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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, stage in the lifecycle and financial sophistication. Advisor effects retain their importance 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 2.6% per year, or 1.6% 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 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.

In contrast, we find that advisor fixed effects have substantial explanatory power. Advisor fixed effects more than double the model's adjusted R^2 from 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 variation in the share of risky assets invested in Canadian equity funds whereas advisor fixed effects explain nearly 28%. 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 all of their clients. Another interpretation is that matching between investors and advisors leads to common variation in portfolio allocations among investors of the same advisor; that is, advisor fixed effects stand in for omitted client characteristics that are common across investors of the same advisor.

We find little support for the latter hypothesis. Our data include investor identifiers that allow us to track 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 controlling flexibly for any unobserved persistent differences across investors and the former capturing the advisor-specific "style" in portfolio allocation. While investor fixed effects add explanatory power beyond observable investor characteristics, advisor fixed effects continue to be pivotal in explaining risky share and home bias. As a result, the joint set of advisor effects display similar statistical significance as the investor effects, and the model's adjusted R^2 increases substantially—from 29% to 47%—when advisor effects accompany investor effects.

If advisors do not base their advice on investor characteristics, then what explains variation in recommendations across advisors? We find that advisors may project their own preferences and beliefs onto their clients. A unique feature of our data is that we observe the portfolio allocations for advisors who maintain investment portfolios at their own firm (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 even after controlling for advisor and client characteristics. The picture that emerges here is that no matter what a client looks like, the advisor views the client as sharing his preferences and beliefs.

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 2.6% 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 1.6 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 18%. 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 the customization of portfolios. Second, we find that advisors are nevertheless a major determinant of individual asset allocation. Understanding the intermediation process is therefore crucial for theories seeking to explain household portfolios. Third, we show that advisors' own risk-taking influences how much risk their clients assume. Although it is reassuring that advisors are willing to hold the portfolio that they recommend, the portfolio that is suitable for the advisor may deviate substantially from what is best for the investor.

The rest of the paper proceeds as follows. Section 2 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] 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.

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 mulitiple 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 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

[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.

[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 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.

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 markedly within the sample. The median advisor has 24 clients, while advisors in the bottom decile have just one client and those in the top decile have over 200 clients. The median advisor has \$916,880 in assets under advice, and advisors in the bottom and top deciles manage under \$5,200 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 cross-sectional variation in investors' portfolios with investor attributes and advisor fixed effects. From the underlying account records we create panel data with one observation per year (as of year-end) for each investor. We estimate regressions of the form:

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

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

[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.

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 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

[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.

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 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 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.

[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.

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 (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.

[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.

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 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 similar coefficients on the investor attributes. The marginal effects are nearly identical. When we add advisor fixed effects we also estimate the coefficients on investor attributes with more precision. The increase in precision implies little collinearity between investor attributes and advisor fixed effects. If investors and advisors are matched by shared attributes that determine portfolio allocations, these attributes must be largely unrelated to age, gender, risk tolerance, and financial knowledge. If the matching 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 risky share only on advisor fixed effects. Column 2's estimates show that if we now collect the residuals from such a first-stage regression and run them against investor attributes, many attributes are statistically more significant in the residual data relative to the raw data. That is, the variation in risky shares that emanates from advisor fixed effects is mostly noise when studied from the vantage point of investor attributes.

Third, the last two regressions in Table 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

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

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 or her clients within one year 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 cleanly the current advisor's input to the portfolio.

[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.

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 and new advisor, respectively ($\text{RiskyShare}_{i,\text{old}}$ and $\text{RiskyShare}_{i,\text{new}}$). 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 leaves the business ($\text{RiskyShare}_{\text{others,old}}$ and $\text{RiskyShare}_{\text{others,new}}$). We then run the following cross-sectional regression to gauge advisors' impact on client risk-taking:

$$\text{RiskyShare}_{i,\text{new}} - \text{RiskyShare}_{i,\text{old}} = \alpha + \beta(\text{RiskyShare}_{\text{others,new}} - \text{RiskyShare}_{\text{others,old}}) + \varepsilon_i. \quad (2)$$

We estimate a positive beta coefficient of 0.16 (t-value 4.30), 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 3.7 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 0.19 with a t-value of 4.45. These results are consistent with the view that advisors exert influence on their clients' portfolios.

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:

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

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 11.8% and 4.4% compared to 12.2% and 4.1%. As in Table 2, the model's explanatory power increases substantially when we include advisor fixed effects.

Table 3's rightmost regression replaces observable investor attributes with investor fixed effects. Although investor age varies over the sample period, the model omits age because it is not possible to identify year, investor and age effects without additional restrictions. Intuitively, investor fixed effects reveal—among all other things!—each investor's birth year, and the birth year together with the year fixed effects recovers age.[14] In the risky-share regression, the explanatory power of the model increases from 35.7% to 46.8% as we swap observable investor attributes for investor fixed effects.

Although investor fixed effects add explanatory power over and above investor attributes, they do not meaningfully "crowd out" the advisor fixed effects. The estimates in the last column of Table 3 show that advisor fixed effects remain strong predictors of risky share. Adding the advisor effects to the model raises the adjusted R^2 substantially, from 28.9% with investor fixed effects alone to 46.8% with both sets of fixed effects. Investor fixed effects provide roughly the same incremental explanatory power; the adjusted R^2 increases from 30.7% with advisor fixed effects alone to 46.8% with both sets of fixed effects. Second, 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 12.2 and 12.0, respectively.

The home-bias regressions in Panel B yield a similar picture. The adjusted R^2 of the model increases from 30.0% to 44.9% when we include advisor fixed effects in addition to investor fixed

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

effects. The two sets of fixed effects also exhibit similar statistical significance. The F-values associated with the advisor and investor fixed effects in the last column's full model translate to (pseudo) t-values of 10.7 and 11.5. The one notable difference about the home-bias analysis is that investor fixed effects provide substantial explanatory power relative to investor attributes. This result suggests that investors indeed have subjective views on the optimal mix of domestic and international equity, but that these views are unrelated to attributes such as age, gender, and risk tolerance.

