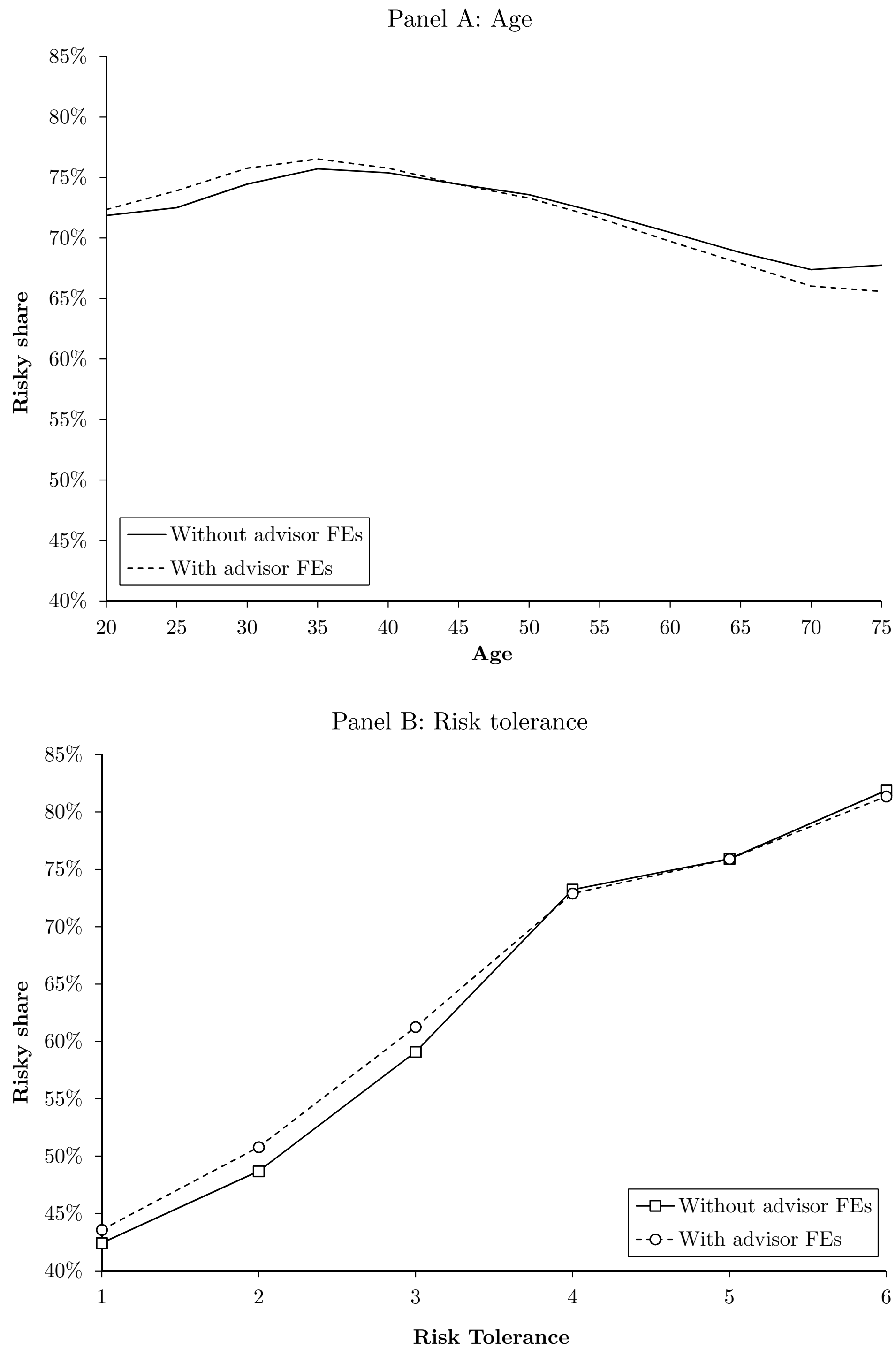

Figure 3: **Investors' average risky share as a function of age and risk tolerance: Marginal effects with and without advisor fixed effects.** The solid line plots marginal effects associated with age groups 21–25, 26–30,. . . , 75–80 (Panel A) and for the six risk-tolerance categories (Panel B) from Table 4's regressions of risky share against investor attributes without advisor fixed effects. The dashed line plots marginal effects from the regression with advisor fixed effects. The level of marginal effects is normalized by setting the values of the other regressor to sample averages.

