Retail Financial Advice: Does One Size Fit All?*

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Abstract

Using unique data on Canadian households, we show that financial advisors exert substantial influence over their clients' asset allocation, but provide limited customization. Advisor fixed effects explain considerably more variation in portfolio risk and home bias than a broad set of investor attributes that includes risk tolerance, age, investment horizon and financial sophistication. Advisor effects remain important even when controlling flexibly for unobserved heterogeneity through investor fixed effects. An advisor's own asset allocation strongly predicts the allocations chosen on clients' behalf. This one-size-fits-all advice does not come cheap. Advised portfolios cost 2.5% per year, or 1.5% more than lifecycle funds.

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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 whether advisors tailor investment risk to clients' characteristics or instead deliver one-size-fits-all portfolios. The data, which were furnished by four large financial institutions, 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 the 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

[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.

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 lifecycle. 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. We find only modest differences in portfolios across occupations and mixed evidence regarding the typical recommendations of portfolio theory. Controlling for risk-tolerance and other characteristics, government workers invest more in equities. This choice fits with the typical prescription of portfolio theory for an occupation with low-risk labor income. On the other hand, self-employed clients and clients working in the finance industry hold modestly higher risky shares despite labor income that is likely to be more volatile and more strongly correlated with market returns (Heaton and Lucas 2000).

The most striking finding from our analysis of portfolio allocations, however, is that clients' observable characteristics jointly explain only 12% 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.

Advisor fixed effects, by contrast, have substantially more explanatory power. On their own, advisor effects explain 22% of the variation in risky share. When added to the model with investor characteristics they more than double the adjusted R^2 from 12% to 30%, 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 the variation in the share of risky assets invested in Canadian equity funds whereas advisor fixed effects explain an additional 24% of the variation. The advisor effects are also 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 many 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 use clients that switch advisors to investigate the latter hypothesis. Our data include investor identifiers that allow us to track clients who switch advisors. We use this feature to implement a two-way fixed effects analysis, similar to research on managerial style (Bertrand and Schoar 2003). We exclude client-initiated switches that may coincide with a change in preferences and focus instead on clients who are forced to switch due to their advisor's death, retirement, or resignation. We show that client portfolios shift away from the allocation common to the old advisor's clients and toward the allocation held by the new advisor's clients. For this subset of investors we also estimate models with both advisor and investor fixed effects. The latter control flexibly for persistent differences in risk-taking due to unobserved preferences and self-directed investments initiated by the client rather than the advisor. The advisor fixed effects capture the advisor-specific "style" in portfolio allocation net of investor effects. While the investor fixed effects add explanatory power beyond the observable characteristics, the advisor fixed effects remain important. As a result, the joint set of advisor effects display similar statistical significance as the investor effects. The models' adjusted R^2s also increase substantially—by more than 10 percentage points for both risky share and home bias—when advisor effects accompany investor effects. We conclude that the advisor effects in our baseline model are not merely an artifact of omitted preferences common among clients of the same advisor.

If advisors do not base their advice on clients' risk tolerance, investment horizon, and income, then what explains the 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 (two-thirds 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 predictors of risk-taking and home bias in their clients' portfolios. 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. In light of potential agency conflicts, it is reassuring that advisors are willing to hold the portfolio that they recommend. However, the portfolio suitable for the advisor may deviate substantially from what is best for the investor, particularly when a risk-seeking advisor provides recommendations to a risk-averse client or, conversely, a risk-averse advisor directs the portfolio of a risk-seeking client. Our data suggest that there is scope for substantial mismatch in this regard. Among the least risk-tolerant clients, the average equity share is 13 percentage points, or 40%, higher when the advisor's personal equity share is in the top quintile as opposed to the bottom quintile. Likewise, for the most risk-tolerant clients, the average equity share is 10 percentage points, or 13%, higher when the advisor is in the top quintile as opposed to the bottom quintile of risk-taking.

Given that advisors provide limited customization, the puzzle in this market is the high cost of advice.[2] We show that advisors do not add value through market timing or fund selection—the gross alphas in our sample are, if anything, negative when we benchmark advised portfolios against passive equity and bond portfolios. Investors' net underperformance of passive benchmarks therefore equals (or exceeds) the fees that they pay. Including all management fees and front-end loads paid to advisors and mutual funds, advised portfolios cost 2.5% of assets per year. Compared to lifecycle funds, which likewise offer diversified portfolios that require little active management by the investor, advised portfolios cost an additional 1.5 percentage points per year. For investors who maintain an advisor, this steady stream of fees compounds quite dramatically, reducing the present value of their savings by as much as 14%. 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 encourage risk-taking (Gennaioli, Shleifer, and Vishny 2015).

Our analysis contributes three insights to the literature on financial advice. First, we find little support for the view that advisors' value added resides in tailoring portfolios to clients' charac-

[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.

terisitics. Second, we find that advisors are nevertheless a major determinant of asset allocation. Understanding the intermediation process is therefore crucial for theories seeking to explain household portfolios. Third, we show that advisors' own risk-taking influences how much risk their clients assume.

The rest of the paper proceeds as follows. Section 2 describes our administrative data on client accounts. Sections 3 and 4 present analysis of portfolio customization and investment performance within these accounts. Section 5 examines the cost of advice and Section 6 concludes.

2 Description of the Data

Four Canadian financial advisory firms—known as Mutual Fund Dealers (MFDs)—supplied the data for our study. These non-bank financial advisors account for the majority of advised assets in Canada—$390 billion, or 55% of household assets under advice as of December 2011 (Canadian Securities Administrators 2012). 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.

Each dealer provided a detailed history of client transactions as well as demographic information on clients and advisors. The resulting sample includes more than 10,000 advisors and provides 11% coverage of MFD advisors. Three of the four dealers furnished identifiers necessary to link advisors to their personal investment portfolio (if held at their own firm). We focus on this three-dealer sample, which still covers more than 6% of MFD advisors, in order to maintain a consistent sample across the main tests. We reserve the fourth dealer for robustness tests reported in the Internet Appendix.

Table 1 provides the key summary statistics for the main sample. The sample includes all individual accounts held at one of the three main dealers between January 1999 and June 2012. We exclude jointly held accounts from the main sample because portfolio allocations may depend on multiple investors' attributes. The final sample includes 5,920 advisors and 581,044 investors who are active at some point during the 14-year sample period, and encompasses $18.9 billion of assets under advice as of June 2012.

Panel A displays the investor and account characteristics. Men and women are equally represented in the data. Age ranges from 33 years old at the bottom decile to 69 years old at the top decile; the median investor is 51 years old. The data contain information on clients' occupations. For the purposes of this study we identify three occupation categories—finance professional, government employee and self-employed—that theoretical models and empirical work have highlighted as important determinants of portfolio choice. Just over 1% of clients work in the finance industry, 4.3% are self-employed and 8% work for the government.

The median investor has been with his current advisor for 3 years as of the end of the sample period and has CND $27,330 invested across 3 mutual funds. Account values are right-skewed, with the average value of CND $68,140 substantially exceeding the median value. Retirement plans, which receive favorable tax treatment comparable to IRA plans in the U.S., are most prevalent (66% of plans), followed by unrestricted general-purpose plans (24% of plans) and education savings plans (5% of plans).

We assess advisors' 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.[3] The risky share, which is 74% for the median investor in our sample, ranges from 44% at the bottom decile to 100% at the top decile. The home bias displays more variation, from 0% at the bottom decile to 100% at the top decile. The median investor's 60% allocation to Canadian equities is similar to typical Canadian households, but represents extreme home bias. An International Monetary Fund survey finds that Canadian equities constitute 3.6% of the global equity portfolio and 59% of Canadians' equity allocations (Pakula et al. 2014).

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 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 20% indicate a horizon of ten

[3] 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.

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."[4] Clients report having little financial knowledge: 43% of investors report "low," 51% report "moderate" and only 6% report "high" financial knowledge.[5] The vast majority of clients (87%) earn less than $100 thousand per year. Incomes are nevertheless higher than in the general Canadian population, within which median income was $31 thousand per year in 2012. Lastly, the majority of clients (58%) report net worth of $200 thousand or more, placing them close to or above the median net worth of Canadian households in 2012 ($244 thousand).[6]

Table 1 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 substantially 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 $5,200 and more than $14.6 million, respectively.

3 Analysis of Portfolio Customization

3.1 Analysis of portfolio risky share

Our analysis begins with regressions that explain the 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

[4] 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.

[5] A short description similar to those provided for the 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.

[6] Statistics Canada reports the distribution of income at http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/famil105a-eng.htm and the distribution of net worth at http://www.statcan.gc.ca/daily-quotidien/140225/dq140225b-eng.htm.

of the form:

$$y_{iat} = \boldsymbol{\mu}_a + \boldsymbol{\mu}_t + \boldsymbol{\theta} \boldsymbol{X}_{it} + \varepsilon_{iat}, \tag{1}$$

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 $\boldsymbol{\mu}_t$ 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, age and geographic location (province fixed effects). 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 3.6. 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 2 Panel A reports the regression estimates for investors' risky shares. The first model includes only investor attributes as independent variables. The sample includes 174,609 investors and 5,083 advisors.[7] The intercept of this regression, 37.1%, 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 risk-taking. The risky share increases monotonically with risk tolerance. Relative to the excluded "very low" category, those with low-to-moderate risk tolerance invest 17.4 percentage points more in equities, while those with moderate risk tolerance invest 30.5 percentage points more in equities. At the top of the range, investors with high risk tolerance hold 38.3 percentage points more in equities.

Investor age is also important in explaining variation in risk-taking. Figure 1 Panel A plots the age coefficients from the first regression. The age profile of risky share is hump-shaped, rising with age and peaking among investors between ages 35 and 39 before declining to its low among investors of retirement age.[8] Figure 1 Panel B provides additional context by plotting the age profile used in

[7] The number of investors is lower than that in Table 1 because of missing values for some investor attributes.

[8] 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. In Fagereng, Gottlieb, and Guiso (2013), the hump-shaped pattern peaks around retirement. Poterba and Samwick (2001) use three Survey of Consumer Finances waves from 1983 through 1992 and find that risky share is generally increasing in age.

Fidelity's Canadian target-date funds beside the age profile in our sample. The target-date funds invest 85% in equities for investors up to age 35 and then reduce the equity exposure almost linearly so that it falls to 40% at the expected retirement age of 65. The risky-share profiles of advised investors differ considerably from target-date allocations. In each risk-tolerance category, investors assume less equity exposure relative to the target-date benchmark when they are young and more when they are old.

The remaining regressors in Table 2 show that women's risky shares—controlling for other demographics such as risk tolerance—are, on average, 1.4 percentage points below those of men. Investors with longer investment horizons assume roughly 7 percentage points more equity risk than those with very short horizons. Investors who report higher levels of financial knowledge have between 2 and 4 percentage points higher risky shares than low-knowledge investors. After accounting for all other investor attributes, income and wealth contribute only modestly to cross-sectional variation in risky shares.