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.

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 "abnormal tilt" (that is, the advisor fixed effect) seen in the 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.

Table 4 examines the extent to which advisor age, gender and number of clients explain cross-sectional variation in Table 2's estimates of advisor fixed effects. Because we extract these fixed effects from regressions that control for investor age and gender (among other investor attributes), no patterns can arise here because investors and advisors match by age and gender; that is, the advisor fixed effects are orthogonal to observable investor attributes. The unit of observation in Table 4's regressions is an advisor. In the first regression, for example, we have the requisite data—the fixed effect from the risky-share regression and advisor age and gender—for 2,956 advisors. We define age in these regressions as the advisor's average age during the sample period.

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.[15] On the other hand, an advisor may choose a portfolio that is good for himself but that is unsuitable for the clients' preferences and stage of the lifecycle. Moreover, advisors pay lower fees than their clients, so their interests are not completely aligned even when they invest in the same funds. In particular, when advisors invest on their own behalf they receive a discount; the fund company pays a sales commission to the selling advisor. The evidence that advisors and clients hold similar portfolios therefore does not rule out conflicted advice: advisors

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

may still knowingly hold and recommend funds that perform well gross of fees but perform poorly net of large sales commissions.

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 gross investment returns 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-end loads. We examine risk-adjusted returns with a series of models that adjust for common equity and bond market risk factors. We begin with the CAPM and then move to the Fama and French (1993) three-factor model by adding size and value factors. The third model adds the momentum factor and two bond factors to account for clients' non-equity allocations. As equity factors, we use the Canadian market return and the North American size, value and momentum portfolios constructed by Ken French. As fixed-income factors, we use the excess return for long-term Canadian Treasuries relative to 90-day Canadian Treasuries and the excess return for Canadian high-yield corporate bonds relative to long-term Canadian Treasuries. The returns on the long-term Treasuries and high-yield corporate bonds are computed from Bank of America Merrill Lynch's 10+ Year Canada and Canada High Yield indexes.

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").

Advisor portfolios earn annualized gross alphas that are small and statistically indistinguishable from zero. In the CAPM, the average dollar's alpha is 10 basis points and the average advisor's alpha is −18 basis points. However, because the average client holds 29% in fixed-income products (Table 1), a failure to control for returns on this segment of the market can overstate client performance. The gross-alpha estimates decline when we add controls for size and value and decline further when we add momentum and the fixed-income factors. For the six-factor model, the gross-alpha estimates are −80 and −99 basis points. 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 0.60 in down markets and 0.59 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 −2.45% in the CAPM and −3.34% in the six-factor model. Examining fees and expenses directly, we find that the average advised dollar pays 2.57% per year in fees, of which 2.33% is mutual fund management expense ratio and 0.24% is front-end load payments. Our fee calculations exclude deferred sales charges assessed when investors sell back-end load funds "too early" (typically within five to seven years of purchase). We exclude these charges because advisors could reimburse their clients for some of these penalties and we lack data on such reimbursements. The net alphas we report are thus upper bounds on investors' realized alphas.

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 −2.6%, while the 10th and 90th percentiles in the distribution of advisors are −6.9% and 2.1%. 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 this distribution is just 0.8.

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

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 is 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 downweigh 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.[16] For each advisor, we calculate

$$\text{Within-advisor } R_a^2 = 1 - \frac{\text{var}(\text{risky share}_{ia} - \widehat{\text{risky share}}_{ia})}{\text{var}(\text{risky share}_{ia})}, \tag{4}$$

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 $R_a^2 = 0$ for negative values and for observations with $\text{var}(\text{risky share}_{ia}) = 0$ so that the final variable ranges from 0 to 1.[17]

The estimates reported in Table 6 reject 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 (0.18) raises annualized alphas by 18 basis points and $t(\hat{\alpha})$s by 0.11. This effect is robust to controlling for other advisor and portfolio characteristics, several of which also 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.[18] 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

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

[17] The right-hand side in equation (4) 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 $\text{var}(\widehat{\text{risky share}}_{ia}) > 0$.

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

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. The number of clients does not show a robust relationship with performance; its coefficient switches signs and is only significant in the $t(\hat{\alpha})$ specifications. The average size of clients' portfolios, however, shows a robust positive correlation with performance. Advisors who create portfolios with fewer funds also perform better than those who create more complex portfolios. The average number of plans per client, by contrast, is largely unrelated to performance. That is, having more plans within an account—such as an education savings plan, a retirement savings plan and a general plan—is not related to performance. Lastly, among advisor characteristics—age, gender and experience—only age correlates with performance. Older advisors perform slightly better than young advisors.

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 lifecycle funds, which offer retirement-oriented investors diversified portfolios that automatically rebalance over time. While lifecycle funds may not match the investment portfolio that clients would hold in the absence of advice, they are likely passive investors' best substitute for financial advice.

Figure 5 displays the estimated division of client fees among the mutual fund, advisor and dealer. In total, clients pay 2.57% of assets per year, with mutual funds capturing a slightly larger fraction (54%) than the advisor and dealer. We estimate that mutual funds receive 1.4% per year through management expense charges assessed on client investments: 0.94% per year as a management fee as well as 0.23% per year respectively to cover operating expenses and taxes. These fund management and operating fees are high relative to index funds but do not stand out relative to the universe of actively managed funds. To evaluate this point, we run simulations in which we replace clients' actual fund investments with random funds drawn from the same style category. The simulated portfolios earn net alphas that are very similar to the actual portfolio.[19] This finding is perhaps unsurprising, given the broad range of mutual funds held in client accounts. Although the dealers in our sample are owned by mutual fund complexes, none of the advisors provide captive distribution for a mutual fund complex; 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 4,000 funds available to Canadian investors during the sample period, more than 90% appear in client accounts. These computations suggest that while mutual fund management fees contribute to the cost of advised portfolios, advisors do not steer client investments into a small set of funds with particularly high management fees and operating expenses.

