The Misguided Beliefs of Financial Advisors[*]

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Abstract

A common view of retail finance is that rampant conflicts of interest explain the high cost of financial advice. Using detailed data on financial advisors and their clients, however, we show that most advisors invest their personal portfolios just like they advise their clients. They trade frequently, chase returns, and prefer expensive, actively managed funds over cheap index funds. Differences in advisors' beliefs affect not only their own investment choices, but also cause substantial variation in the quality and cost of their advice. Advisors do not hold expensive portfolios only to convince clients to do the same—their own performance would actually improve if they held exact copies of their clients' portfolios, and they exhibit similar trading behavior even after they leave the industry. This evidence suggests that many advisors offer well-meaning, but misguided, recommendations rather than self-serving ones. Eliminating conflicts of interest may therefore reduce the cost of advice less than policymakers hope.

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1 Introduction

A common criticism of the financial advisory industry is that conflicts of interest compromise the quality, and raise the cost, of advice. Many advisors require no direct payment from clients but instead draw compensation from commission payments on the mutual funds they sell. Within this structure, advisors may be tempted to recommend products that maximize commissions instead of serving the interests of their clients. A growing academic literature has assessed conflicts of interest and has shown suggestive evidence that sales commissions raise costs and distort portfolios. Policymakers, in turn, have pushed to end commission-based pricing and impose greater fiduciary responsibilities on advisors.

In this paper we find strong support for an alternative, if not mutually exclusive, explanation of costly and low-quality advice that carries starkly different policy implications. Advisors are willing to hold the investments they recommend—indeed they invest very similarly to clients—but they have misguided beliefs. They recommend frequent trading and expensive, actively managed products because they believe active management, even after commissions, dominates passive management. Eliminating conflicts of interest may therefore reduce the cost of advice less than policymakers hope.

Our analysis uses data provided by three Canadian financial institutions. Advisors within these firms provide advice on asset allocation and serve as mutual fund dealers, recommending the purchase or sale of unaffiliated mutual funds. The data include comprehensive trading and portfolio information on more than 5,000 advisors and 500,000 clients between 1999 and 2013. Our data also include, for the vast majority of advisors, the personal trading and account information of the advisor himself. This unique feature proves fruitful for our analysis. The advisor's own trades reveal his beliefs and preferences regarding investment strategies, which allows us to test whether client trades that are criticized as self-serving emanate from misguided beliefs rather than misaligned incentives.

We begin by characterizing the trading patterns of advisors and clients in our sample. We measure trading behaviors in dimensions that previous research has suggested as being important for performance: high turnover, preference for actively managed funds, return chasing, disposition effect, home bias, and preference for growth over value.[1] We find that both clients and advisors strongly lean toward trading patterns documented previously for self-directed investors. The average client and advisor, for example, purchase funds with better-than-average historical returns and prefer expensive, actively managed funds. Passive funds account for 1.4% of the average client's portfolio, and even less within the average advisor's portfolio. This similarity in trading patterns suggests that advisors do not dramatically alter their recommendations when acting as agents rather than principals.

Further analysis of portfolio returns likewise shows no evidence that advisors recommend more expensive funds to clients than they hold themselves. After adjusting for risk, both clients and advisors earn net alphas between −3% and −2% per year. Advisors benefit from their status when managing their own assets; they earn sales and trailing commissions when serving as agent for their

[1] These behavioral patterns have been studied extensively. See, for example, Nofsinger and Sias (1999), Grinblatt and Keloharju (2001b), Barber and Odean (2008), and Kaniel, Saar, and Titman (2008) for analyses of how investors trade in response to past price movements; Shefrin and Statman (1985), and Odean (1998), Grinblatt and Keloharju (2001b), Feng and Seasholes (2005), Dhar and Zhu (2006), Linnainmaa (2010), and Chang, Solomon, and Westerfield (2015) for studies of the disposition effect; and Odean (1999), Barber and Odean (2000), and Grinblatt and Keloharju (2009) for analyses of trading activity; French and Poterba (1991), Coval and Moskowitz (1999), and Grinblatt and Keloharju (2001a) for studies of the home bias; French (2008) for a discussion of the underperformance of active management; and Grinblatt, Keloharju, and Linnainmaa (2011), Betermier, Calvet, and Sodini (2015), and Cronqvist, Siegel, and Yu (2015) for analyses of individual investors' preference for growth investing.

own purchases. Even after adjusting for these rebates, the average advisor's performance is within 21 basis points of his clients' performance.