We find limited variation in risk-taking across occupations. Investors in finance-related occupations hold modestly higher risky shares (2.3 percentage points) conditional on other characteristics, while self-employed clients show no significant difference in risk-taking relative to peers. These findings run counter to the typical implication of portfolio theory that investors whose labor income is riskier—more strongly correlated with stock returns or exposed to more idiosyncratic "background risk"—should take less investment risk.[9] On the other hand, government workers allocate slightly more (1 percentage point) to equities as portfolio theory would predict for a group with less labor income risk. None of these coefficients, however, is economically significant. In a robustness test we explore occupation effects more exhaustively. We find modest portfolio differences across occupations, similar to variation observed across categories of financial knowledge and income, but much less than the variation observed across risk tolerance, age and investment horizon.[10]

The most striking finding in this analysis of risky share is that all of the regressors in the model—there are 47 variables excluding the year fixed effects—jointly explain only one-eighth of the cross-sectional variation in risky shares. That is, although differences in risk tolerance translate

[9] 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).

[10] In this analysis, we include in the regression separate indicators for each of the 46 two-digit occupation categories in Canada's National Occupation Classification. The largest point estimate of 3.1% corresponds to management jobs in public administration, while the smallest point estimate of −1.3% corresponds to senior management occupations.

to significant differences in *average* risky shares, the model's R^2 is just 12.2%. 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 on investor attributes—Calvet and Sodini (2014) use administrative data—do not depress the R^2 measure.

3.1.1 Caveats and robustness

The estimates reported in Table 2 hold throughout the data. In this section, we summarize robustness checks that divide the data into various subsamples. We report the full details in the Internet Appendix.

One limitation of our data is that we may have incomplete information on household financial assets. Assets accumulated through work pensions, for example, are unlikely to be covered in our data. Investors may also maintain multiple investment accounts, particularly when they have a family. If those accounts are held with other brokers or dealers, they will escape our notice. In these instances, one might worry that investor attributes have poor explanatory power in our sample results because we have an incomplete view of households' investments.

We evaluate the importance of outside assets as follows. First, we examine the relevance of work pensions to our findings. Using household survey data from the Canadian Financial Monitor, we distinguish occupations based on their pension generosity, as measured by the proportion of pension assets relative to the household's total financial assets. We find that, on average, government occupations have the most generous pensions and low-skill service occupations such as waiters and housekeepers have the least generous pensions. We then separate clients in the dealer data into high- and low-pension groups based on their reported occupation. Within these two subsamples we find that the explanatory power and slope coefficients for investor attributes are similar to the full sample. Unobserved pension assets are therefore not responsible for the modest explanatory power of investor attributes in the main sample. Second, we evaluate whether assets held outside the dealer matter for the main findings. We use the net worth reported on the "Know Your Client" forms to compute advised assets-to-net worth ratio for each client. We find that investor attributes are equally important among clients with ratios above and below the median.

Another limitation of our data is that an individual's preferences, for example risk tolerance, may provide an imperfect measure of the joint preferences across multiple family members. Although we exclude jointly held accounts from our analysis for this reason, our sample of individual accounts still includes married individuals with dependents. To address this concern, we estimate the same model for the subset of single households. We find no evidence that the weak explanatory power of individual characteristics results from measurement error among portfolios managed in joint interest—the adjusted R^2 with the full set of investor attributes is 12.1% for both single and multi-person households.

3.2 Analysis of portfolio home bias

The explanatory power of investor attributes is even lower in Table 2 Panel B's home-bias regressions. The same set of regressors yields an adjusted R^2 of just 4.1% 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 18 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 international equities should be largely invariant to investor characteristics.[11] Any cross-sectional variation in home bias probably emanates from differences in beliefs, transaction costs or other frictions. One such friction is Canada's Foreign Property Rule. Prior to its repeal in 2005, this rule prevented investors from allocating more than 30% of registered retirement accounts to non-Canadian assets. Despite its influence on the level of home bias, the Foreign Property Rule does not affect our findings on the explanatory power of investor attributes. In the Internet Appendix, we show that investor attributes explain only 5.0% of the variation in home bias in accounts that faced no restriction on foreign holdings.

We also examine the complement to home bias—the fraction of equities allocated to non-Canadian funds. Outside of Canadian funds, investors in our sample hold primarily global funds

[11]In a model in which labor income correlates with asset returns, the optimal mix of domestic and international equities would vary across investors if there are differences in how labor income correlates with returns on domestic and international equities. In Section 3.5.1, we address the role of omitted variable such as this correlation.

(40.5% on average) and make only modest allocations to U.S.-only funds (2.4% of equity allocation on average). We find that allocations to U.S.-only funds vary substantially with clients' proximity to the U.S. border. For this analysis we regress the fraction of U.S. equities (as % of total equities) on the investor's distance from the U.S. border and the same set of investor attributes and fixed effects as in Table 2. Figure 2 plots the marginal effect of the distance to the U.S. border. The average share of U.S.-only funds is modest at 2.3%, but increases substantially with proximity to the U.S. border. Investors living more than 200 miles away from the border allocate just 1.7% in U.S. equities, while those within five miles from the border allocate 3.3% in U.S. equities. The marginal effect for this category is 1.6% with a t-values of 3.0. Perhaps due to familiarity with U.S. companies or exposure to U.S. news, these investors allocate more of their portfolios to U.S. assets.

3.3 Statistical and economic significance of advisor fixed effects

The second regression model within each panel of Table 2 modifies the first by adding advisor fixed effects. The results reveal remarkably powerful advisor effects. The adjusted R^2 in Panel A's risky-share regression more than doubles from 12.2% to 30.2% as we add the advisor fixed effects. In Panel B's home-bias regression the adjusted R^2 increases from 4.1% to 27.9%. These findings indicate substantial common variation in portfolios among clients of the same advisor.

A further test shows that the advisor fixed effects increase the explanatory power because they identify differences across individual advisors and not because they control for systematic variation across dealer firms. The adjusted R^2 of the investor attributes-only regression remains unchanged at 12.2% when we add dealer fixed effects instead of advisor fixed effects.

Figure 3 plots the distributions of the advisor fixed effects from Table 2's regressions. These distributions illustrate that the advisor effects are economically important sources of cross-sectional variation in portfolio choices. 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 2). It is important to emphasize that the fixed-effect estimates are orthogonal to the investor attributes of column 2; they measure differences in risky share and home bias after accounting for differences in investor attributes such as age, gender, and risk tolerance.

The increases in adjusted R^2 that we observe are not mechanically related to adding a large number of regressors. The formula for adjusted R^2 includes a correction for the degrees of freedom lost when adding new regressors. Adding a new variable increases the adjusted R^2 if its absolute t-value exceeds 1.0. There is, however, some disagreement on whether this adjustment is sufficient (Greene 2011, Chapter 3). We therefore implement a bootstrapping procedure that computes the distribution of the adjusted R^2 under the null hypothesis that advisors do not influence their clients' portfolio choices.

We randomly reassign advisors across clients, resampling advisors without replacement. This resampling scheme ensures that the distribution of clients per advisor in each randomized sample is the same as that in the actual sample. We then estimate the regression model with a fixed effect for each randomized client grouping. We repeat this procedure 1,000 times. The adjusted R^2 in every simulation lies between 12.13% and 12.21%. On average, then, the randomized fixed effects add no explanatory power over investor characteristics, which alone produce an adjusted R^2 of 12.17%. Furthermore, the tight distribution of the simulated adjusted R^2 indicates that the 30.2% adjusted R^2 that we find using real advisor fixed effects is not a spurious result.

3.4 Interpreting advisor fixed effects

How should we interpret our finding that advisor fixed effects explain a substantial amount of the 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 risk-return 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 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 3.5. Before describing that analysis, however, we first observe that the results in Table 2 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, age, financial knowledge, investment horizon, and wealth to be at the top of the list. Nevertheless, these variables jointly explain just 12% of the variation in risky shares and 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.

Further tests in the Internet Appendix show that the common variation in client portfolios is not driven, for example, by shared geography. The advisor fixed effects retain their importance when we control for municipality fixed effects instead of province fixed effects. In this case, the adjusted R^2 still rises substantially, from 15% to 32% with the addition of advisor effects.[12] The municipality fixed effects themselves display modest explanatory power, raising the adjusted R^2 of the investor attributes-only regression from 12% to 15%.

Second, when we include advisor fixed effects, moving from the first regression to the second in Table 2, we estimate nearly identical coefficients on the investor attributes. 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 were related to the variables included in the model, then the advisor fixed effects—perfect proxies for the shared link—would kill the statistical significance of an 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 the 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

[12] In this specification, we include fixed effects for the 2,954 Canadian census subdivisions.

emanates from advisor fixed effects is mostly noise when studied from the vantage point of investor attributes.

Third, the last two regressions in Table 2 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.

3.5 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. 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 prepare a sample of such investors 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' 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 clients within six

[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.

months of the move and if he has at least ten clients at the time of the move. After identifying investors 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 2—we study the average risky share and home bias for new investments made with the current advisor. Portfolio-level measures will persist if advisors do not reset new clients' portfolios overnight. An investor, for example, may be locked into some investments through back-end loads on redemptions. Focusing instead on the new investments allows us to measure more cleanly the current advisor's input to the portfolio.

3.5.1 Convergence in risk-taking following a change of advisors

We begin by describing the shift in investors' portfolio allocations following a change of advisor. For each investor i that changes advisors, we measure the risky share for investments made with the old advisor ($\text{RiskyShare}^{\text{pre}}_{i,a_1}$) and the new advisor ($\text{RiskyShare}^{\text{post}}_{i,a_2}$). As a measure of each advisor's stance toward risk-taking, we also measure the risky share of the advisor's other clients (excluding investor i) during the time period before the old advisor stops advising clients ($\text{RiskyShare}^{\text{pre}}_{-i,a_1}$ and $\text{RiskyShare}^{\text{pre}}_{-i,a_2}$). We then run the following cross-sectional regression to gauge advisors' impact on client risk-taking:

$$\text{RiskyShare}^{\text{post}}_{i,a_2} - \text{RiskyShare}^{\text{pre}}_{i,a_1} = \alpha + \beta(\text{RiskyShare}^{\text{pre}}_{-i,a_2} - \text{RiskyShare}^{\text{pre}}_{-i,a_1}) + \varepsilon_i. \quad (2)$$

We estimate a positive beta coefficient of 0.12 (t-value 7.20), which implies that the investor's portfolio allocation shifts towards the average portfolio held by the new advisor's clients and away from the average portfolio held by the old advisor's clients. This coefficient estimate implies that an investor's risky share increases by 2.8 percentage points when moving from an advisor at the 25th percentile of risk-taking (60.3%) to the 75th percentile of risk-taking (83.6%). We obtain similar estimates when we examine changes in clients' home bias around advisor changes. In a regression analogous to equation (2), the slope estimate is 0.13 with a t-value of 6.04. These results are consistent with the view that advisors exert influence on their clients' portfolios.