The dealer and financial advisor receive the remaining 46% of fees, or 1.17% of assets per year. They receive payments from two sources: front-end load payments of 0.24% per year paid directly by clients and estimated sales commissions of 0.93% per year paid by mutual funds but ultimately passed on to clients through management expense charges.[20] After accounting for the share of fees retained by the dealer, we estimate that the average advisor in our sample earns 0.91% of assets per year. The implied annual pay of $47 thousand (the average advisor manages $5.1 million) is in the 70th percentile of the Canadian income distribution. The picture that emerges is that expensive mutual funds and expensive advice both contribute to the cost of advised portfolios, but that advisors themselves do not individually capture substantial rents.

In addition to examining the division of fees, it is useful to compare the cost of advised portfolios to lifecycle funds. Although cheaper index funds are available to investors, the benefit of lifecycle funds is that they require no active trading by the client, similar to advised portfolios. 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 $2.57\% - 1.02\% = 1.55\%$ per year if we assume zero gross alpha on

[19] The bootstrapped 95% confidence interval (100 simulations) for the six-factor alpha is $[-3.19\%, -3.14\%]$, compared to the actual alpha of -3.09%.

[20] A 2010 study of the top ten Canadian dealers reports that advisors received, on average, 78% of the commission payments (Fusion Consulting 2011).

advised investments in the future, or $3.34\% - 1.02\% = 2.22\%$ per year if we assume the same gross alpha in the future as in the past.[21]

Over the course of the lifecycle, this steady stream of fees compounds quite dramatically. To illustrate how much investors pay in present value terms, 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 net alpha of 2% decreases the present value of the investor's savings by 18%.[22] This estimate means that the typical investor in our sample pays nearly a fifth of his retirement savings for financial advice.

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 customize their advice on risk-taking. In total, a broad set of investor characteristics including risk tolerance and the point in the lifecycle explain only 12% of the variation in risky 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.

[21] 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 loss computations.

[22] 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 $r_2 = 6\%$ gives $\frac{\text{PV}_1}{\text{PV}_2} = 0.82$.

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 2.6% of assets per year for advice—or 1.6% 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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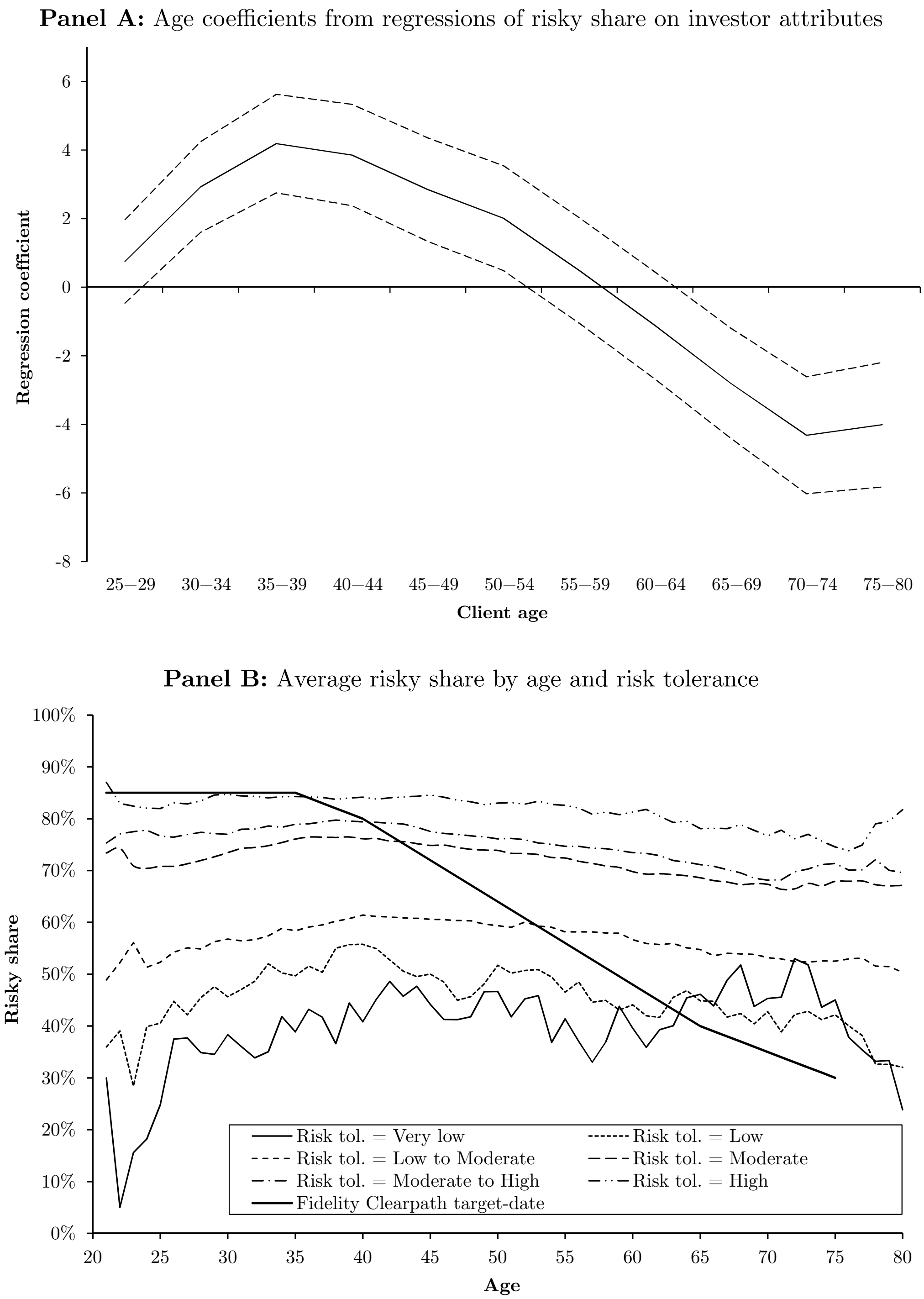