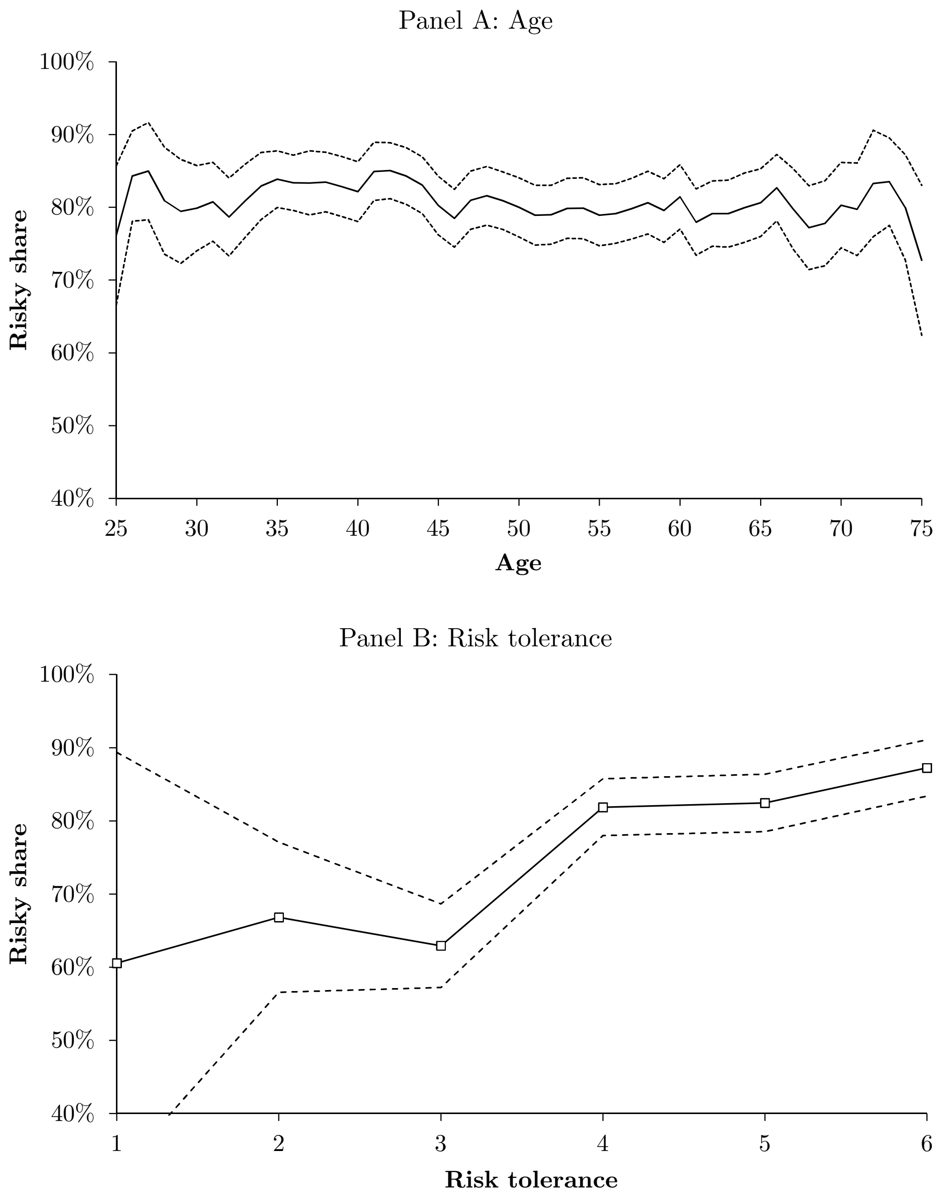

Figure 4: **Advisor risky share as a function of age and risk tolerance.** This figure plots average risky share for advisors' own portfolios as a function of advisor age (Panel A) and risk tolerance (Panel B). The dotted lines denote the 95% confidence interval around the sample average. Averages and confidence intervals are computed by estimating regressions of risky share against age-indicator variables (risk tolerance-indicator variables) and year fixed effects. Standard errors are clustered by advisor.

Table 1: Descriptive statistics from survey data

This table reports summary statistics from the Canadian Financial Monitor survey of Canadian households conducted by Ipsos-Reid. Age is that of the head of household. Education is the maximum level of education of the head of household and spouse. The indicator Retired takes the value of one if the head of household is retired. The data are from 24,904 advised and 37,779 unadvised households.

	Advised			Unadvised		
	Mean	SD	Median	Mean	SD	Median
Age	46.3	14.6	45.0	47.9	16.1	45.0
Income (000s)	58.7	35.5	50.0	44.6	32.8	40.0
Financial assets (000s)	91.7	185.4	29.5	46.2	122.4	6.6
Asset allocation						
% cash	37.3	38.6	18.0	57.0	42.3	60.0
% fixed income	29.9	32.3	19.2	22.8	32.5	0.0
% equity	32.8	35.3	20.5	20.1	32.3	0.0
Education						
HS or less (%)	22.8	42.0	0.0	36.2	48.0	0.0
Some college (%)	23.0	42.1	0.0	22.0	41.4	0.0
College diploma (%)	41.2	49.2	0.0	33.9	47.3	0.0
Graduate degree (%)	12.9	33.6	0.0	8.0	27.1	0.0
Homeowner (%)	72.9	44.4	100.0	63.1	48.3	100.0
Retired (%)	11.9	32.4	0.0	17.2	37.8	0.0