In the analysis described above, we limit the sample to clients who are displaced when their old advisors disappear. We classify client i's switch from advisor A to B as voluntary if advisor A continues to advise other clients after client i's departure. The behavior of these clients also converges that of the new advisor's clients. The degree of convergence is slightly larger than for involuntary switches: in the risky-share regression, the beta estimate increases slightly from 0.12 to 0.13 (t-value = 9.10), and in the home-bias regression, the beta estimate increases substantially from 0.13 to 0.21 (t-value = 11.79).[14]

3.5.2 Do investor fixed effects crowd out advisor fixed effects?

To provide further insight into the relative explanatory power of investor and advisor fixed effects, we adapt the regression model used to examine portfolio customization in Section 3.1. We replace the investor attributes with investor fixed effects, and estimate panel regressions of the form:

$$y_{iat} = \boldsymbol{\mu}_i + \boldsymbol{\mu}_a + \boldsymbol{\mu}_t + \varepsilon_{iat}, \tag{3}$$

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.

The first two columns in Table 3 replicate the regressions from Table 2 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 7.7% and 6.1% compared to 12.2% and 4.1%. As in Table 2, the model's explanatory power increases substantially when we include advisor fixed effects, by three-fold for risky share and five-fold for home bias.

[14] Voluntary switches do not appear to be prompted by the poor relative investment performance of the old advisor. For every client who switches advisors, we compare the client's actual return to the return he would have earned had he already been with his future advisor. If a client switches advisors in, say, May 2009, we compare the client's actual pre-May 2009 monthly returns to the value-weighted pre-May 2009 returns earned by the clients of the future advisor. We then aggregate the data to three time series—actual return with the old advisor, hypothetical return with the future advisor, and the difference between the two—by computing averages each month. The average net CAPM alpha is −25 and −24 basis points per month for the actual and hypothetical ("new advisor") portfolio, and the difference between the two is statistically insignificant with a t-value of 0.67. That is, clients who switch advisors would not have earned significantly different returns had they switched advisors sooner. The decision to switch advisors therefore appears to be driven by factors other than performance.

Table 3's rightmost regression replaces observable investor attributes with investor fixed effects.[15] The investor fixed effects add considerable explanatory power. In the risky-share regression, the explanatory power of the model increases from 7.7% to 28.2% as we swap observable investor attributes for investor fixed effects. In the home-bias regression, the R^2 rises from 6.1% to 30.9%. One possible explanation for this pattern is that clients have a style in their self-directed investments that persists through the change in advisors. For example, clients may have subjective views on the optimal mix of domestic and international equity, but that are unrelated to attributes such as age, gender, and risk tolerance.

Even after controlling for investor fixed effects, however, the advisor fixed effects remain strong predictors of risky share and home bias. The estimates in the last column of Table 3 show that advisor effects raise the adjusted R^2 substantially, from 28.2% with investor fixed effects alone to 39.1% with both sets of fixed effects. Furthermore, the F-statistics reported in Table 3 show that both sets of fixed effects are highly statistically significant. 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 and then recover these percentiles from the normal distribution, the advisor and investor fixed effects are significant with "t-values" of 16.0 and 13.5. The home-bias regressions in Panel B yield a similar picture. The adjusted R^2 of the model increases from 30.9% to 41.3% 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 15.1 and 12.7.

3.6 Explaining advisor fixed effects using advisor attributes

We documented in Sections 3.3 and 3.5 the importance of advisors' input in explaining portfolio allocations and in Figure 3 the remarkable dispersion in recommendations across advisors. We now ask why advisors differ so much in their recommendations.

[15] 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 other things, each investor's birth year, and the birth year together with the year fixed effects recovers age. Ameriks and Zeldes (2004) discuss the importance of the problem of (unrestricted) identification of age, time, and cohort effects.

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 tests. This link allows us to observe many advisors' personal portfolios and to test whether the personal portfolio explains the style they exhibit in managing clients' portfolios.

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 advisors' personal risky shares, unlike those of their clients, 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. 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 $= -3.5$). In analogous home-bias regressions women invest 5.8 percentage points (t-value $= 4.1$) more in Canadian equities.

The analysis presented in Table 4 examines the extent to which advisors' characteristics and portfolio choices explain cross-sectional variation in their estimated fixed effects. We estimate the cross-sectional regression:

$$\hat{\mu}_a = \alpha + \boldsymbol{\beta} \boldsymbol{X}_a + \varepsilon_a, \tag{4}$$

in which $\hat{\mu}_a$ is advisor a's estimated fixed effect from the risky share or home bias regressions reported in Table 2, and the vector $\boldsymbol{X}_a$ contains various advisor characteristics. Because we extract the advisor fixed effects from regressions that control for investor age and gender (among other investor attributes), the patterns that arise here do not reflect investor-advisor matching by age or gender; that is, the advisor fixed effects are orthogonal to observable investor attributes. We define age in these regressions as the advisor's average age during the sample period. We have the requisite data—the fixed effect from the risky-share regression and advisor characteristics—for 2,956 advisors.

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 4 indicate that advisors between ages 60 and 74 allocate at least ten percentage points more 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. French-speaking advisors take less risk on clients' behalf—an estimated 3.7 percentage points lower risky share—even after controlling for regional differences through province fixed effects. Number of clients is only weakly related to the advisor effect. The coefficient on log(# of clients) of -0.37 (t-value $= -1.9$) suggests a modest tilt toward less risky portfolios among advisors with more clients.

The second regression in Table 4 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 estimates indicate that more risk-tolerant advisors allocate roughly 3 percentage points more of their clients' assets to equities.

The final regression in Table 4 adds the advisor's own average risky share as a regressor. The positive and highly significant slope estimate of 25.2 (t-value $= 15.5$) indicates that advisors' own risk-taking correlates with their clients' risk-taking even after controlling for investor and advisor attributes. 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 coefficients on advisor age, gender and number of clients increase in magnitude and statistical significance. An advisor's age therefore influences recommendations for reasons other than heterogeneity in advisors' beliefs or preferences about the risk-return tradeoff. The final specification explains 17.4% of the cross-sectional variation in advisors' risky-share fixed effects.

The home-bias regressions of Table 4 yield a similar picture in which advisors' own holdings are strong predictors of clients' holdings. In the first regression, advisor gender correlates with home bias. The "abnormal" share of domestic equity is 2.3 percentage points (t-value $= 2.2$) higher among female advisors. Risk tolerance also correlates with advisor-driven home bias: the estimates in the second regression show that more risk-tolerant advisors allocate 6 to 8 percentage points more to Canadian equity. The remaining covariates—advisors' age, language and number of clients—do not exhibit statistically significant relationships with advisor-driven home bias. The last column shows that advisors' own home bias correlates significantly with the home-bias fixed effect. The slope on this variable is 33.8 (t-value = 22.7) and the full regression explains more than one-fifth of the variation in advisor fixed effects. In contrast to the 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 gender has no reliable association with the home-bias fixed effect.

Our main finding—that advisor's own asset allocation is the strongest predictor of the allocations chosen on clients' behalf—has ambiguous welfare implications. On the one hand, it is reassuring that advisors are willing to hold similar portfolios as they recommend to clients. By doing so, they align themselves with their clients as optimal contracting in principal-agent arrangements often prescribes.[16] On the other hand, an advisor may choose a portfolio that is good for himself but that is unsuitable for his clients' preferences and stage of the lifecycle.

In Figure 5, we show that an advisor's risk-taking strongly influences his clients' risk-taking, even when the clients are stratified by risk tolerance. We plot the average risky share for different combinations of client risk tolerance and the advisor's own risky share. Within each risk-tolerance category, client risk-taking increases markedly with the advisor's risk-taking. The span in risky share is largest for clients of moderate risk tolerance, which constitute the majority (see Table 1). Their average risky share is 78% when they work with an advisor in the top quintile of risk-taking and 61% when they work with an advisor in the bottom quintile. This 17-percentage point increase exceeds the effect of raising the clients' risk tolerance directly, from moderate to high. The advisor's own risk-taking also matters among the least and most risk-tolerant clients. The average equity share for the most risk-averse clients increases by 13 percentage points, or 40% proportionally, when moving from advisors in bottom-quintile to the top-quintile of risk-taking. The average equity share for the least risk-averse clients differs by 10 percentage points, or 13%, between the bottom and top quintiles. While we lack an unequivocal measure of the optimal risky share for each

[16] To our knowledge, dealer firms do not impose any contracting scheme to align clients' and advisors' incentives.

risk-tolerance category, we see clearly that the client's portfolio may deviate substantially from the optimal portfolio, whatever that may be, depending on the advisor's own preferences and beliefs.

4 Analysis of Investment Returns in Advised Accounts

4.1 Client performance gross of fees

We assess advisors' skill in mutual fund selection and market timing by comparing the gross investment returns on their clients' accounts to a variety of passive benchmarks. 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- and back-end sales charges. 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 the 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 the yield on 30-day Canadian Treasury bills and the return on Canadian high-yield corporate bonds over investment grade bonds. The returns on the long-term Treasuries and corporate bonds are computed from Bank of America Merrill Lynch's total return indexes. We use the US dollar-Canadian dollar spot exchange rate, when applicable, to convert US dollar-denominated returns to Canadian dollar denomination.

The first two panels of Table 5 present the performance results for the aggregate advised portfolio. We aggregate returns in two ways, first weighting each advisor by assets under advice ("average advised dollar") and second weighting each advisor equally ("average advisor").

The advised portfolios earn annualized gross alphas that are small and statistically indistinguishable from zero. In the CAPM, the average dollar's alpha is -45 basis points and the average advisor's alpha is -35 basis points. However, because the average client holds 29% in fixed income (Table 1), a failure to control for returns on this segment of the market can bias estimates of client performance. The gross-alpha estimates decline when we add controls for size and value and decline further when we add momentum and fixed-income factors. For the six-factor model, the annualized gross-alpha estimates are -1.44% and -1.34%. These estimates, while negative, are not statistically distinguishable from zero.

As a test of market timing ability we estimate the Henriksson and Merton (1981) model, in which the up- and down-market betas can differ. In this test, reported in Panel B, we find virtually no difference in market exposures—a beta of 0.58 in down markets and 0.54 in up markets. Overall, these results suggest that the average investment advisor is not able (or does not attempt) to profit by timing the market or selecting mutual funds.