Figure 1: **Advised investors' risky share as a function of age and risk tolerance.** Panel A plots estimated regression coefficients and 95% confidence intervals from regressions of risky share on age-group fixed effects and other investor attributes (Table 2 Panel A). Panel B plots average risky shares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

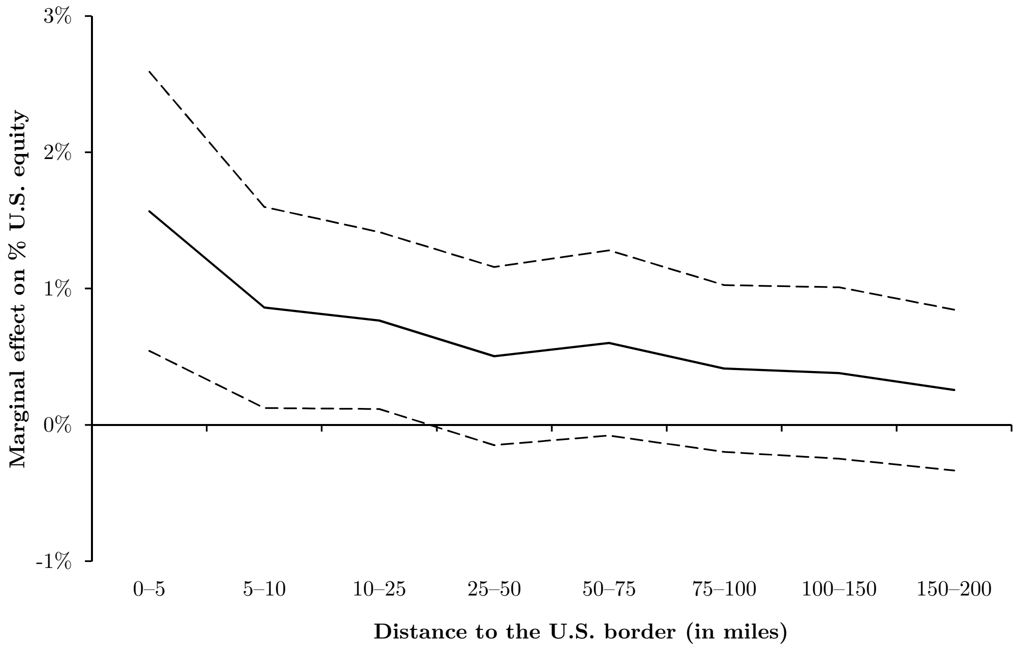

Figure 2: **Allocation to U.S. equities as a function of distance to the U.S. border.** We estimate a panel regression that explains variation in the allocation to U.S. equities (as % of total equities) with investor attributes and year fixed effects. In addition to the investor attributes reported in 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.