Table 2: The effect of financial advisors on households' risk-taking

Mutual fund dealers and their agents, financial advisors, were required to register with the Mutual Fund Dealers Association of Canada (MFDA) as of February 2001 to continue operating. This registration requirement, which forced dealers to follow the rules and regulations of the MFDA, did not apply to the province of Quebec. Panel A uses monthly Ipsos-Reid household survey data from January 1999 through January 2004 and estimates the effect of the registration requirement on the households' likelihood of using financial advisor. Household-level controls consist of control variables for income, education, age, and retirement status. Panel B measures the effect of financial advisors on household log-income, and investment in risky assets. The log-income regression in Panel B excludes income controls from the set of household-level controls. Robust standard errors, clustered at the province level, are reported in brackets. Panel B reports the adjusted R^2 from the two-stage least squares model.

Panel A: The effect of the Registration requirement on the use of a financial advisor

	Dependent variable (mean): Use Advisor (0.40)		
Regressor	(1)	(2)	(3)
Register × Post	−0.039***	−0.042***	−0.043***
	[0.007]	[0.009]	[0.009]
Register	0.020**	−0.004	
	[0.007]	[0.006]	
Post	−0.030***	−0.031***	
	[0.000]	[0.002]	
Observations	62,683	62,683	62,683
R^2	0.3%	6.3%	6.8%
Household-level controls?	N	Y	Y
Province and month FEs?	N	N	Y

Panel B: The effect of the Registration requirement on income, participation, and risky share

Dependent variable	Sample	The Effect of Financial Advisors: OLS	The Effect of Financial Advisors: IV	N	R^2	HH-level controls?	Province and month FEs?
Log(Income)	All	0.206***	0.050	62,683	36.1%	Y	Y
		[0.012]	[0.203]				
Participation	All	0.135***	0.592***	59,033	3.6%	Y	Y
		[0.008]	[0.155]				
Risky share	All	0.069***	0.302***	59,033	7.6%	Y	Y
		[0.008]	[0.095]				

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Descriptive statistics from dealer data

This table reports summary statistics for investors (Panel A) and financial advisors (Panel B). "Investor set-up since" is the number of years an investor has been with any advisor. Both variables are computed as of June 2012. Risky share is the fraction of the portfolio invested in equity and home bias is the fraction of the equity invested in Canadian companies.

Panel A: Investors (N = 581,044)

		Percentiles					
Variable	Mean	10th	25th	50th	75th	90th	SD
Female	0.51						
Age	51.18	33	41	51	61	69	13.65
Investor set-up since	3.62	1	1	3	6	7	2.56
Number of accounts	1.94	1	1	1	2	4	1.91
Number of funds	5.19	1	2	3	7	12	5.67
Account value, $K	68.14	2.15	8.15	27.33	75.56	161.16	576.37
Portfolio							
Risky share	0.69	0.47	0.50	0.70	0.88	1.00	0.23
Home bias	0.59	0.00	0.37	0.64	0.88	1.00	0.33
Occupation							
Finance professional	1.1%						
Self-employed	4.5%						

Panel A: Investors (cont'd)

Account types	
General	24.1%
Retirement savings or income	59.4%
Retirement income	6.6%
Education savings	5.1%
Tax-free	4.5%
Others	0.4%

Time horizon	
1–3 years	3.2%
4–5 years	9.4%
6–9 years	68.0%
10+ years	19.5%

Risk tolerance	
Very low	4.2%
Low	4.3%
Low to Moderate	8.5%
Moderate	51.5%
Moderate to High	19.7%
High	11.9%

Salary	
$30-50k	35.8%
$50-70k	35.0%
$70-100k	16.5%
$100-200k	12.1%
$200-300k	0.2%
Over $300k	0.3%

Financial knowledge	
Low	42.8%
Moderate	51.4%
High	5.8%

Net worth	
Under $35k	4.9%
$35-60k	7.6%
$60-100k	10.3%
$100-200k	18.5%
Over $200k	58.8%

Panel B: Financial Advisors (N = 5,920)

		Percentile					
Variable	Mean	10th	25th	50th	75th	90th	SD
Female	0.26						
Age	51.33	36	44	52	59	65	10.74
Tenure	4.43	1	2	4	6	8	2.74
Number of clients	74.32	1	3	24	100	217	122.92
Number of accounts/client	1.71	1	1.14	1.60	2.00	2.48	0.91
Number of funds/client	4.20	1	2.00	3.74	5.60	7.54	2.82
Assets under advice, $K	5,064.03	5.19	55.44	916.88	5,493.64	14,575.30	16,420.04

Table 4: Regressions of risky share and home bias on investor attributes and advisor fixed effects