4.2 Client performance net of fees

After subtracting the fees paid for advice and mutual fund management, we find substantially negative net alphas. The average advised dollar earns a net alpha of -2.98% in the CAPM and -3.98% in the six-factor model. The fees consist of mutual fund management expense ratios, front- and back-end loads, and administration fees. We also adjust returns for the rebates that clients occasionally receive from advisors (commission rebates) and mutual funds (management fee rebates). Examining fees directly, we find that the average advised dollar pays 2.52% per year, of which 2.32% is mutual fund management expense charges and 0.20% is the sum of the additional fees minus rebates.

The advisors in our sample do not steer client investments into a small set of funds with particularly high fees. While the total cost of 2.52% per year is high relative to the cost of an index fund, it does not stand out relative to the universe of Canadian mutual funds, for which Khorana, Servaes, and Tufano (2009) calculate a value-weighted total cost of 2.41% per year. To further evaluate this point, we run simulations in which we replace clients' actual fund investments with random funds of the same style and load structure. The simulated portfolios earn net alphas that are very similar to the actual portfolios.[17] This finding is perhaps unsurprising, given the broad range of mutual funds held in client accounts. The dealers in our sample, though owned by mutual fund complexes, do not provide captive distribution—only 2.9% of client assets are held in affiliated mutual funds. Instead, advisors direct clients into a broad range of mutual funds. Of the nearly

[17]The average six-factor net alpha over 100 simulations is -4.01%, slightly lower than the actual alpha of -3.98%.

4,000 funds available to Canadian investors during the sample period, more than 90% appear in client accounts.

4.3 Cross-sectional variation in performance, advisor attributes and portfolio customization

Within our sample, we observe substantial differences in net performance across advisors. Table 5 Panel C reports the distribution of net alpha estimates across advisors. The median advisor has a six-factor alpha of -3.39%, while the 10th and 90th percentiles in the distribution of advisors are -6.26% and 1.62%. The distribution of $t(\hat{\alpha})$s reveal scant evidence of outperformance net of fees. Although we might expect to find statistically significant positive alphas just by luck (Fama and French 2010), even the 90th percentile of the $t(\hat{\alpha})$ distribution is just 0.61.

We combine our portfolio customization and performance analyses by examining whether customization and other advisor attributes correlate with performance. One explanation of why advisors ignore client characteristics is that customization can be costly. While tailored portfolios may be of higher quality, untailored portfolios may still be preferable if they are sufficiently less expensive. The analysis reported in Table 6 evaluates this possibility.

The main dependent variable in this analysis is the advisor's six-factor net alpha. In an additional specification, we use the t-value as the dependent variable to downweight those advisors whose alphas are estimated imprecisely (Fama and French 2010). The estimates we report are therefore similar to those obtained from weighted regressions in which the weights are proportional to the inverse of the variance of the estimation error.

The main independent variable is the degree of portfolio customization the advisor provides. We measure customization by computing the proportion of clients' risky shares explained by individual attributes in the first regression of Table 2.[18] For each advisor, we calculate

$$\text{Within-advisor } R_a^2 = 1 - \frac{\text{var}(\text{risky share}_{ia} - \widehat{\text{risky share}}_{ia})}{\text{var}(\text{risky share}_{ia})}, \tag{5}$$

[18] We used the same predicted values for risky share to divide the sample into low- and high-dispersion advisors.

in which $\widehat{\text{risky share}}_{ia}$ is investor i's predicted risky share from the estimates given in Table 2 column (1). We set $R^2_a = 0$ for negative values and for observations with $\text{var}(\text{risky share}_{ia}) = 0$ so that the final variable ranges from 0 to 1.[19]

The estimates reported in Table 6 do not support the view that customized portfolios are more costly. The positive coefficients on the customization measure in column (1) for $\hat{\alpha}$ and column (3) for $t(\hat{\alpha})$ show that advisors who give their clients more tailored portfolios also deliver slightly better net performance. A one-standard deviation increase in customization (0.16) raises annualized alphas by 16 basis points and $t(\hat{\alpha})$s by 0.12. The estimates are still positive, but become statistically insignificant once we control for other advisor and portfolio characteristics, several of which correlate with net performance. We document these patterns below, but are cautious in our interpretation since these estimates may not measure causal relationships.

Advisors whose clients hold riskier portfolios deliver worse performance.[20] One interpretation of this finding, which is also borne out in the Canadian Securities Administration's (2012) overview of the Canadian mutual fund industry, is that equity mutual funds are systematically more expensive than bond and money market funds. We note that this finding is not simply driven by poor in-sample performance of equities; the alpha estimates adjust for exposure to market risk over the sample period. Both the number of clients and the average size of clients' portfolios show robust correlations with performance. Advisors who advise many clients with small portfolios perform worse than those with few large clients. Advisors who create portfolios with fewer funds also perform better than those who create more complex portfolios. The average number of plans per client is uncorrelated with performance in column (2)'s alpha regression and negatively correlated in column (4)'s t-value regression. Lastly, among advisor characteristics—age, gender and experience—only age correlates with performance. Controlling for industry experience, old advisors deliver significantly lower returns than young advisors.

[19] The right-hand side in equation (5) is negative when there is more variation in unexplained portfolio allocations than in actual portfolio allocations. An extreme case occurs when all clients hold the same portfolio and $\text{var}(\text{risky share}_{ia}) = 0$, although the risky shares predicted by their attributes still vary, so $\text{var}(\widehat{\text{risky share}}_{ia}) > 0$.

[20] In this analysis, we measure clients' risky shares and portfolio sizes at time 0.

5 The Cost of Financial Advice

In the final section of the paper we investigate whether the high cost of advised portfolios emanates from costly financial advice or from costly mutual fund management. To isolate the cost of financial advice per se, we make two additional calculations. First, we decompose the total fees in our sample into the portions paid to the mutual fund, the financial advisor and the dealer firm. Second, we compare the cost of advised portfolios to the cost of a lifecycle fund, an investable alternative for passive investors.

Figure 6 displays the division of client fees among the mutual fund, advisor, and dealer. As noted above in Section 4.2, clients pay an average of 2.52% of assets per year. Although mutual funds *collect* the vast majority of these fees through fund expense and deferred sales charges, they *retain* only a slight majority of the fees (54%) after paying commissions to the advisor and dealer firm. Mutual funds receive 1.35% per year, composed of 1.16% from management expense charges on client investments (net of commissions paid to advisors) and 0.19% from deferred sales charges on client redemptions.[21] Of the 1.35% per year that they collect, mutual funds designate 0.89% as a management fee and 0.23% respectively as pass-through charges for operating expenses and taxes. The dealer and financial advisor receive the remaining 46% of fees, or 1.17% of assets per year. They earn 0.56% per year from sales commissions paid at the time of clients' mutual fund purchases and 0.61% per year from trailing commissions paid as long as clients remain invested. The dealer retains roughly one-fifth of those fees, or 0.26% of assets per year, and the average advisor keeps the remaining 0.91% of assets per year. The average advisor's implied annual pay of $46.4 thousand (0.91% of $5.1 million, the average of assets under advice) is at the 70th percentile of the Canadian income distribution. The picture that emerges, then, is that mutual funds and advice contribute almost equally to the cost of advised portfolios, and that the typical advisor does not earn an extraordinarily high income.

In addition to examining the division of fees, it is useful to compare the cost of advised portfolios to the cost of a lifecycle fund. Although cheaper index funds are available to investors, a lifecycle fund provides a diversified portfolio that automatically rebalance and requires no active trading by the client, similar to an advised portfolio. A lifecycle fund, nevertheless, may not match the

[21] Investors pay back-end loads, or deferred sales charges, when they sell back-end load funds "too early" (typically within five to seven year of purchase.

investment portfolio that a client would hold in the absence of advice, so it provides a benchmark of what an investor *could* earn without advice rather than what an investor *would* earn without advice. The average management expense ratio on Fidelity Clearpath funds—the largest Canadian 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 $2.52\% - 1.02\% = 1.5\%$ per year if we assume zero gross alpha on advised investments in the future, or $3.98\% - 1.02\% = 2.96\%$ per year if we assume the same gross alpha in the future as in the past.[22]

Over the course of the lifecycle, this steady stream of fees compounds quite dramatically. To illustrate how much investors pay for financial advice, suppose that an investor sets aside a fixed amount every year, and will retire in 30 years. If the expected return on the portfolio—consisting of both equity and fixed income instruments—is 8%, an annual fee of 1.5% decreases the present value of the investor's savings by 14%. An annual net alpha of -2.96% decreases the present value of savings by more than a quarter.[23]

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 do relatively little to tailor their advice on risk-taking to clients' characteristics. In total, a broad set of investor characteristics including risk tolerance, age and investment horizon explain only 12% of the variation in risky

[22] 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 5 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 5. 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 net return comparison.

[23] French (2008) makes a similar computation to evaluate how much active investors spend, as a fraction of the total market capitalization of U.S. equities, to beat the market. The computation here is the following. The present value of the investment described is an annuity with a present value of $\text{PV} = \left(\frac{C}{r}\right)\left(1 - \frac{1}{(1+r)^T}\right)$, where C is the annual dollar savings, r is the rate of return on the investment, and T is the investment horizon. The ratio of present values under the rates of return of r_1 and r_2 is then $\frac{\text{PV}_1}{\text{PV}_2} = \left(\frac{r_2}{r_1}\right)\left(1 - \frac{1}{(1+r_1)^T}\right)\Big/\left(1 - \frac{1}{(1+r_2)^T}\right)$. Plugging in the rates of $r_1 = 8\%$ and $r_2 = 6.5\%$ gives $\frac{\text{PV}_1}{\text{PV}_2} = 0.86$. A rate of $r_2 = 5.04\%$ gives $\frac{\text{PV}_1}{\text{PV}_2} = 0.74$.

share across clients. Second, advisor fixed effects explain an additional 18% of the variation in risky share and predict remarkably large differences in risk-taking. A movement from the 25th to the 75th percentile equates to a 20-percentage point increase in risky share. Third, the amount of risk an advisor takes in his own portfolio is the strongest predictor of the risk taken by his 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 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 2.5% of assets per year for advice—or 1.5% in excess of lifecycle funds.

The findings described above are not unique to the three dealers in our main sample. In further results reported in the Internet Appendix, we add data from another large dealer. This four-dealer sample covers nearly 11% of the Canadian mutual fund dealer sector. We confirm our findings on customization and investment performance within this extended sample.

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 2015) or eliciting feelings of trust (Guiso, Sapienza, and Zingales 2008) rather than improving investment performance. Evaluating these benefits is an important topic for future work.