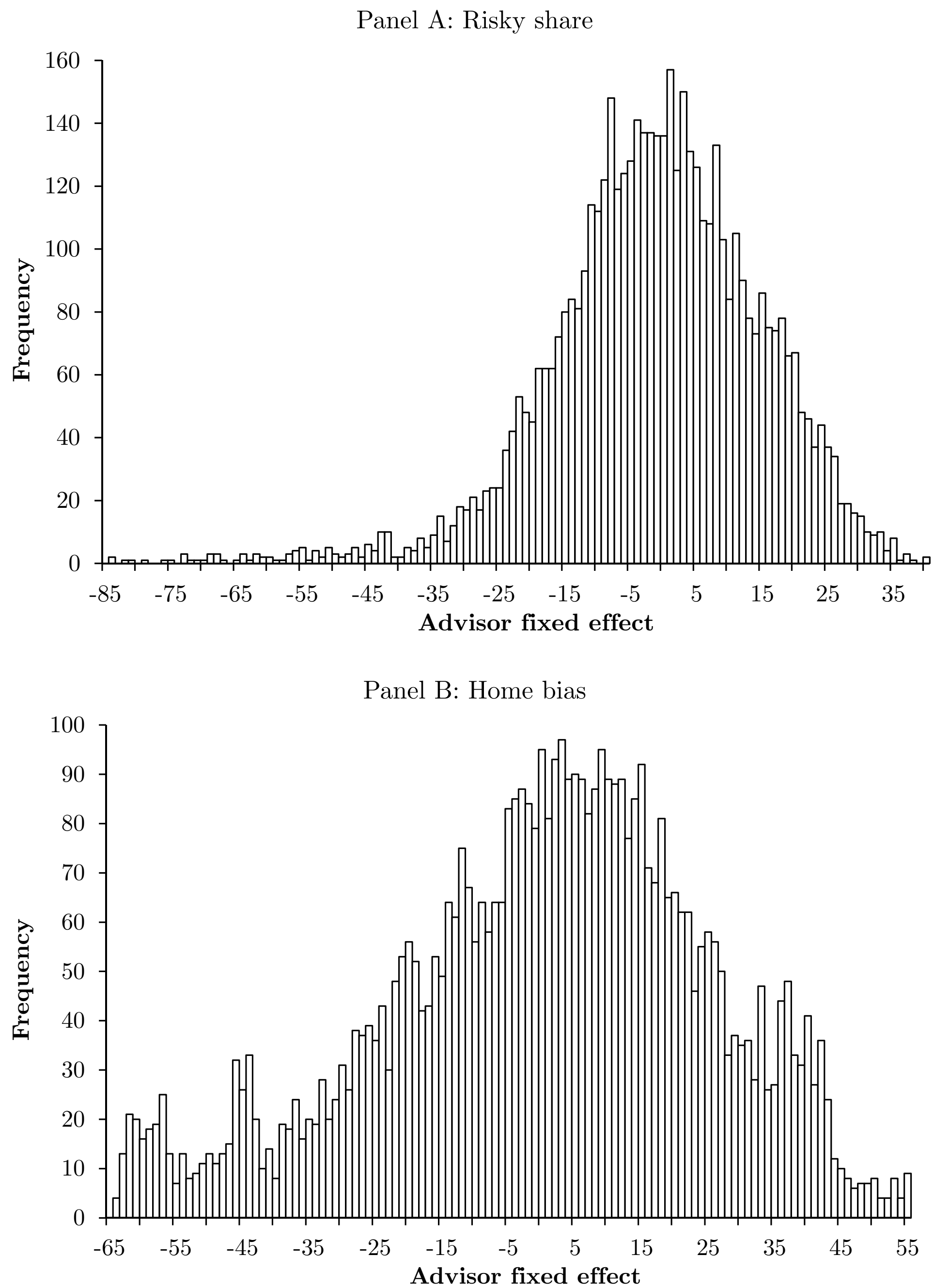

Figure 3: **Distributions of advisor fixed effects in risky-share and home-bias regressions.** This figure plots the distributions of advisor fixed effects from the risky-share and home-bias regressions of Table 2. In addition to the advisor fixed effects, the regressions include investor attributes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

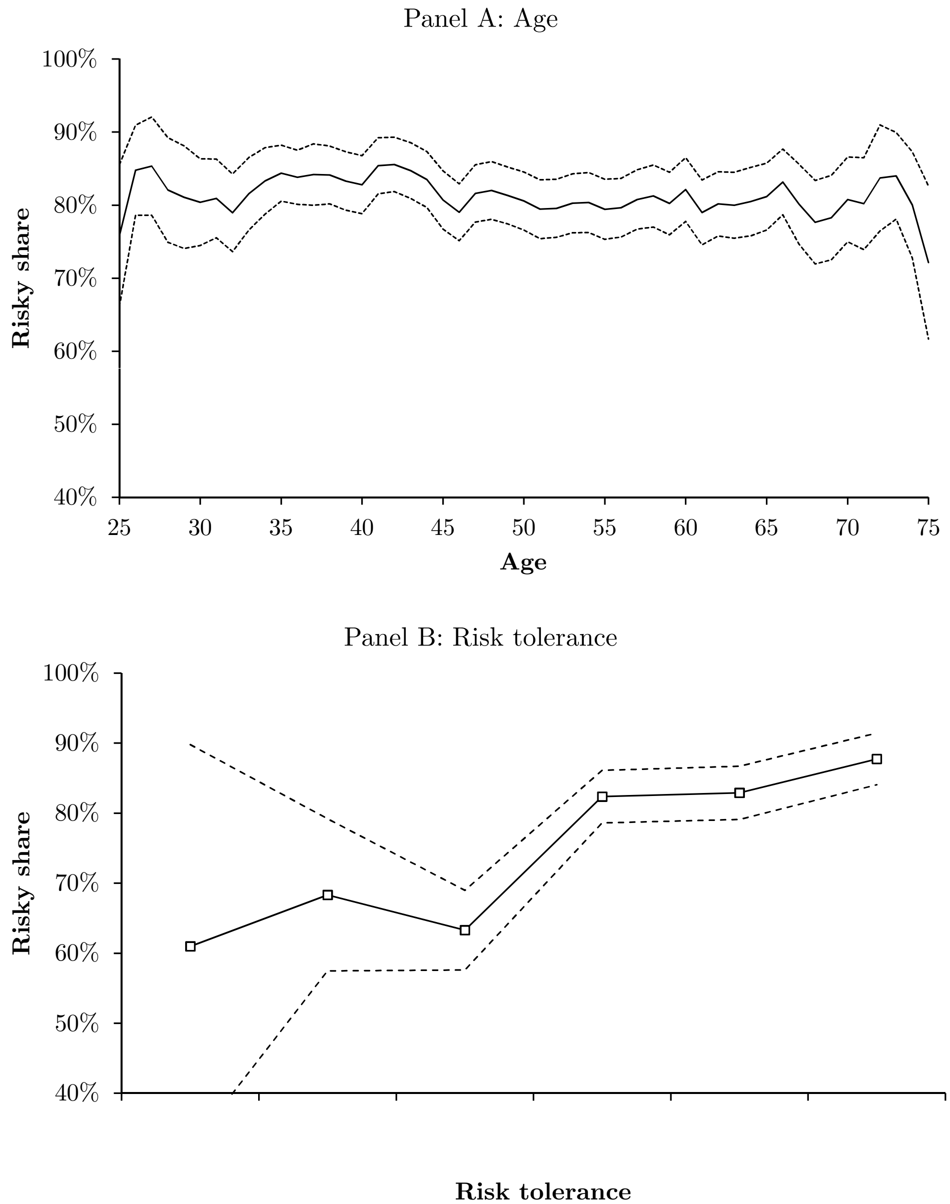

Figure 4: **Advisor risky share as a function of age and risk tolerance.** This figure plots the average risky share and 95% confidence interval for advisors' own portfolios as a function of advisor age (Panel A) and risk tolerance (Panel B). We compute these estimates from regressions of risky share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