This table reports estimates from panel regressions of risky share (Panel A) and home bias (Panel B) on investor attributes, year fixed effects, and advisor fixed effects. Risky share is the fraction of wealth invested in equity and home bias is the fraction of equity invested in Canadian companies. We measure risky share and home bias for each investor at year-ends 1999 through 2011. We always omit the indicator variable for the lowest category. The first two regressions are estimated using data on all advisors. The regressions in the low-dispersion and high-dispersion columns divide advisors each year into two groups of equal size based on client heterogeneity. The measure of heterogeneity is the within-advisor standard deviation of the fitted values from column (1)'s regression. The last row, "Adjusted R^2 w/o advisor FEs," reports the adjusted R^2 from an alternative model that does not include the advisor fixed effects. Standard errors are clustered by advisor.

Panel A: Dependent variable = Risky share

Independent variable	All advisors $\hat{b}$	All advisors t	All advisors $\hat{b}$	All advisors t	Low-dispersion advisors $\hat{b}$	Low-dispersion advisors t	High-dispersion advisors $\hat{b}$	High-dispersion advisors t
Constant	37.90	12.68	36.13	14.52	40.25	6.70	33.05	11.73
Age, 25–29	0.65	1.06	1.56	2.95	0.92	1.34	1.97	2.65
30–34	2.60	3.94	3.43	6.39	3.00	4.10	3.76	5.22
35–39	3.86	5.38	4.17	7.51	3.48	4.48	4.67	6.42
40–44	3.53	4.79	3.42	6.06	2.83	3.52	3.86	5.27
45–49	2.57	3.42	2.06	3.58	1.72	2.09	2.31	3.09
50–54	1.71	2.25	0.95	1.65	0.41	0.50	1.36	1.81
55–59	0.22	0.29	−0.72	−1.25	−1.31	−1.64	−0.28	−0.37
60–64	−1.41	−1.80	−2.63	−4.49	−3.21	−3.90	−2.18	−2.82
65–69	−3.07	−3.78	−4.47	−7.47	−5.16	−6.29	−3.94	−4.99
70–74	−4.48	−5.16	−6.33	−9.97	−6.74	−7.66	−5.94	−7.09
75–80	−4.11	−4.47	−6.78	−10.05	−7.79	−8.17	−6.06	−6.86
Female	−1.29	−9.25	−1.25	−12.65	−1.16	−8.64	−1.33	−10.09
Risk tolerance								
Low	6.27	2.54	7.21	3.45	−1.75	−0.32	7.56	3.48
Low to Moderate	16.67	6.58	17.68	8.58	16.84	3.18	17.60	8.22
Moderate	30.82	12.01	29.32	13.76	28.77	5.39	29.23	13.16
Moderate to High	33.50	12.80	32.33	15.10	32.25	6.06	31.74	14.22
High	39.47	15.17	37.78	17.11	36.86	6.96	37.94	16.05
Time horizon								
Short	2.71	3.39	3.47	5.37	2.72	2.70	3.60	4.63
Moderate	6.28	8.31	4.92	8.20	4.01	4.20	5.19	7.23
Long	6.60	7.84	5.36	8.76	3.97	4.05	6.04	8.26
Fin. knowledge								
Moderate	2.08	5.16	1.46	10.59	1.14	5.81	1.66	9.63
High	2.75	4.71	2.75	10.05	1.80	5.42	3.39	9.05
Salary								
$30-50k	0.65	3.78	0.73	5.94	0.73	4.52	0.72	4.31
$50-70k	0.48	2.09	1.01	7.02	0.91	5.01	1.06	5.32
$70-100k	0.07	0.24	1.01	6.51	0.89	4.45	1.08	5.08
$100-200k	−4.51	−2.28	−0.45	−0.55	0.77	0.68	−1.51	−1.41
Over $200k	−4.01	−1.99	−0.38	−0.40	−0.85	−0.59	0.05	0.05
Net worth								
$35-60k	0.59	1.05	0.94	2.33	0.62	1.09	1.11	2.19
$60-100k	1.28	2.17	1.48	3.64	1.15	2.03	1.67	3.19
$100-200k	1.90	3.54	1.69	4.50	1.30	2.50	1.92	3.99
Over $200k	1.57	2.62	1.18	2.99	0.71	1.31	1.50	2.92
Occupation								
Finance professional	1.70	2.24	0.80	1.14	−0.54	−0.65	1.93	1.91
Self-employed	1.00	2.88	0.63	2.26	0.25	0.73	0.95	2.36
Year FEs	Yes		Yes		Yes		Yes	
Advisor FEs	No		Yes		Yes		Yes	
# of observations	807,802		807,802		351,520		452,674	
# of investors	186,105		186,105		98,241		118,364	
# of advisors	5,163		5,163		2,881		2,603	
Adjusted R^2	13.1%		31.6%		30.3%		30.8%	
w/o advisor FEs	.		13.1%		8.1%		14.6%	