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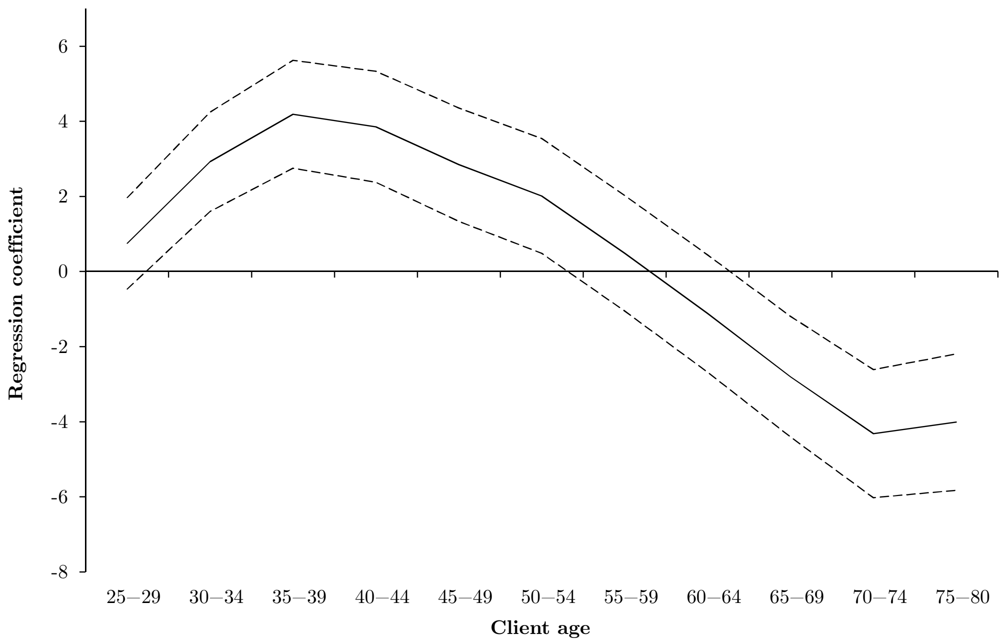
Panel A: Age coefficients from regressions of risky share on investor attributes



Panel B: Average risky share by age and risk tolerance

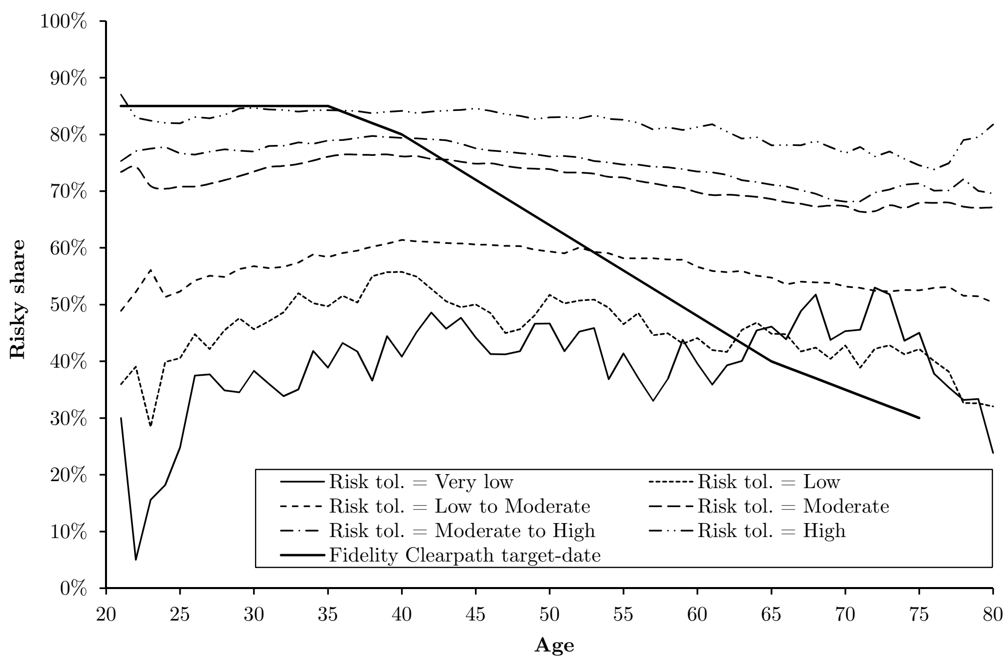


Figure 1: **Advised investors' risky share as a function of age and risk tolerance.** Panel A plots estimated regression coefficients and 95% confidence intervals from regressions of risky share on age-group fixed effects and other investor attributes (Table 2 Panel A). Panel B plots average risky shares for the six risk-tolerance categories as a function of age. The solid line plots the risky share of Fidelity Clearpath target-date funds.

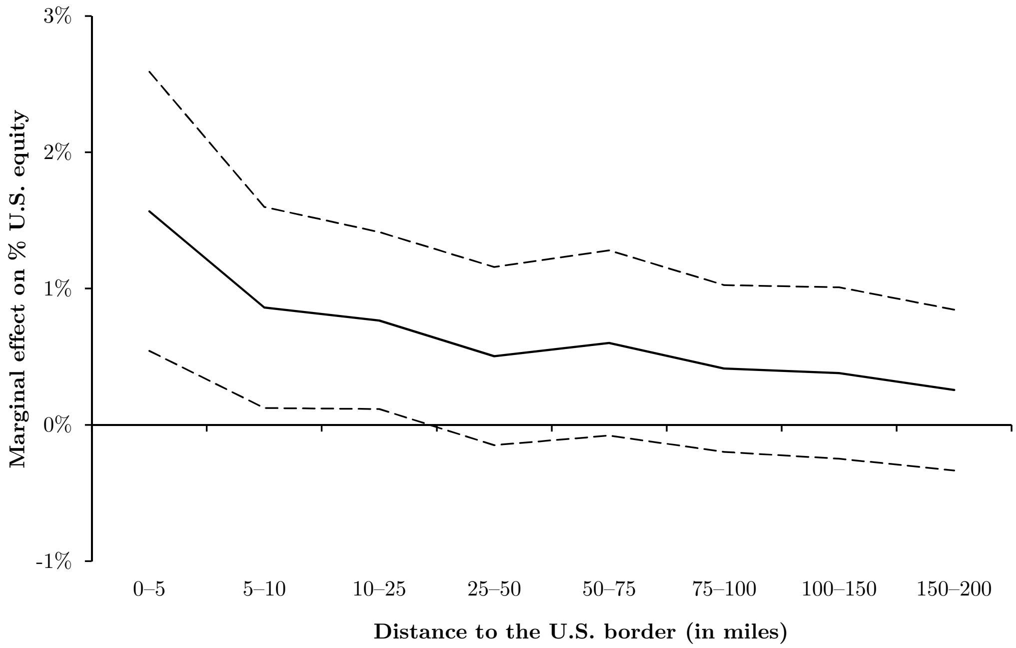


Figure 2: **Allocation to U.S. equities as a function of distance to the U.S. border.** We estimate a panel regression that explains variation in the allocation to U.S. equities (as % of total equities) with investor attributes and year fixed effects. In addition to the investor attributes reported in Table 2, we also include eight indicator variables for the distance to the U.S. border. We omit the greater-than-200 miles category. This figure plots the point estimates and 95% confidence intervals for the distance indicator variables.

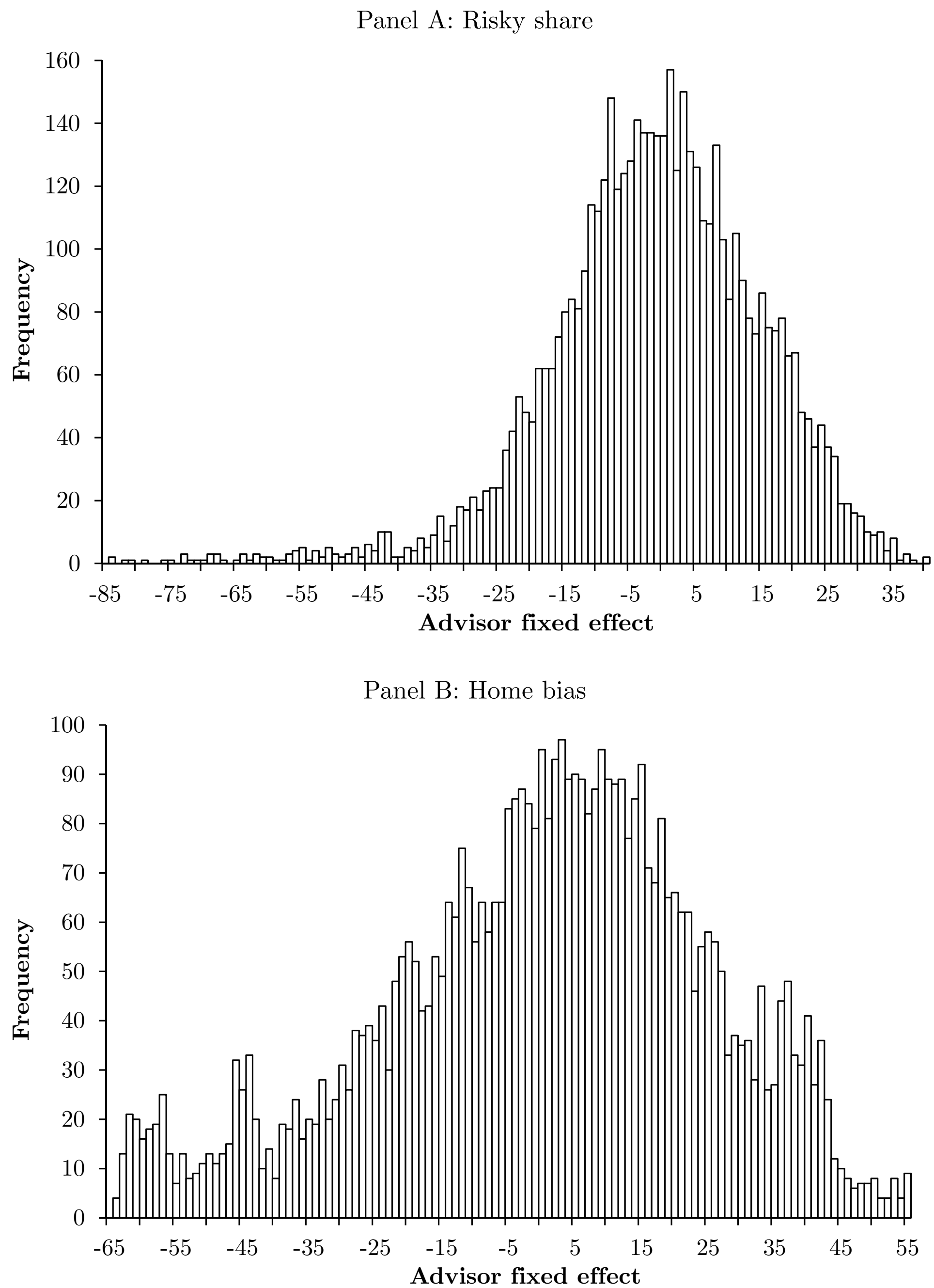


Figure 3: **Distributions of advisor fixed effects in risky-share and home-bias regressions.** This figure plots the distributions of advisor fixed effects from the risky-share and home-bias regressions of Table 2. In addition to the advisor fixed effects, the regressions include investor attributes and year fixed effects.