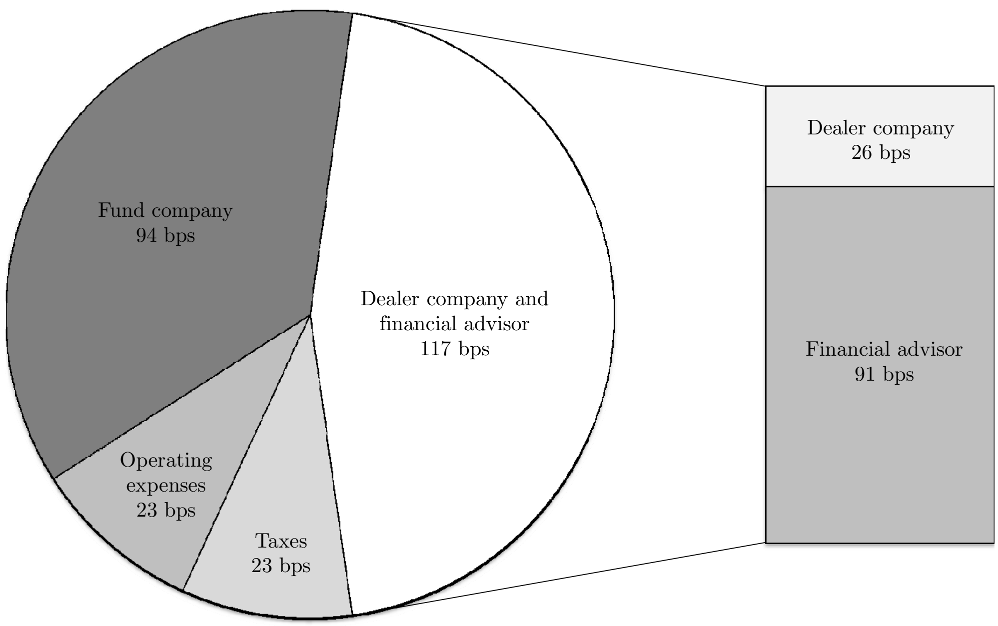

Figure 5: **Estimated division of fees among mutual fund, dealer and financial advisor.** Using the dealer data, we measure total fees paid by the investor, comprised of mutual fund management expense ratios and front-end loads. The dealer receives the front-end loads in full and a portion of the management expense ratio ("trailing commission"). The fund company keeps the remainder of the management expense ratio, from which we separate out estimated taxes and operating expenses. We use estimates from Canadian Securities Administrators (2012) to divide management expense charges into trailing commissions, taxes and operating expenses. We also use the estimates from Fusion Consulting (2011) to divide the payments between the dealer and financial advisor.

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		Time horizon	
General	24.1%	1–3 years	3.2%
Retirement savings or income	66.0%	4–5 years	9.4%
Education savings	5.1%	6–9 years	68.0%
Tax-free	4.5%	10+ years	19.5%
Others	0.4%		

Risk tolerance		Salary	
Very low	4.2%	$30–50k	35.8%
Low	4.3%	$50–70k	35.0%
Low to Moderate	8.5%	$70–100k	16.5%
Moderate	51.5%	$100–200k	12.1%
Moderate to High	19.7%	$200-300k	0.2%
High	11.9%	Over $300k	0.3%

Financial knowledge		Net worth	
Low	42.8%	Under $35k	4.9%
Moderate	51.4%	$35–60k	7.6%
High	5.8%	$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. The last row, "Adjusted R^2 w/o advisor FEs," reports the adjusted R^2 from an alternative model that does not include the advisor fixed effects. 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%	

Panel B: Dependent variable = Home bias

Independent variable	All advisors $\hat{b}$	All advisors t	All advisors $\hat{b}$	All advisors t	Low-dispersion advisors $\hat{b}$	Low-dispersion advisors t	High-dispersion advisors $\hat{b}$	High-dispersion advisors t
Constant	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%	

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 3,561 client-advisor pairs from 1,694 clients and 662 advisors and the distributions of the F-statistics for the advisor and investor fixed effects are $F(447, 1407)$- and $F(1693, 1407)$-distributed under the null; Panel B uses data on 3,332 client-advisors pairs from 1,588 clients and 633 advisors and the distributions of the F-statistics for the advisor and investor fixed effects are $F(426, 1305)$- and $F(1587, 1305)$-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	35.38	2.95	41.40	2.42		
Risk tolerance						
Low	11.32	1.16	15.29	2.41		
Low to Moderate	20.39	2.31	26.06	4.38		
Moderate	29.56	3.42	32.10	5.54		
Moderate to High	31.82	3.63	34.61	5.94		
High	36.90	4.20	38.44	6.49		
Fin. knowledge						
Moderate	4.96	3.95	0.62	0.59		
High	6.46	3.44	0.91	0.53		
Time horizon						
Short	0.89	0.22	2.22	0.67		
Moderate	5.96	1.63	3.51	1.21		
Long	7.34	1.89	3.93	1.28		
Female	−2.87	−3.23	−2.70	−3.27		
French speaking	−9.85	−3.59	−0.09	−0.03		
Salary						
\$30–50k	0.76	0.71	0.69	0.68		
\$50–70k	0.71	0.61	0.84	0.72		
\$70–100k	0.17	0.11	1.00	0.74		
\$100–200k	−3.47	−0.60	−1.50	−0.23		
Over \$200k	−10.29	−1.54	−7.55	−0.57		
Net worth						
\$35–60k	1.01	0.24	4.70	1.32		
\$60–100k	−2.90	−0.72	0.42	0.13		
\$100–200k	−1.56	−0.40	0.86	0.25		
Over \$200k	−1.48	−0.38	0.14	0.04		
Occupation						
Finance professional	−0.41	−0.08	−4.73	−0.86		
Self-employed	1.96	0.82	2.22	0.95		
Government	0.60	0.26	0.68	0.33		
Advisor FEs (F-test)	**No**		**Yes** (2.97)		**Yes** (2.40)	
Investor FEs (F-test)	**No**		**No**		**Yes** (1.86)	
Age groups	Yes		Yes		No	
Year FEs	Yes		Yes		Yes	
Province FEs	Yes		Yes		No	
Adjusted R^2	11.8%		35.7%		46.8%	
w/o advisor FEs	.		11.8%		28.9%	
w/o investor attributes	.		30.7%		.	