Panel B: Dependent variable = Home bias

Independent variable	All advisors		All advisors		Low-dispersion advisors		High-dispersion advisors	
	$\hat{b}$	t	$\hat{b}$	t	$\hat{b}$	t	$\hat{b}$	t
Constant	56.23	20.44	58.15	23.87	55.65	17.46	59.48	17.26
Age, 25–29	0.20	0.22	0.59	0.77	0.52	0.45	0.76	0.76
30–34	−0.68	−0.64	0.53	0.62	0.73	0.58	0.51	0.48
35–39	−1.81	−1.62	0.31	0.36	−0.25	−0.20	0.91	0.85
40–44	−2.16	−1.91	0.27	0.31	−0.35	−0.27	0.90	0.84
45–49	−2.16	−1.90	0.17	0.19	−0.41	−0.31	0.86	0.80
50–54	−2.19	−1.93	−0.05	−0.06	−0.58	−0.44	0.54	0.51
55–59	−1.79	−1.55	0.20	0.23	−0.38	−0.29	0.80	0.73
60–64	−1.16	−0.97	0.70	0.76	−0.14	−0.10	1.61	1.40
65–69	−0.55	−0.44	1.61	1.74	0.26	0.19	3.06	2.66
70–74	0.23	0.17	2.93	2.96	1.19	0.84	4.86	3.83
75–80	1.09	0.80	3.66	3.70	1.63	1.15	6.02	4.72
Female	0.70	2.85	0.37	2.38	0.33	1.74	0.41	1.83
Risk tolerance								
Low	2.72	1.52	−0.03	−0.02	0.13	0.06	0.01	0.00
Low to Moderate	0.12	0.07	−0.42	−0.27	−1.23	−0.66	1.02	0.45
Moderate	0.91	0.56	−0.28	−0.19	−0.52	−0.29	0.01	0.01
Moderate to High	−3.49	−2.04	−4.24	−2.86	−4.02	−2.26	−4.19	−1.93
High	−17.03	−9.04	−14.90	−9.44	−15.81	−7.72	−14.46	−6.52
Time horizon								
Short	0.98	0.86	0.83	0.96	0.87	0.73	0.91	0.78
Moderate	0.28	0.25	1.61	1.95	1.50	1.32	1.95	1.76
Long	−0.43	−0.35	2.06	2.46	1.56	1.36	2.80	2.49
Fin. knowledge								
Moderate	2.08	3.38	−0.76	−3.70	−0.69	−2.82	−0.78	−2.55
High	2.64	2.81	−1.63	−3.66	−2.16	−3.46	−1.31	−2.28
Salary								
\$30-50k	−0.50	−1.88	−0.34	−1.77	−0.21	−0.85	−0.50	−1.85
\$50-70k	−1.24	−3.75	−1.17	−5.28	−1.15	−4.03	−1.20	−4.03
\$70-100k	−3.06	−6.52	−1.94	−7.72	−2.02	−6.48	−1.92	−5.49
\$100-200k	−0.70	−0.29	−1.71	−1.26	−1.89	−1.09	−1.57	−0.77
Over \$200k	1.06	0.44	−1.09	−0.86	−1.39	−0.95	−0.84	−0.47
Net worth								
\$35-60k	1.20	1.47	0.65	1.08	0.49	0.60	0.80	1.01
\$60-100k	1.02	1.27	−0.14	−0.24	−0.23	−0.31	−0.02	−0.03
\$100-200k	0.12	0.15	−0.01	−0.02	0.29	0.39	−0.38	−0.52
Over \$200k	−0.22	−0.27	−0.17	−0.31	−0.32	−0.43	−0.06	−0.09
Occupation								
Finance professional	−1.66	−1.22	−1.02	−0.94	−0.38	−0.23	−1.40	−1.07
Self-employed	−0.99	−1.81	−0.39	−0.95	−0.38	−0.76	−0.48	−0.85
Year FEs	Yes		Yes		Yes		Yes	
Advisor FEs	No		Yes		Yes		Yes	
# of observations	787,766		787,766		377,050		407,246	
# of investors	182,343		182,343		106,500		109,739	
# of advisors	5,133		5,133		2,872		2,540	
Adjusted R^2	3.6%		27.9%		29.0%		26.4%	
w/o advisor FEs	.		3.6%		3.0%		3.4%	

Table 5: Analysis of portfolio allocations with investor fixed effects

This table reports estimates from regressions of average risky share (Panel A) and home bias (Panel B) on investor attributes, year fixed effects, advisor fixed effects, and investor fixed effects. The unit of observation is a client-advisor pair. We measure the average risky share and home bias of investments initiated during the client-advisor relationship. We restrict the sample to investors who switch advisors during the sample period due to the disappearance of their former advisor. The first two columns repeat Table 4's analyses using this subsample of investors. The third regression replaces investor attributes with investor fixed effects. The numbers in parentheses on the fixed-effects rows report F-values from tests that the fixed effects are jointly zero. Panel A's regressions use data on 3,827 client-advisor pairs from 1,824 clients and 690 advisors; Panel B uses data on 3,575 client-advisors pairs from 1,707 clients and 668 advisors. Rows "Adjusted R^2 w/o advisor FEs" and "Adjusted R^2 w/o investor attributes" report the adjusted R^2s from alternative models that do not include the advisor fixed effects or investor attributes. Standard errors are clustered by advisor.