We next evaluate the role of financial advice in shaping clients' investment decisions. We do not observe advisors' recommendations directly, but instead infer them from trading patterns common among their clients. We find that common variation, as measured through advisor fixed effects, dominates variation explained by client characteristics such as age, risk tolerance, investment horizon and income. The identity of the advisor, it turns out, is the single most important piece of information for predicting nearly all of the client trading behaviors.

An important question to consider is whether the similarity in trading within client groupings results from common input provided by the advisor or instead from shared preferences. Our analysis suggests common input from the advisor.

First, when we control for a wide variety of client characteristics, the importance of advisor fixed effects does not diminish. Shared observable characteristics therefore are not driving common trading. Second, the strong advisor effects are also robust to controlling for client unobservable traits. We examine such latent differences within the subsample of clients that are forced to move from one advisor to another after the death, retirement or resignation of the advisor. Controlling for both client and advisor fixed effects, we find that clients change their trading patterns coincident with the switch. For example, a client who moves from an advisor recommending contrarian trades to one recommending return-chasing trades will begin to chase returns. While client fixed effects prove important in explaining portfolio choices, the marginal explanatory power of the advisor effects remains strong. Finally, we use detailed transaction data—the timing of trades and the specific funds purchased or sold—to establish the importance of advisors' trading input. While common strategies, such as return chasing, may coincidentally emerge among client groupings, it is unlikely that clients would buy specifically the same funds at the same time. The results from this exercise show that advisors strongly influence trading.

We move next to the question of what motivates advisors to promote specific investments and trading strategies. Using trading patterns evident in advisors' own portfolios, we trace differences in their recommendations to their own beliefs and preferences. Controlling for client characteristics, advisor's personal behavior explains a substantial amount of variation in client behavior. An advisor who encourages his clients to chase returns, for example, typically also chases returns himself. These correlations are significant for nearly all of the trading patterns that we evaluate.

Advisors do not appear to engage in "window dressing," that is, they do not make personal trades that contradict their beliefs just to keep up the appearances. We track advisors after they leave the industry and show that their trading behavior remains largely unchanged. They continue to chase returns, invest in actively managed funds, and choose funds that are as expensive as those they chose before. Moreover, if advisors held expensive portfolios only to convince their clients to do the same, advisors' personal portfolios should perform no worse than those of their clients. By contrast, the average advisor would be better off by holding the exact copy of his clients' portfolios.

We conclude with an analysis of how advisors' beliefs and preferences influence the quality and cost of advice that they deliver. Differences in advisors' beliefs do not merely add noise to client returns, they predict substantial differences in investment performance. We sort advisors into deciles based on the gross performance of their personal portfolio, and we compare the average client returns between top- and bottom-decile advisors. Clients advised by bottom-decile advisors earn 1.2% lower returns than clients advised by top-decile advisors. A similar pattern holds for portfolio cost: advisors who hold portfolios in the top decile of cost deliver portfolios that are 0.4% more expensive than their counterparts who hold portfolios in the bottom decile of cost. Together, the cross-sectional patterns in gross returns and fees indicate that differences in advisors' beliefs cause substantial variation in bottom-line portfolio returns.

Our results are important for policy. If advisors give bad advice because they believe that active management adds value even after fees, then policies that target conflicts of interests may prove ineffective. Correcting advisors' misguided beliefs, through screening or education, may do more to improve the quality of advice. The market, of course, may not reward such actions, despite low barriers to entry. Financial advisors self-select into the industry, so those who believe that active management adds value are more likely to become advisors than those who believe in market efficiency.