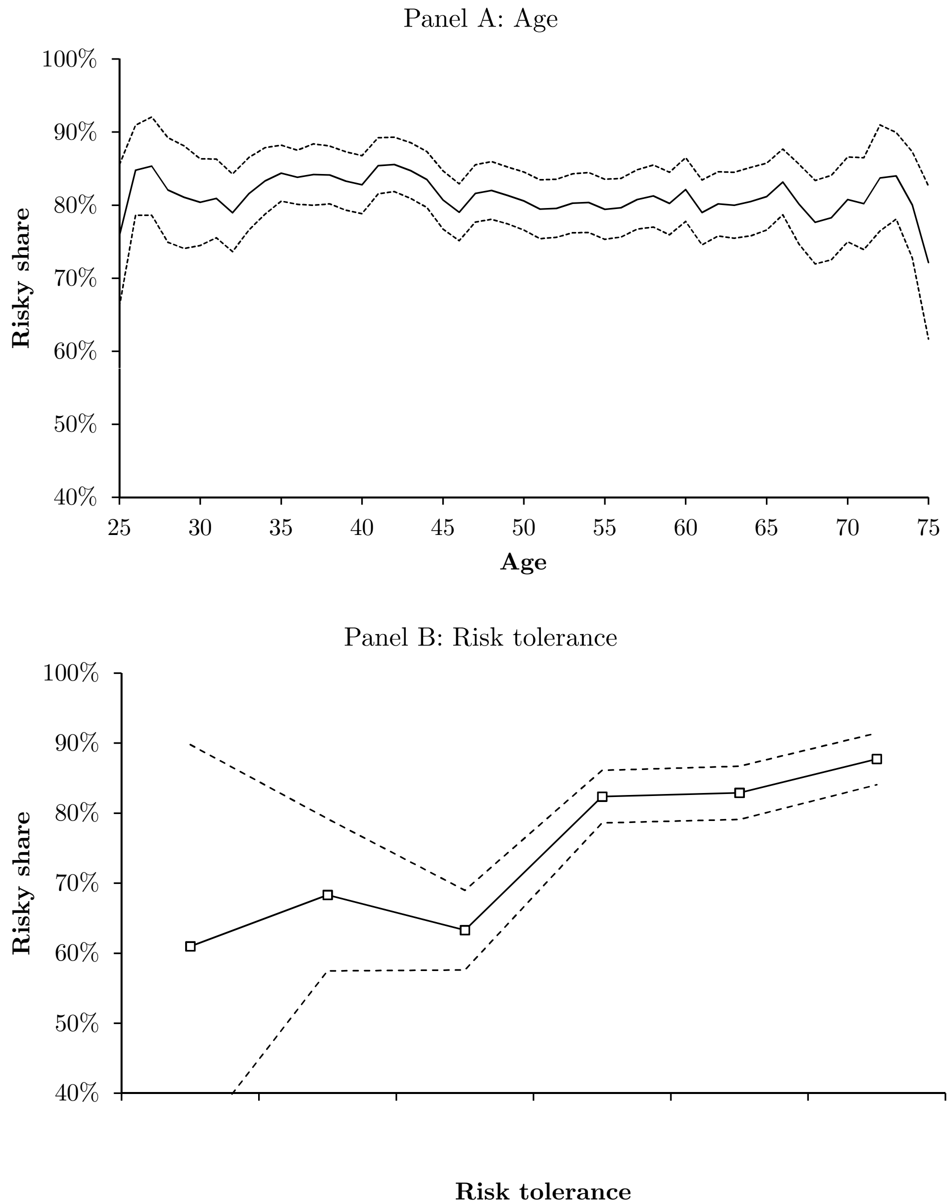


Figure 4: **Advisor risky share as a function of age and risk tolerance.** This figure plots the average risky share and 95% confidence interval for advisors' own portfolios as a function of advisor age (Panel A) and risk tolerance (Panel B). We compute these estimates from regressions of risky share against age- and risk tolerance-indicator variables and year fixed effects.

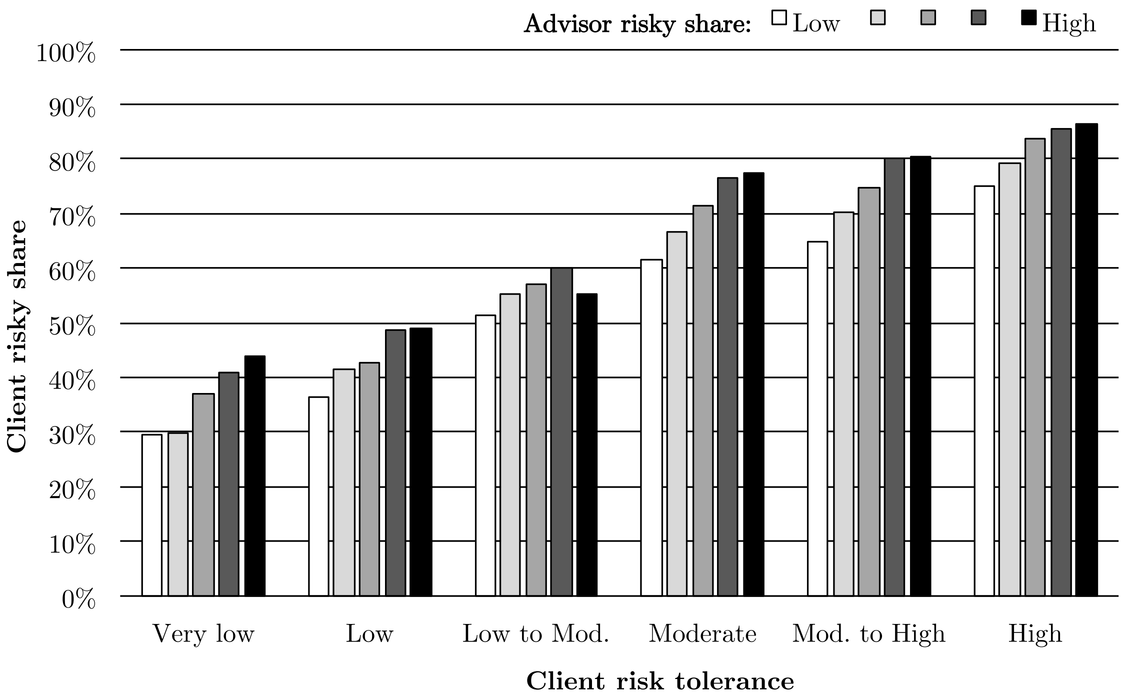
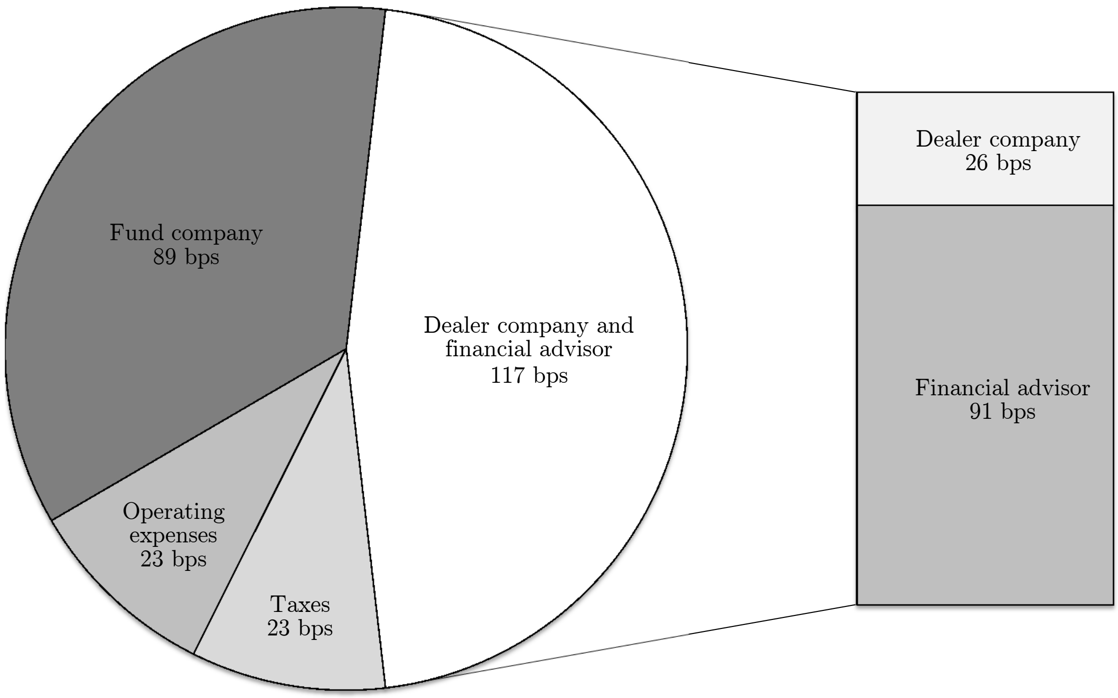


Figure 5: **Client risky share as a function of client risk tolerance and advisor risky share.** This figure sorts clients into six categories by risk tolerance and their advisors into quintiles based on the advisors' personal risky shares. We report the average client risky share for each client risk tolerance-advisor risky share combination. The leftmost group of bars contains the very low-risk tolerance clients; the rightmost group contains the high-risk tolerance clients. Within each group, the individual bars are shaded to indicate the advisors' personal risky shares, ranging from the lowest quintile on the left to the highest quintile on the right.



Total annual fee = 252 basis points

Figure 6: **Division of fees among mutual fund, dealer and financial advisor.** Using the dealer data, we measure total fees paid by the investor, comprised of mutual fund management expense charges, front-end loads and deferred-sales charges ("back-end loads"). We further divide these fees into payments to the dealer, which consist of front-end loads paid by clients and sales and trailing commissions paid by mutual funds, and payments to the mutual fund, which consist of management expense and deferred-sales charges net of dealer commissions. We use the dealer data to divide the dealer's compensation—front-end loads and sales commissions—between the dealer and the financial advisor. We use estimates from Canadian Securities Administrators (2012) to divide the mutual funds net fees into management fees to the fund company, taxes and operating expenses.

Table 1: Descriptive statistics from dealer data

This table reports summary statistics for investors (Panel A) and financial advisors (Panel B). "Account age (years)" is the number of years an investor has been with any advisor. All variables are measured as of June 2012.