Panel A: Risky-share analysis with investor fixed effects

Independent variable	(1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Constant	47.94	4.33	41.92	3.28		
Age, 25–29	−9.00	−1.81	−2.43	−0.53		
30–34	−3.88	−0.83	1.11	0.25		
35–39	−5.40	−1.16	−0.97	−0.22		
40–44	−5.39	−1.14	−1.57	−0.35		
45–49	−6.98	−1.48	−2.57	−0.58		
50–54	−8.25	−1.69	−4.86	−1.09		
55–59	−6.29	−1.29	−3.61	−0.80		
60–64	−9.04	−1.73	−8.46	−1.85		
65–69	−7.47	−1.44	−7.36	−1.56		
70–74	−14.58	−2.41	−11.75	−2.31		
75–80	−14.09	−2.35	−13.51	−2.48		
Female	−2.87	−3.16	−2.63	−3.26		
Risk tolerance						
Low	3.86	0.41	10.12	1.65		
Low to Moderate	12.77	1.44	22.45	3.88		
Moderate	23.20	2.68	27.90	4.96		
Moderate to High	25.16	2.86	30.09	5.33		
High	31.66	3.63	35.48	6.21		
Time horizon						
Short	2.90	0.74	2.28	0.69		
Moderate	7.08	1.96	3.22	1.11		
Long	6.71	1.74	3.17	1.03		
Fin. knowledge						
Moderate	4.30	3.29	0.24	0.23		
High	5.20	2.57	0.79	0.47		
Salary						
$30-50k	0.47	0.42	0.56	0.57		
$50-70k	0.76	0.63	1.04	0.92		
$70-100k	−0.02	−0.01	1.54	1.15		
$100-200k	−3.72	−0.63	−1.05	−0.16		
Over $200k	−16.37	−3.25	−7.64	−0.56		
Net worth						
$35-60k	0.33	0.08	1.74	0.52		
$60-100k	−2.15	−0.56	−1.19	−0.37		
$100-200k	−1.11	−0.30	−0.09	−0.03		
Over $200k	0.16	0.04	−0.87	−0.28		
Occupation						
Finance professional	1.65	0.31	−4.10	−0.80		
Self-employed	−1.28	−0.55	−0.86	−0.42		
Year FEs	Yes		Yes		Yes	
Advisor FEs (F-test)	No		Yes (3.22)		Yes (2.31)	
Investor FEs (F-test)	No		No		Yes (1.87)	
Adjusted R^2	8.9%		35.1%		47.5%	
w/o advisor FEs	.		8.9%		31.3%	
w/o investor attributes	.		30.3%		.	

Panel B: Home-bias analysis with investor fixed effects

Independent variable	(1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Constant	62.71	2.93	51.38	2.47		
Age, 25–29	−12.25	−1.98	−8.54	−1.33		
30–34	−11.38	−1.94	−6.84	−1.10		
35–39	−18.03	−3.09	−12.66	−2.04		
40–44	−18.09	−3.09	−11.40	−1.84		
45–49	−16.05	−2.73	−11.80	−1.90		
50–54	−13.45	−2.29	−9.27	−1.49		
55–59	−12.32	−2.05	−8.28	−1.31		
60–64	−14.94	−2.35	−9.10	−1.42		
65–69	−13.89	−2.24	−8.81	−1.33		
70–74	−15.40	−2.06	−14.31	−1.98		
75–80	−17.24	−2.20	−9.66	−1.25		
Female	−0.14	−0.12	0.11	0.10		
Risk tolerance						
Low	12.17	0.65	−4.99	−0.36		
Low to Moderate	14.10	0.76	−7.06	−0.53		
Moderate	8.24	0.45	−11.18	−0.84		
Moderate to High	7.15	0.39	−14.72	−1.10		
High	−2.62	−0.14	−22.75	−1.71		
Time horizon						
Short	12.87	2.29	9.48	1.97		
Moderate	7.43	1.47	11.08	2.61		
Long	14.40	2.80	13.57	3.04		
Fin. knowledge						
Moderate	1.78	0.90	0.90	0.60		
High	4.92	1.85	1.48	0.61		
Salary						
$30-50k	−0.59	−0.37	−0.95	−0.67		
$50-70k	−2.14	−1.24	−2.06	−1.30		
$70-100k	−4.92	−2.33	−1.48	−0.78		
$100-200k	−7.33	−0.89	−3.79	−0.41		
Over $200k	28.75	3.55	36.37	1.97		
Net worth						
$35-60k	2.37	0.44	2.83	0.57		
$60-100k	3.57	0.66	4.42	0.93		
$100-200k	6.67	1.28	7.02	1.48		
Over $200k	4.30	0.84	3.98	0.86		
Occupation						
Finance professional	−4.41	−0.64	4.89	0.67		
Self-employed	−0.05	−0.02	2.45	0.84		
Year FEs	Yes		Yes		Yes	
Advisor FEs (F-test)	No		Yes (3.23)		Yes (2.2)	
Investor FEs (F-test)	No		No		Yes (1.88)	
Adjusted R^2	3.5%		32.1%		45.9%	
w/o advisor FEs	.		3.5%		30.0%	
w/o investor attributes	.		30.9%		.	