Our results relate to studies of the financial advisory industry.[2] Mullainathan, Nöth, and Schoar (2012), for example, find that advisors encourage return chasing and recommend expensive, actively managed mutual funds even to clients who start with well-diversified, low-fee portfolios. Our research also contributes to the literature that studies the importance of beliefs in explaining behavior in principal-agent problems. Cheng, Raina, and Xiong (2014), for example, find that mid-level managers in securitized finance held positive views about the state of the housing market

[2] See, for example, Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012), Gennaioli, Shleifer, and Vishny (2015), Hackethal, Inderst, and Meyer (2012), Mullainathan, Nöth, and Schoar (2012), Anagol, Cole, and Sarkar (2013), Christoffersen, Evans, and Musto (2013), Hoechle, Ruenzi, Schaub, and Schmid (2015), Chalmers and Reuter (2015), and Egan, Matvos, and Seru (2015).

leading up the Great Recession, and suggest that these findings highlight "the need to expand the incentives-based view of the crisis to incorporate a role for beliefs."[3]

Our setting relates to that in Levitt and Syverson (2008), who examine how real estate agents behave when they sell a client's home versus when they sell their own homes. They find that real estate agents' own homes stay on the market for longer and sell at higher prices.

The rest of the paper is organized as follows. Section 2 describes the data and the sample. Section 3 describes our measures of trading behavior and shows that advisors trade similarly to how they advise their clients. Section 4 examines investment performance and shows that advisors and clients earn comparable alphas. Section 5 explores whether advisors shape client portfolios as they do their own portfolio. Section 6 examines the correlation between client and advisor performance. Section 7 examines changes in advisors' behavior after they exit the industry. Section 8 concludes.

2 Data

We use administrative data on client investments and advisory relationships provided by three Canadian Mutual Fund Dealers (MFDs). Non-bank financial advisors of this type are the main source of financial advice in Canada—they account for \$390 billion (55%) of household assets under advice as of December 2011 (Canadian Securities Administrators 2012). The three firms for which we have data advise just under \$20 billion of assets, so represent roughly 5% of the MFD sector.

[3]Dvorak (2015) shows that advisory firms' own 401(k) plans are similar to the plans they design for their clients. The plans often have identical categories of fund families and funds—but when they differ, the funds specific to the clients' plans are more expensive. Foerster et al. (2015) show that advisors tend to override their clients' preferences and recommend that they assume the same amount of risk as they do themselves. Roth and Voskort (2014) find the same effect in an experimental setting. When experienced professionals are asked to predict the risk preferences of others, their predictions significantly correlate with their own.

Advisors within these firms are licensed to sell mutual funds and precluded from selling individual securities and derivatives. They make recommendations and execute trades on clients' behalf but cannot engage in discretionary trading.[4] They do not provide captive distribution for particular mutual fund complexes. Rather, they are free to recommend all mutual funds and the breadth of their clients' holdings reflects this freedom, as discussed below.

Each dealer provided a detailed history of client transactions as well as demographic information on clients and advisors. Both clients and advisors are tagged by unique identifiers that are derived from social insurance numbers. We use these identifiers to link advisors to their personal investment portfolio, if held at their own firm. Our ability to link advisors to their portfolios is incidental, and so advisors' actions should not depend on this aspect of the data. These portfolios would not be visible to the public, for example, and would only be visible to clients if the advisor disclosed of their own volition.

Most advisors maintain a personal portfolio at their own firm. Out of 5,917 advisors, 4,733 appear in the data also as clients. The advisors who do not have their personal portfolio at the firm are usually just starting out. For example, among the 1,131 advisors who never attract more than four clients—and typically disappear quickly—only 63% have personal portfolios at the firm. But among the 2,531 advisors who go on to advise at least 50 clients, 92% appear in the data also as clients.

We supplement these administrative data with pricing data—returns, fees and net asset values—from Fundata, Morningstar and Univeris.

[4] Under Canadian securities legislation, advisors do not have fiduciary duty, but they have a duty to make suitable investment recommendations, based on their clients' investment goals and risk tolerance. They are not required to put the client's interests before their own, but they are legally mandated to "deal fairly, honestly and in good faith with their clients" (Canadian Securities Administrators 2012).

2.1 Advisors and their clients

Table 1 provides the key summary statistics for the clients and financial advisors. The sample includes all individual accounts held at one of the three dealers between January 1999 and December 2013. The sample includes the 4,733 advisors whose personal portfolios appear in the data and the 565,780 clients who are active at some point during the 14-year sample period. The total amount of assets under advice as of June 2012 is $18.9 billion.