Panel A: Investors (N = 581,044)

		Percentiles					
Variable	Mean	10th	25th	50th	75th	90th	SD
Female (%)	51.4						
Age	51.2	33	41	51	61	69	13.6
Account age (years)	3.6	1	1	3	6	7	2.6
Number of plans	1.9	1	1	1	2	4	1.9
Number of funds	5.2	1	2	3	7	12	5.7
Account value, $K	68.1	2.15	8.15	27.33	75.56	161.16	576.4
Portfolio allocations							
Equity (% of total assets)	70.9	44.4	50.0	73.6	97.0	100.0	25.8
Canadian equity (% of equity)	55.1	0.0	23.7	60.1	89.1	100.0	36.2
U.S. equity (% of equity)	2.5	0.0	0.0	0.0	0.0	5.8	9.9
Global equity (% of equity)	42.4	0.0	7.3	36.2	71.5	100.0	36.0
Occupation							
Finance professional	1.1%						
Self-employed	4.3%						
Government	8.0%						

Panel A: Investors (cont'd)

Plan types	
General	24.1%
Retirement savings or income	66.0%
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 (%)	25.7						
Age	51.3	36	44	52	59	65	10.7
Tenure	4.4	1	2	4	6	8	2.7
Number of clients	74.3	1	3	24	100	217	122.9
Number of plans/client	1.7	1	1.1	1.6	2.0	2.5	0.9
Number of funds/client	4.2	1	2.0	3.7	5.6	7.5	2.8
Client assets, \$ thousands	5064.0	5.2	55.4	916.9	5,493.6	14,575.3	16420.0

Table 2: 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, advisor fixed effects and year fixed effects. Risky share is the fraction of wealth in equity and home bias is the fraction of equity in Canadian funds. We measure risky share and home bias at year-ends 1999 through 2011. We omit the indicator variables for the lowest categories. 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. Rows "Adjusted R^2, w/o advisor FEs" and "Adjusted R^2, only advisor FEs" report the adjusted R^2 from alternative models that either exclude the advisor fixed effects or include only the advisor FEs. The adjusted R^2 that we report measures incremental explanatory power over a model with year fixed effects. Figure 1 Panel A reports the age-coefficient estimates from column (1)'s regression. Standard errors are clustered by advisor.

Panel A: Dependent variable = Risky share

Independent variable	(1) All advisors $\hat{b}$	(1) t	(2) All advisors $\hat{b}$	(2) t	(3) Low-dispersion advisors $\hat{b}$	(3) t	(4) High-dispersion advisors $\hat{b}$	(4) t
Constant	37.12	10.32	35.73	13.46	39.77	6.48	33.06	10.98
Risk tolerance								
Low	6.78	2.65	6.58	3.06	−4.51	−0.76	7.05	3.17
Low to Moderate	17.44	6.59	17.38	8.15	15.26	2.91	17.41	7.90
Moderate	30.52	11.45	28.90	13.16	27.36	5.23	28.90	12.69
Moderate to High	32.94	12.09	31.88	14.48	30.80	5.91	31.39	13.76
High	38.29	14.03	37.25	16.46	35.30	6.81	37.57	15.61
Fin. knowledge								
Moderate	2.87	7.58	1.46	10.16	1.23	5.73	1.61	9.07
High	3.99	7.09	2.76	9.68	1.94	5.45	3.30	8.54
Time horizon								
Short	3.98	4.90	3.81	5.75	3.58	3.26	3.75	4.75
Moderate	6.16	8.28	5.20	8.37	4.88	4.67	5.20	7.10
Long	6.57	8.07	5.62	8.91	4.84	4.52	6.03	8.10
Female	−1.37	−9.56	−1.34	−13.46	−1.28	−9.44	−1.40	−10.62
French speaking	−2.96	−2.37	−0.97	−2.01	−0.12	−0.14	−1.30	−2.33
Salary								
$30–50k	0.42	2.39	0.69	5.58	0.75	4.49	0.65	3.88
$50–70k	0.25	1.14	0.92	6.19	0.81	4.38	0.99	4.75
$70–100k	−0.10	−0.35	0.94	5.87	0.82	3.99	1.02	4.62
$100–200k	−3.09	−1.82	−0.86	−1.06	0.71	0.62	−2.21	−2.03
Over $200k	−3.67	−2.02	−0.70	−0.72	−0.89	−0.59	−0.36	−0.33
Net worth								
$35–60k	1.13	1.97	1.05	2.51	1.11	1.90	1.01	1.88
$60–100k	1.77	2.97	1.52	3.63	1.63	2.85	1.42	2.59
$100–200k	2.16	3.96	1.79	4.61	1.77	3.37	1.78	3.52
Over $200k	1.29	2.10	1.23	3.04	1.09	1.98	1.35	2.53
Occupation								
Finance professional	2.29	2.88	1.65	2.32	0.22	0.26	3.05	2.95
Self-employed	0.54	1.47	0.61	2.07	0.13	0.36	1.05	2.43
Government	0.97	2.95	0.85	3.84	1.05	3.43	0.72	2.48
Advisor FEs	**No**		**Yes**		**Yes**		**Yes**	
Age groups	Yes (Fig. 1)		Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes		Yes	
Province FEs	Yes		Yes		Yes		Yes	
# of observations	758,058		758,058		327,235		427,242	
# of investors	174,609		174,609		92,314		111,520	
# of advisors	5,083		5,083		2,829		2,546	
Adjusted R^2	12.2%		30.2%		28.3%		29.6%	
w/o advisor FEs	.		12.2%		7.3%		13.5%	
only advisor FEs	.		22.4%		24.1%		19.1%	

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	64.86	18.38	59.57	22.60	57.05	11.04	59.56	18.89
Risk tolerance								
Low	0.34	0.19	−0.72	−0.43	2.98	0.65	−0.81	−0.47
Low to Moderate	−2.01	−1.12	−1.09	−0.70	0.42	0.11	−1.13	−0.70
Moderate	−0.55	−0.34	−0.80	−0.54	0.01	0.00	−0.68	−0.44
Moderate to High	−4.82	−2.81	−4.72	−3.17	−3.67	−1.02	−4.69	−3.03
High	−17.67	−9.30	−15.44	−9.68	−13.69	−3.78	−15.87	−8.97
Fin. knowledge								
Moderate	1.11	1.96	−0.78	−3.65	−0.74	−2.44	−0.81	−2.99
High	0.97	1.11	−1.70	−3.76	−2.06	−3.21	−1.46	−2.51
Time horizon								
Short	0.11	0.09	0.57	0.64	2.21	1.36	0.10	0.10
Moderate	0.61	0.53	1.42	1.67	2.82	1.79	1.06	1.10
Long	−0.03	−0.02	1.84	2.12	3.55	2.25	1.19	1.20
Female	0.65	2.60	0.34	2.12	0.14	0.59	0.51	2.44
French speaking	2.40	1.40	1.52	2.03	1.68	1.34	1.47	1.65
Salary								
\$30–50k	−0.32	−1.21	−0.26	−1.36	−0.16	−0.59	−0.33	−1.31
\$50–70k	−1.32	−3.92	−1.29	−5.70	−1.08	−3.21	−1.44	−5.03
\$70–100k	−2.86	−6.16	−1.97	−7.72	−1.82	−5.19	−2.09	−6.17
\$100–200k	−2.70	−1.19	−2.22	−1.71	−2.22	−1.12	−2.07	−1.24
Over \$200k	0.64	0.29	−1.86	−1.47	−0.67	−0.39	−2.67	−1.64
Net worth								
\$35–60k	0.88	1.07	0.88	1.38	0.71	0.73	0.87	1.11
\$60–100k	0.32	0.40	−0.15	−0.25	−0.58	−0.64	0.05	0.06
\$100–200k	−0.01	−0.02	−0.01	−0.01	−0.24	−0.27	0.07	0.10
Over \$200k	−0.06	−0.08	−0.13	−0.22	−0.35	−0.39	−0.09	−0.13
Occupation								
Finance professional	−1.33	−0.94	−0.84	−0.71	−0.54	−0.37	−1.23	−0.76
Self-employed	−0.98	−1.69	−0.42	−0.94	−0.17	−0.30	−0.79	−1.25
Government	1.44	2.72	0.78	2.43	0.60	1.32	0.86	2.05
Advisor FEs	**No**		**Yes**		**Yes**		**Yes**	
Age groups	Yes		Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes		Yes	
Province FEs	Yes		Yes		Yes		Yes	
# of observations	739,687		739,687		321,707		414,531	
# of investors	171,145		171,145		90,993		108,664	
# of advisors	5,055		5,055		2,826		2,542	
Adjusted R^2	4.1%		27.9%		29.3%		27.1%	
w/o advisor FEs	.		4.1%		4.9%		4.1%	
only advisor FEs	.		26.3%		28.0%		25.4%	

Table 3: 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, advisor fixed effects, investor fixed effects and year fixed effects. The unit of observation is a client-advisor pair. We measure the average risky share and home bias of new investments made with the current advisor. We restrict the sample to investors who switch advisors during the sample period due to the disappearance of their former advisor. The first two regressions repeat Table 2'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 8,032 client-advisor pairs from 3,939 clients and 1,018 advisors and the distributions of the F-statistics for the advisor and investor fixed effects are $F(3938, 3419)$- and $F(661, 3419)$-distributed under the null; Panel B uses data on 7,485 client-advisor pairs from 3,668 clients and 980 advisors and the distributions of the F-statistics for the advisor and investor fixed effects are $F(3667, 3174)$- and $F(630, 3174)$-distributed under the null. 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: Dependent variable = Risky share

Independent variable	(1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Constant	44.93	4.29	45.29	5.02		
Risk tolerance						
Low	5.54	0.70	4.53	0.74		
Low to Moderate	13.97	1.77	13.95	2.42		
Moderate	23.39	2.98	21.82	3.83		
Moderate to High	24.55	3.09	23.46	4.10		
High	30.69	3.85	28.48	4.95		
Financial knowledge						
Moderate	1.42	1.65	0.65	0.91		
High	4.23	3.13	2.46	2.05		
Time horizon						
Short	−0.57	−0.16	−1.68	−0.56		
Moderate	0.11	0.03	−1.53	−0.56		
Long	1.54	0.43	−0.70	−0.25		
Female	−1.89	−3.34	−1.93	−3.38		
French speaking	−5.94	−2.57	−4.46	−1.84		
Salary						
$30-50k	0.79	1.00	1.40	2.01		
$50-70k	0.99	1.05	1.51	1.85		
$70-100k	−0.17	−0.16	0.30	0.32		
$100-200k	4.70	0.92	2.87	0.45		
Over $200k	8.74	1.78	8.01	0.98		
Net worth						
$35-60k	2.67	0.97	2.80	1.12		
$60-100k	1.73	0.65	0.30	0.13		
$100-200k	2.83	1.04	1.66	0.72		
Over $200k	2.24	0.88	1.06	0.47		
Occupation						
Finance professional	1.25	0.34	2.32	0.56		
Self-employed	−0.34	−0.17	1.68	0.99		
Government	2.05	1.52	1.00	0.80		
Advisor FEs (F-test)	**No**		**Yes** (2.94)		**Yes** (2.11)	
Investor FEs (F-test)	**No**		**No**		**Yes** (1.71)	
Age FEs	Yes		Yes		No	
Year FEs	Yes		Yes		Yes	
Province FEs	Yes		Yes		No	
Adjusted R^2	7.7%		26.0%		39.1%	
w/o advisor FEs	.		7.7%		28.2%	
w/o investor attributes	.		22.8%		.	