Table 6: Regressions of advisor fixed effects on advisor attributes

This table reports estimates from cross-sectional analyses of the estimated advisor fixed effects from Table 4. The explanatory variables consist of advisor age, gender, risk-tolerance, and the risky share and home bias in the advisor's own portfolio.

Panel A: Risky-share fixed effects

Independent variable	Regression (1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t	(4) $\hat{b}$	(4) t
Age, 25–29	2.61	0.57	6.41	1.26	7.23	1.58	7.02	1.54
30–34	1.91	0.43	5.47	1.10	6.78	1.51	6.86	1.54
35–39	4.38	1.00	6.08	1.23	6.42	1.45	6.68	1.53
40–44	5.46	1.26	7.56	1.55	8.03	1.83	8.03	1.85
45–49	5.15	1.19	7.80	1.60	9.28	2.12	9.20	2.12
50–54	6.47	1.50	8.85	1.82	10.17	2.33	10.17	2.35
55–59	5.78	1.33	8.32	1.70	9.41	2.14	9.26	2.13
60–64	10.15	2.33	12.29	2.50	13.56	3.08	13.54	3.11
65–69	9.69	2.18	11.89	2.35	12.72	2.81	13.16	2.92
70–74	16.63	3.65	18.38	3.59	19.13	4.09	19.17	4.12
75–79	8.94	0.90	15.67	2.50	17.91	3.21	17.49	3.12
Female	0.32	0.49	1.04	1.56	1.30	2.16	1.34	2.17
Risk tolerance								
Moderate			4.97	2.98			0.16	0.09
Moderate to High			3.65	2.20			−1.54	−0.93
High			5.36	3.29			−1.16	−0.70
Advisor's risky share					24.49	15.57	25.38	15.47
# of observations	3,622		2,798		2,883		2,798	
Adjusted R^2	2.7%		3.2%		14.9%		15.4%	

Panel B: Home-bias fixed effects

Independent variable	Regression (1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t	(4) $\hat{b}$	(4) t
Age, 25–29	−11.53	−1.69	−4.02	−0.52	−3.60	−0.52	−3.04	−0.45
30–34	−19.86	−3.01	−18.00	−2.41	−15.77	−2.41	−15.96	−2.51
35–39	−16.02	−2.47	−12.60	−1.72	−9.73	−1.51	−9.50	−1.52
40–44	−17.27	−2.68	−14.46	−2.00	−10.22	−1.61	−10.01	−1.62
45–49	−16.04	−2.49	−14.65	−2.02	−10.75	−1.69	−10.57	−1.71
50–54	−17.35	−2.70	−15.28	−2.11	−10.98	−1.73	−10.57	−1.71
55–59	−11.93	−1.85	−8.66	−1.20	−6.34	−1.00	−5.53	−0.90
60–64	−12.81	−1.98	−8.27	−1.14	−6.95	−1.09	−6.25	−1.01
65–69	−14.61	−2.20	−12.07	−1.62	−9.84	−1.51	−10.29	−1.62
70–74	−13.36	−1.90	−7.64	−0.99	−6.12	−0.89	−5.32	−0.79
75–79	−2.67	−0.34	−4.18	−0.51	−5.60	−0.77	−4.51	−0.63
Female	2.21	2.27	2.38	2.26	1.46	1.54	1.17	1.22
Risk tolerance								
Moderate			6.38	2.43			5.05	2.01
Moderate to High			7.31	2.82			7.43	3.00
High			4.45	1.74			7.95	3.24
Advisor's home bias					31.65	22.51	33.13	22.97
# of observations	3,605		2,792		2,843		2,763	
Adjusted R^2	1.3%		2.9%		19.7%		21.2%	