Among clients, men and women are equally represented, and client ages range from 32 years old at the bottom decile to 67 years old at the top decile. The typical client has one account invested in three mutual funds. The distribution of client assets is right-skewed: while the median client has CND 19,300 in assets, the average account size is CND 48,200. Advisors are slightly different from their clients. Three-quarters of advisors are men, and advisors' own account values are typically greater than those of their clients. The average advisor's account value is CND 80,100, which is nearly twice that of the average client. The majority of investors—75% of clients and 65% of advisors—have retirement plans, which receive favorable tax treatment comparable to IRA and 401K plans in the U.S. The next most common account type is the unrestricted general-purpose plan, which is held by 29% of clients and 44% of advisors. In some of our analyses, we separate retirement and general accounts because of differences in tax treatment.

The second panel shows the distributions of risk tolerance, financial knowledge, salary, and net worth for clients and advisors. Financial advisors collect this information through "Know Your Client" forms at the start of the advisor-client relationship, and they are required to file these forms also for themselves.[5] Most advisors report either moderate-to-high or high risk tolerance, whereas

[5]Foerster et al. (2015) give examples of the descriptions that accompany some of the risk-tolerance and financial-knowledge categories on the Know Your Client forms.

the average client is only moderately risk tolerant. Advisors also tend to report higher salaries and net worth than those reported by their clients. Most advisors report having high financial knowledge although, perhaps surprisingly, a handful of advisors report having "low" financial knowledge, which corresponds to a person who has "some investing experience but does not follow financial markets and does not understand the basic characteristics of various types of investments."

2.2 Investment options, fund types, and fees

The clients in the data invest in 3,023 different mutual funds. In the Morningstar data, a total of 3,764 mutual funds were available to Canadian investors at some point during the 1999–2013 sample period. Most mutual funds are offered with different load structures. The most common structures are front-end load, back-end load (or deferred-sales charge), low load, and no load. All options are available to clients, but it is the advisor who decides the fund type in consultation with the client. These vehicles differ in how costly they are to the investor, how (and when) they compensate the advisor, and how they restrict the investor's behavior. We provide an overview of fund fees and commissions below, along with more detailed discussion in Appendix A.

In measuring clients' investment performance we measure returns net of all fees paid to the mutual fund and the financial advisor. Those fees include recurring management expense charges—assessed in proportion to the investment value—deducted daily by the mutual fund company as well as transaction charges such as front-end and back-end load payments. In their own trading advisors face the same conditions and fees as non-advisors do. For example, if the advisor sells a back-end load fund too early, he incurs the same back-end load (or deferred-sales) charge as clients. Advisors do, however, benefit from serving as the agent for their own purchases—they receive commissions from the mutual fund that reduce their cost of investing. Specifically, advisors receive up-front sales commissions that act as discounts on new purchases and recurring "trailing" commissions that lower the effective management expense ratio for as long as they maintain their investments. When measuring advisors net investment performance, we account for all fees net of such "rebates".[6]

3 Trading behavior of advisors and clients

We compare investors and advisors using six summary measures of trading behavior—return chasing, preference for actively managed funds, turnover, disposition effect, home bias and growth tilt—and two measures of portfolio cost. Below, we define each measure and discuss the summary statistics reported in Table 2. We calculate these summary statistics using all trades and holdings in open accounts and retirement accounts, and, where relevant, report the estimates separately by account type. For all behaviors except turnover and disposition effect we measure the behavior using data on the flow of purchases rather than the stock of portfolio holdings.

Both clients and advisors purchase funds with better recent performance. We define **return chasing** as in Grinblatt, Keloharju, and Linnainmaa (2012), by ranking all mutual funds based on their net returns over the prior one year period and computing the average percentile rank of the funds purchased by investors. A high measure implies that investors purchase funds with high prior one-year returns. Clients purchase funds in the 60th percentile of prior year performance, on average. Advisors display slightly more return chasing, with average purchases in the 63rd percentile of prior year performance.

[6] Advisors do share their commissions with their dealer firms. A 2010 industry study of the top ten Canadian dealers reports that advisors received, on average, 78% of the commission payments (Fusion Consulting 2011). We therefore assume that advisors keep 78% of commissions in calculating their net cost of investment.

Clients and advisors are also similar in their overwhelming preference for actively managed mutual funds. We define **active management** as the fraction of (non-money market) assets invested in actively managed mutual funds. We classify as passive those funds that are identified as index funds in Morningstar or that call themselves "index fund" or "target-date fund". The average client invests almost exclusively in actively managed mutual funds, with only 1.4% allocated to passive funds. Likewise, advisors allocate only 1.1% to passive funds.