Panel B: Dependent variable = Home bias

Independent variable	(1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Constant	67.36	3.73	57.28	3.71		
Risk tolerance						
Low	−2.15	−0.13	−15.44	−1.24		
Low to Moderate	10.45	0.63	−5.72	−0.48		
Moderate	8.93	0.54	−7.75	−0.66		
Moderate to High	6.98	0.42	−7.61	−0.65		
High	−8.13	−0.49	−17.28	−1.47		
Financial knowledge						
Moderate	0.21	0.18	−1.38	−1.39		
High	2.33	1.10	−0.47	−0.29		
Time horizon						
Short	−3.64	−0.68	2.83	0.67		
Moderate	−1.17	−0.24	3.86	0.99		
Long	0.24	0.05	4.69	1.17		
Female	−0.49	−0.55	0.43	0.54		
French speaking	−0.63	−0.19	−6.67	−1.89		
Salary						
$30-50k	−2.25	−1.93	−2.50	−2.60		
$50-70k	−2.41	−1.80	−3.58	−3.17		
$70-100k	−1.89	−1.43	−0.79	−0.61		
$100-200k	−22.52	−2.81	−7.80	−0.92		
Over $200k	−7.63	−1.06	−1.22	−0.11		
Net worth						
$35-60k	−1.80	−0.41	−2.53	−0.72		
$60-100k	1.03	0.26	1.72	0.52		
$100-200k	1.55	0.39	0.90	0.28		
Over $200k	1.13	0.30	0.41	0.13		
Occupation						
Finance professional	−6.23	−1.02	−9.04	−1.63		
Self-employed	0.24	0.10	4.55	1.90		
Government	−1.42	−0.69	1.07	0.63		
Advisor FEs (F-test)	**No**		**Yes** (3.82)		**Yes** (2.07)	
Investor FEs (F-test)	**No**		**No**		**Yes** (1.69)	
Age FEs	Yes		Yes		No	
Year FEs	Yes		Yes		Yes	
Province FEs	Yes		Yes		No	
Adjusted R^2	6.1%		31.5%		41.3%	
w/o advisor FEs	.		6.1%		30.9%	
w/o investor attributes	.		30.6%		.	

Table 4: Regressions of advisor fixed effects on advisor attributes

This table reports estimates from regressions of advisor fixed effects on advisor attributes: age, gender, language, risk tolerance, the average number of clients and the risky share and home bias in the advisor's own portfolio. The fixed-effect estimates are from the second regression in Table 2.

Panel A: Dependent variable = Risky-share fixed effect

Independent variable	Regression (1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Age, 25–29	6.98	1.52	7.23	1.55	6.69	1.59
30–34	3.76	0.84	4.70	1.04	6.09	1.51
35–39	5.63	1.28	6.07	1.37	6.72	1.70
40–44	7.63	1.75	7.28	1.66	8.02	2.05
45–49	7.74	1.78	8.00	1.82	9.31	2.37
50–54	8.58	1.98	8.72	1.99	10.09	2.58
55–59	8.08	1.84	8.26	1.87	9.39	2.39
60–64	11.30	2.57	11.71	2.65	12.83	3.25
65–69	11.33	2.51	11.98	2.61	13.34	3.24
70–74	18.93	4.11	18.38	3.95	19.17	4.49
75–79	6.14	0.58	13.52	2.25	15.18	2.86
Female	0.79	1.20	1.04	1.58	1.24	2.01
French speaking	−3.71	−2.33	−4.26	−2.91	−4.52	−2.99
log(# of clients)	−0.37	−1.90	−0.37	−1.80	−0.40	−2.05
Risk tolerance						
Moderate			3.32	2.03	−1.37	−0.84
Moderate to High			1.80	1.10	−3.28	−2.03
High			2.90	1.79	−3.38	−2.09
Advisor's risky share					25.17	15.51
Advisor province FEs	Yes		Yes		Yes	
# of observations	2,956		2,631		2,631	
Adjusted R^2	5.1%		5.6%		17.4%	

Panel B: Dependent variable = Home-bias fixed effect

Independent variable	Regression (1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Age, 25–29	−4.43	−0.56	−2.40	−0.31	−1.77	−0.27
30–34	−17.96	−2.37	−16.95	−2.28	−15.02	−2.43
35–39	−11.54	−1.54	−10.57	−1.44	−7.33	−1.21
40–44	−11.90	−1.60	−11.96	−1.65	−7.95	−1.32
45–49	−13.81	−1.86	−14.34	−1.98	−9.98	−1.66
50–54	−14.06	−1.90	−14.18	−1.96	−9.16	−1.53
55–59	−7.97	−1.07	−7.59	−1.05	−4.88	−0.81
60–64	−8.15	−1.09	−6.69	−0.92	−4.50	−0.75
65–69	−9.40	−1.23	−9.82	−1.32	−7.77	−1.26
70–74	−9.03	−1.11	−6.79	−0.86	−4.69	−0.70
75–79	−2.35	−0.28	−2.24	−0.27	−3.11	−0.45
Female	2.27	2.16	2.54	2.33	1.10	1.12
French speaking	−0.48	−0.20	−0.19	−0.07	−1.17	−0.54
log(# of clients)	0.38	1.19	0.20	0.60	0.39	1.28
Risk tolerance						
Moderate			6.77	2.49	5.25	2.05
Moderate to High			8.41	3.13	7.90	3.11
High			6.06	2.28	9.12	3.62
Advisor's home bias					33.83	22.67
Advisor province FEs	Yes		Yes		Yes	
# of observations	2,947		2,626		2,599	
Adjusted R^2	2.7%		4.0%		22.5%	

Table 5: Estimates of advisors' gross and net alphas and market-timing abilities

Panel A 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 column "avg. dollar" represents the performance of the average advised dollar, weighting each advisor by assets under advice; "avg. advisor" represents the performance of the average advisor, weighting each advisor equally. Adjusted R^2s are from the average-dollar regressions. Panel B reports slope estimates from the Henriksson and Merton (1981) model in which the down- and up-market betas can differ: $r_i - r_f = \alpha_i + \beta_{i,\text{mkt}}(r_{\text{mkt}} - r_f) + \beta^{\text{up}}_{i,\text{mkt}} \max(r_{\text{mkt}} - r_f, 0) + \varepsilon_i$. We estimate this model and the CAPM using gross returns earned by the average dollar and report the beta estimates and their standard errors (in square brackets). Panel C reports distributions of $\hat{\alpha}$s and $t(\hat{\alpha})$s from 5,825 advisor-level regressions that explain net returns using the six-factor model. Alpha estimates are annualized and reported in percentages.

Panel A: Gross and net alpha estimates

		Gross returns		Net returns		
Model	Factors	Avg. dollar	Avg. advisor	Avg. dollar	Avg. advisor	R^2
CAPM	Mkt-Rf	−0.45	−0.35	−2.98	−2.93	83.3%
		(−0.43)	(−0.35)	(−2.86)	(−2.91)	
Fama-French	Mkt-Rf, SMB, HML	−0.92	−0.78	−3.45	−3.36	83.8%
		(−0.88)	(−0.78)	(−3.32)	(−3.35)	
Extended	Mkt-Rf, SMB, HML,	−1.44	−1.34	−3.98	−3.92	86.1%
Fama-French	MOM, DEF, TERM	(−1.45)	(−1.39)	(−4.00)	(−4.06)	

Panel B: Market-timing estimates

	Parameter		
Model	$\hat{\beta}_{\text{mkt}}$	$\hat{\beta}^{\text{up}}_{\text{mkt}}$	R^2
CAPM	0.558		83.3%
	[0.020]		
Henriksson-Merton	0.578	−0.043	83.2%
	[0.035]	[0.064]	

Panel C: Distributions of advisor-level $\hat{\alpha}$s and $t(\hat{\alpha})$s

	Percentiles				
Estimate	10th	25th	50th	75th	90th
$\hat{\alpha}$	−6.26	−4.65	−3.39	−1.60	1.62
$t(\hat{\alpha})$	−3.70	−2.98	−1.99	−0.63	0.61

Table 6: Customization, advisor attributes, and cross-sectional variation in performance

We estimate cross-sectional regressions of advisor-level annualized alpha ($\hat{\alpha}$) and $t(\hat{\alpha})$ against variables measuring portfolio and advisor attributes. The key independent variable is a measure of customization; within-advisor $R_a^2 = 1 - \frac{\text{var}(\text{risky share}_{ia} - \widehat{\text{risky share}}_{ia})}{\text{var}(\text{risky share}_{ia})}$, in which $\widehat{\text{risky share}}_{ia}$ is investor i's predicted risky share from the estimates given in Table 2 column (1). Advisor experience is measured from the date the advisor receives his license or, if missing, the date the advisor joins the dealer. We measure risky share and average client assets at time 0. For the other independent variables, we compute the time-series averages of these variables. We report heteroskedasticity-consistent t-values in parentheses.

Independent variable	Dependent variable: $\hat{\alpha}$ (1)	$\hat{\alpha}$ (2)	$t(\hat{\alpha})$ (3)	$t(\hat{\alpha})$ (4)
Portfolio information				
Customization	1.03	0.71	0.78	0.30
	(2.21)	(1.56)	(3.67)	(1.45)
Risky share at $t = 0$		−1.47		−0.46
		(−4.17)		(−2.72)
log(# of clients)		−0.17		−0.35
		(−3.51)		(−12.71)
log(Avg. AUM per client at $t = 0$)		0.29		0.21
		(2.88)		(3.23)
log(# of funds per client)		−0.35		−0.27
		(−2.31)		(−3.36)
log(# of plans per client)		0.26		−0.30
		(0.97)		(−2.38)
Advisor information				
log(Age)		−0.76		−0.81
		(−2.40)		(−5.99)
Female		−0.07		−0.04
		(−0.44)		(−0.48)
log(Experience)		−0.13		−0.05
		(−1.19)		(−0.95)
N	2,901	2,901	2,901	2,901
Adjusted R^2	0.2%	2.0%	0.4%	9.9%