Panel B: Dependent variable = Home bias

Independent variable	(1) $\hat{b}$	(1) t	(2) $\hat{b}$	(2) t	(3) $\hat{b}$	(3) t
Constant	83.14	4.35	89.13	3.14		
Risk tolerance						
Low	−13.73	−0.89	−13.29	−0.83		
Low to Moderate	−11.12	−0.75	−15.29	−0.98		
Moderate	−16.28	−1.09	−19.20	−1.25		
Moderate to High	−17.86	−1.18	−23.05	−1.49		
High	−26.29	−1.73	−30.14	−1.94		
Fin. knowledge						
Moderate	0.16	0.08	−0.11	−0.07		
High	2.26	0.89	0.28	0.11		
Time horizon						
Short	15.79	2.73	10.91	2.24		
Moderate	10.00	1.93	11.61	2.73		
Long	16.37	3.12	14.74	3.28		
Female	0.50	0.42	−0.01	−0.01		
French speaking	−1.51	−0.42	−2.77	−0.60		
Salary						
$30–50k	−0.47	−0.29	−0.48	−0.32		
$50–70k	−2.87	−1.64	−2.03	−1.22		
$70–100k	−5.45	−2.56	−2.10	−1.08		
$100–200k	−8.09	−1.01	−3.64	−0.40		
Over $200k	26.38	2.93	36.27	1.98		
Net worth						
$35–60k	3.27	0.59	−0.99	−0.19		
$60–100k	3.25	0.60	1.83	0.36		
$100–200k	9.68	1.80	5.15	1.03		
Over $200k	5.92	1.12	1.23	0.25		
Occupation						
Finance professional	−4.10	−0.51	2.81	0.35		
Self-employed	0.79	0.23	1.18	0.36		
Government	−8.07	−2.58	−8.23	−2.79		
Advisor FEs (F-test)	**No**		**Yes** (3.05)		**Yes** (2.21)	
Investor FEs (F-test)	**No**		**No**		**Yes** (1.86)	
Age groups	Yes		Yes		No	
Year FEs	Yes		Yes		Yes	
Province FEs	Yes		Yes		No	
Adjusted R^2	4.4%		31.5%		44.9%	
w/o advisor FEs	.		4.4%		28.5%	
w/o investor attributes	.		30.0%		.	

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	0.10	−0.18	−2.45	−3.00	85.2%
		(0.09)	(−0.17)	(−2.28)	(−2.88)	
Fama-French	Mkt-Rf, SMB, HML	−0.28	−0.47	−2.83	−3.29	85.5%
		(−0.26)	(−0.44)	(−2.61)	(−3.12)	
Extended Fama-French	Mkt-Rf, SMB, HML, MOM, DEF, TERM	−0.80	−0.99	−3.34	−3.81	88.0%
		(−0.77)	(−0.97)	(−3.22)	(−3.76)	

Panel B: Market-timing estimates

	Parameter		
Model	$\hat{\beta}_{\text{mkt}}$	$\hat{\beta}^{\text{up}}_{\text{mkt}}$	R^2
CAPM	0.591		85.3%
	[0.021]		
Henriksson-Merton	0.596	−0.011	85.2%
	[0.035]	[0.069]	

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

	Percentiles				
Estimate	10th	25th	50th	75th	90th
$\hat{\alpha}$	−6.87	−4.50	−2.61	0.04	2.13
$t(\hat{\alpha})$	−3.12	−2.38	−1.17	0.01	0.80

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	1.13	1.02	0.69	0.53
	(2.21)	(1.99)	(3.67)	(2.81)
Risky share at $t = 0$		−2.65		−1.01
		(−7.64)		(−7.18)
log(# of clients)		0.06		−0.13
		(1.30)		(−5.90)
log(Avg. AUM per client at $t = 0$)		0.59		0.34
		(5.60)		(7.72)
log(# of funds per client)		−0.52		−0.53
		(−3.05)		(−7.26)
log(# of plans per client)		0.41		−0.03
		(1.45)		(−0.25)
Advisor information				
log(Age)		0.79		0.26
		(2.78)		(2.06)
Female		0.23		0.11
		(1.40)		(1.54)
log(Experience)		0.07		−0.14
		(0.68)		(−3.10)
N	2,898	2,898	2,898	2,898
Adjusted R^2	0.2%	5.3%	0.4%	7.2%

Internet Appendix to
"Retail Financial Advice: Does One Size Fit All?"

A Robustness within Extended Sample of Dealer Data

The main sample in the paper includes data from three mutual fund dealers. We also obtained data from a fourth dealer. The fourth firm's data covers a shorter time period (January 2001 through December 2010) and lacks two variables that we use in the main analysis. Front-end load payments are not included, nor are the personal identifiers needed to match advisors to their own portfolios. In order to maintain a consistent sample across the main tests, we exclude the fourth dealer from the main sample and reserve it instead for the robustness tests reported below. To avoid disclosing firm-specific information about the anonymous data provider, we analyze an "extended sample" that pools the data of all four firms.

The first two panels of Table A1 summarize the extended sample and provide a comparison to the main sample. The extended sample includes 814,000 investors, 40% more than the main sample. Investors' mean and median account values are somewhat lower in the extended sample, but the average portfolio allocations—roughly 70% to risky assets and just under 60% to Canadian equity—are almost the same as in the main sample. The extended sample covers over 10,000 advisors, 4,000 more than the main sample. The size of the median advisor's business is similar in both samples, whether measured in number of clients or in assets under advice.

The third panel of Table A1, labeled "Advisor influence," reports the adjusted R^2 for models explaining clients' portfolio allocations. The results within the extended sample confirm our earlier findings. In the extended-sample analysis of risky share, advisor fixed effects roughly double the model's explanatory power—from 15.6% to 30.5%—compared to a specification with investor characteristics alone. Similarly, for the sample of clients that switch advisors, advisor fixed effects add explanatory power over investor fixed effects; advisor effects increase the adjusted R^2 from 29% to 45%. Advisors' influence on home bias is even more striking. In the extended-sample analysis, advisor fixed effects raise the cross-sectional model's explanatory power almost ten-fold from 2.9% to 22.3% and the two-way fixed effect model's explanatory power almost two-fold from 22.7% to 41.4%.