Advisors trade more actively than clients, particularly in non-retirement accounts. We define **turnover** as the market value of funds bought and sold divided by the beginning-of-the-month market value of the portfolio, as in Barber and Odean (2000). We split the sample between tax-deferred retirement accounts and general-purpose (or "open") accounts within which income and capital gains are taxed annually. Clients and advisors display similar levels of turnover in retirement accounts—annual purchases and sales for both groups comprise just under 30% of account value, on average. Advisors trade substantially more in open accounts, with average turnover of 40.5% compared to 27.5% for clients.

Clients and advisors display reverse disposition effect in their trading. We follow Odean (1998) in defining **disposition effect** as the proportion of gains realized-minus-proportion of losses (PGR-PLR). Every month an investor sells shares of at least one mutual fund, we compute the proportions of gains and losses realized using the average purchase price as the reference point. A positive value of PGR-PLR implies that investors are more likely to sell funds for which they have paper gains. As with turnover, we measure the disposition effect separately within retirement accounts and open accounts due to tax considerations. An investor who realizes capital gains outside a retirement account may face a larger tax bill if there are no offsetting capital losses, so tax considerations may dissuade positive disposition effect in open accounts. Both clients and advisors are more likely to sell mutual funds with paper losses. Although pattern is strongest for open accounts, consistent with tax-loss harvesting, it also holds for retirement accounts, for which tax considerations are moot. This reverse disposition effect in mutual fund trades is consistent with the findings of Chang, Solomon, and Westerfield (2015), who find a positive disposition effect in direct equity transactions but a reverse disposition effect in mutual fund transactions.

We next consider international diversification and find pronounced home bias among both clients and advisors. To measure **home bias** we compute the fraction of the equity holdings invested in Canadian equities. The average client invests 55% of the assets, pooled across the open and retirement accounts, in Canadian equities, while that fraction is 47% for the advisors. These proportions significantly exceed Canada's share of the global market portfolio, which is just under 4% (Pakula et al. 2014).

On the final measure of trading behavior—relative allocation to growth and value funds—we find growth tilt in both groups, with clients displaying slightly greater preference for growth than advisors. We compute **growth tilt** as the difference between the fraction of purchases that are growth funds and the fraction of purchases that are value funds. We identify growth and value funds by whether they include "growth" or "value" in their name. Growth funds, on average, represent an 11-percentage point larger share of client purchases than value funds. For advisors, growth funds likewise outweigh value funds, but with a smaller difference of 9 percentage points.

Finally, we consider the cost of funds purchased and find similar, but slightly higher, costs in advisor accounts compared to client accounts. We measure the average cost of funds purchased in two ways. The first measure is the average annualized management expense ratio (MER) of the funds purchased. The second measure is the average percentile rank of management expense ratio, computed separately within five asset classes: equities, balanced, fixed income, money market, and alternatives.[7] This measure is neutral with respect to asset allocation. A high percentile rank implies that clients hold mutual funds that are expensive compared to other funds in the same class. Both advisors and clients invest in expensive mutual funds. The average annualized MERs are 2.36% and 2.41% for clients and advisors, and the difference between the two is statistically significant. This difference also holds within asset classes: the average fund bought by a client lies in the 44th percentile while that bought by the advisor is in the 45th percentile. The difference between these ranks is statistically significant with a t-value of -6.25.

To summarize, the estimates in Table 2 show broad similarity in the trading of advisors and clients. Not only do advisors and clients display similar patterns such as return chasing and reverse disposition effect, they also invest in funds of similar cost.

4 Investment performance of advisors and clients

Table 3 summarizes the investment performance of advisors and clients. For both advisors and clients, we compute value-weighted returns, and use three alternative asset pricing models to estimate alphas. We measure both gross and net returns. In calculating net returns we consider both mutual fund expense ratios and further fees paid on transactions. These fees consist of front-end loads and deferred sales charges. When measuring advisors' net returns, we include the sales commissions and trailing commissions that mutual funds rebate to them on their personal fund pur-

[7]The category "alternatives" includes funds classified as commodity, real estate, and retail venture capital.

chases and holdings. Due to these rebates, advisors' net returns inclusive of fees and commissions are almost always higher than their returns net of mutual fund expense ratios.