Table 7: Estimates of advisors' gross and net alphas

This table reports estimates of advisors' gross and net alphas from the CAPM, Fama and French's (1993) three-factor model, and a six-factor model that adds the momentum factor and two fixed-income factors. These fixed-income factors are the return differences between the ten-year and 90-day Treasuries ("term") and between high-yield corporate bonds and ten-year Treasuries ("default"). Net returns adjust for management expense ratios and investors' front-end load payments. The row "average dollar" represents the performance of the average advised dollar, weighting each advisor by assets under advice; "average advisor" represents the performance of the average advisor, weighting each advisor equally; and "average client" represents the performance of the average advisor, weighting each advisor by the number of their clients. Adjusted R^2s are from the average-dollar regressions. The bottom part of the table reports the distributions of t-values of alphas estimated from 4,821 advisor-specific regressions. Column "Ref." reports the reference t-distribution estimated using the Fama and French (2010) bootstrapping methodology. Row "% Skilled" reports the estimated fraction of advisors with reliably positive net alphas.

		Factors: MKT			Factors: MKT, HML, SMB			Factors: MKT, HML, SMB, MOM, DEF, TERM		
		Gross	Net	Ref.	Gross	Net	Ref.	Gross	Net	Ref.
Alphas	Average dollar	0.10	−2.45		−0.28	−2.83		−0.80	−3.34	
		(0.09)	(−2.28)		(−0.26)	(−2.61)		(−0.77)	(−3.22)	
	Adj. R^2	85.3%	85.2%		85.6%	85.5%		88.0%	88.0%	
	Average advisor	−0.16	−3.02		−0.44	−3.29		−0.95	−3.80	
		(−0.15)	(−2.92)		(−0.42)	(−3.16)		(−0.94)	(−3.81)	
	Average client	0.04	−2.61		−0.32	−2.96		−0.84	−3.48	
		(0.03)	(−2.43)		(−0.30)	(−2.74)		(−0.81)	(−3.37)	
Distributions of t-values of alphas from advisor-level regressions										
Percentile	1	−2.33	−4.06	−2.08	−2.31	−4.00	−2.13	−2.68	−4.73	−2.35
	5	−1.42	−2.90	−1.41	−1.42	−2.96	−1.41	−1.91	−3.67	−1.51
	10	−0.92	−2.41	−1.08	−0.94	−2.47	−1.07	−1.49	−3.19	−1.13
	25	−0.26	−1.72	−0.56	−0.27	−1.74	−0.54	−0.87	−2.46	−0.54
	50	0.58	−0.84	0.02	0.62	−0.80	0.04	0.01	−1.27	0.11
	75	1.57	0.15	0.60	1.67	0.27	0.63	1.12	−0.05	0.76
	90	2.60	1.01	1.14	2.78	1.15	1.17	1.97	0.73	1.34
	95	3.32	1.46	1.47	3.53	1.66	1.50	2.42	1.16	1.72
	99	4.87	2.74	2.18	5.29	3.04	2.24	3.71	2.06	2.57
% Skilled			6.4%			11.0%			0.0%	

Table 8: Robustness analysis using an extended sample

This table summarizes key estimates from the analyses presented in Tables 3–5 and 7 using both the main sample and an extended sample. The extended sample adds data from a fourth mutual fund dealer. Compared to the main sample, the extended sample covers a shorter time period (January 2001 through 2010) and lacks information on front-end load payments. Column "Main sample" summarizes the estimates reported in the other tables and column "Extended sample" reports these estimates for the extended sample. The row "Net alpha" adjusts gross returns for management-expense ratios; "Net alpha (all expenses)" adjusts for both management-expense ratios and front-end load payments.

Variable	Sample: Main	Extended
Investor Characteristics		
Number of investors	581,044	814,056
Account value per investor, \$K		
Mean	68.14	58.66
Median	27.33	21.13
Portfolio		
Risky share	0.69	0.70
Home bias	0.59	0.57
Advisor Characteristics		
Number of Advisors	5,920	10,275
Clients per advisor		
Mean	74.32	69.67
Median	24	25
Assets under advice per advisor, \$K		
Mean	5,064.03	4,086.40
Median	916.88	933.50
Advisor Influence		
Adjusted R^2, portfolio risky share		
Investor characteristics	13.1%	16.0%
Investor characteristics + advisor FEs	31.6%	31.4%
Investor FEs (movers-sample)	31.3%	31.9%
Investor FEs + advisor FEs (movers-sample)	47.5%	47.1%
Adjusted R^2, portfolio home bias		
Investor characteristics	3.6%	2.3%
Investor characteristics + advisor FEs	27.9%	22.4%
Investor FEs (movers-sample)	30.0%	23.1%
Investor FEs + advisor FEs (movers-sample)	45.9%	41.1%
Investment performance in the six-factor model		
Gross alpha	−0.80	−1.28
	(−0.77)	(−1.14)
Net alpha	−3.12	−3.61
	(−3.00)	(−3.24)
Net alpha (with all expenses)	−3.34	
	(−3.22)	