The final panel of Table A1 reports the gross and net alpha estimates. The six-factor gross alpha is -1.28% per year, lower than in the main sample but still statistically indistinguishable from zero. After subtracting fees—in this case, management expense fees, but not front-end load fees—we estimate a six-factor net alpha of -3.61% per year.

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

B Explanatory Power of Investor Attributes and Advisor Fixed Effects in Subsamples

Table 2 in the paper estimates regressions of risky share and home bias against investor attributes and advisor fixed effects using data on all investors with sufficient information. In Table A2 below, we estimate analogous regressions—with and without advisor fixed effects—for various subsamples. The adjusted R^2s are comparable to the statistics reported in Table 2, columns (1) and (2). The subsamples are defined as follows:

1. **Number of clients.** We classify advisors into those with low or high number of clients relative to the median. We re-sort advisors each year.

2. **Account value / net worth.** We compute the account value-to-net worth ratio using the net worth information reported on the "Know Your Client" forms. We use the midpoint of each net worth category except for the \$200+ thousand category, for which we assume a value of \$300 thousand.

3. **Workplace pension generosity.** We use the Canadian Financial Monitor survey to classify occupations based on their pension generosity. We find that government occupations (e.g.,

armed services, policeman, fireman and government official) have the most generous pensions: 77% of workers have a pension (compared to 48% for non-government workers) and the pension assets comprise 47% of their total financial assets (compared to 26% for non-government workers). On the opposite end of the spectrum, low-skill occupations (e.g., bartender, waiter, cashier, housekeeper and janitor) have the least generous pensions: 31% of workers have a pension and pension assets comprise 17% of their total financial assets. We merge this information to the dealer data and divide the sample into occupations with low-generosity and high-generosity pensions.

4. **Household size.** We use the "number of family members" information from the "Know Your Client" forms to divide the sample into single and multi-member households.

5. **Plan types.** We divide the sample into retirement accounts and open accounts.

The regressions reported in the paper include fixed effects for the 13 provinces and territories of Canada. In the specifications reported at the bottom of Table A2, we estimate the regressions without province effects and, alternatively, with fixed effects for the 2,954 Canadian census subdivisions observed in our sample.

Table A1: Robustness analysis using an extended sample

This table summarizes key estimates from the analyses presented in Tables 1–3 and 5 using both the main sample and an extended sample. The extended sample adds data from a fourth mutual fund dealer. Compared to the main sample, the extended sample covers a shorter time period (January 2001 through 2010) and lacks information on front-end load payments and advisors' own portfolios. Column "Main sample" summarizes the estimates reported in the other tables and column "Extended sample" reports these estimates for the extended sample. The row "Net alpha" adjusts gross returns for management-expense ratios; "Net alpha (all expenses)" adjusts for both management-expense ratios and front-end load payments.

Variable	Sample: Main	Extended
Investor characteristics		
Number of investors	581,044	814,056
Account value per investor, $ thousands		
Mean	68.1	58.7
Median	27.3	21.1
Portfolio		
Risky share	69.0	70.4
Home bias	59.5	57.0
Advisor characteristics		
Number of Advisors	5,920	10,275
Clients per advisor		
Mean	74.3	69.7
Median	24	25
Assets under advice per advisor, $ thousands		
Mean	5,064.0	4,086.4
Median	916.9	933.5
Advisor influence		
Adjusted R^2, portfolio risky share		
Investor characteristics	12.2%	15.6%
Investor characteristics + advisor FEs	30.2%	30.5%
Investor FEs (movers-sample)	28.9%	29.2%
Investor FEs + advisor FEs (movers-sample)	46.8%	44.9%
Adjusted R^2, portfolio home bias		
Investor characteristics	4.1%	2.9%
Investor characteristics + advisor FEs	27.9%	22.3%
Investor FEs (movers-sample)	28.5%	22.7%
Investor FEs + advisor FEs (movers-sample)	44.9%	41.4%
Investment performance in the six-factor model		
Gross alpha	−0.80	−1.28
	(−0.77)	(−1.14)
Net alpha	−3.12	−3.61
	(−3.00)	(−3.24)
Net alpha (with all expenses)	−3.34	
	(−3.22)	

Table A2: Regressions of risky share and home bias on investor attributes and advisor fixed effects: Subsample analyses

This table reports adjusted R^2s from panel regressions of risky share and home bias on investor attributes and advisor fixed effects. We create subsamples based on advisor and investor attributes, restrict the analysis to registered retirement accounts or open accounts, or modify the full-sample regression by using alternative geographic fixed effects. The first four specifications divide the sample based on: (a) the number of clients an advisor has; (b) an investor's account value relative to total net worth; (c) an occupation-based proxy for the generosity of the workplace pension; and (d) the size of the investor's household. The main specification reported in Table 2 controls for geography by including fixed effects for the 13 provinces and territories in Canada. The final specification below uses instead fixed effects for the 2,954 Canadian census subdivisions.

	Dependent variable			
Subsample	Risky share		Home bias	
definition	No advisor FE	Advisor FE	No advisor FE	Advisor FE
Number of clients				
Below median	10.7%	30.2%	4.4%	29.7%
Above median	14.2%	30.8%	4.4%	26.6%
Account value / net worth				
Below median	12.4%	28.9%	6.0%	26.8%
Above median	12.4%	35.5%	2.8%	34.5%
Workplace pension generosity				
Low	10.9%	56.0%	5.9%	55.7%
High (government)	11.9%	44.3%	5.3%	42.5%
Household size				
Single	12.1%	35.4%	5.3%	36.1%
Multiple (spouse and/or children)	12.1%	33.0%	4.5%	30.6%
Plan types				
Registered retirement accounts	11.6%	31.4%	4.6%	29.6%
Open account	7.2%	29.1%	5.0%	36.0%
Geographic controls				
No location FEs	12.0%	30.2%	3.5%	27.9%
Province FEs	12.2%	31.1%	4.1%	28.9%
Census subdivision FEs	15.0%	31.9%	7.6%	29.9%