The three asset pricing models are labeled I, II, and III in Table 3. Model I is the Sharpe (1964)-Lintner (1965) capital asset pricing model with the excess return on the Canadian equity market as the market factor. Model II adds the return difference between the long-term and short-term Canadian government bonds, a factor measuring the term spread in bonds. Model III adds the North American size, value, and momentum factors, and the return difference between high-yield Canadian corporate debt and investment grade debt. We include bond market factors to account for clients' and advisors' bond holdings, and the size, value, and momentum factors to adjust for any style tilts. We report the estimates for all three models to assess whether the alpha estimates are sensitive to the choice of factors.

Panel A of Table 3 reports annualized alphas and Panel B reports the factor loadings and model fits. Both clients and advisors earn gross alphas that are statistically indistinguishable from zero. In Model I, gross alpha is 32 basis points (t-value $= 0.34$) per year for clients and -72 basis points (t-value $= -0.70$) per year for advisors. The addition of the other factors in models II and III does not markedly lower the alpha estimates. Panel B shows that the full model with six factors explains 86% to 88% of the time-series variation in the value-weighted returns on the client and advisor portfolios.

The alpha on the return difference between clients and advisors, which is equivalent to taking a \$1 short position on the advisor portfolio and investing that in the client portfolio, is statistically highly significant in all three models. The alpha on this return difference is measured more precisely because the difference removes much of the time-series variation in returns. In the full model, the alpha for the difference in gross returns is 76 basis points per year (in the clients' favor), and this difference is significant with a t-value of 3.31. The factor loadings in Panel B show that advisors hold riskier portfolios than the clients. The market beta for the client-advisor return difference is -0.07 (t-value $= -11.29$), the size beta is -0.04 (t-value $= -5.05$), and the value beta is 0.05 (t-value $= 9.51$). That is, advisors take more market and small-stock risks, and tilt their portfolios towards growth stocks.[8]

Because both clients and advisors invest in funds with high management expense ratios (see Table 2), their net alphas—computed after management expense ratios but before other fees—are substantially negative. The annualized six-factor model alphas are -2.37% (t-value $= -2.61$) for clients and -3.17% (t-value $= -3.27$) for advisors. Foerster et al. (2015) discuss clients' negative net alphas and their implications for long-term wealth accumulation in detail.

The additional fees—front-end loads and deferred sales charges—reduce clients' alphas by an additional 30 basis points per year. The sales commissions rebated to advisors, net of deferred sales charges, raise advisors' net alpha by 72 basis points per year. Net of all mutual fund expenses, fees and commission rebates, then, the total performance of advisors and clients is similar. In the six-factor model, clients lag advisors by 21 basis points per year, which is less than one standard error from zero.

[8] The difference in market betas between clients and advisors is consistent with the information provided on the Know Your Client forms. Table 1 shows that the modal response to the risk-tolerance question is "moderate" for clients but "high" for advisors.

5 Explaining cross-sectional variation in client behavior with advisor fixed effects and advisor behavior

In this section we measure advisors' influence on client portfolios and explore whether advisors pursue similar trading strategies for clients as they pursue themselves. We use the return chasing behavior to introduce the methodology in detail and then present the key results for the remaining trading patterns and fee measures.

5.1 Return chasing behavior

Figure 1 demonstrates that return chasing behavior varies considerably in the cross section of clients. In this figure we plot the distribution of return chasing measures for all clients who make at least 10 purchases during the sample period. Although the mean of the distribution is positive, a non-trivial fraction of clients have estimates indicative of contrarian tendencies. The objective of the tests that follow is to investigate whether clients who share the same advisor behave similarly. That is, to understand whether the advisor's own behavior explains where his clients fall within the distribution in Figure 1.

Table 4 displays estimates from the following regression model:

$$y_{ia} = \boldsymbol{\mu}_a + \boldsymbol{\theta}\boldsymbol{X}_i + \varepsilon_{ia}, \tag{1}$$

in which the dependent variable, y_{ia}, is the average percentile rank of the funds bought by client i when advised by advisor a. The vector $\boldsymbol{X}_i$ includes investor attributes summarized in Table 1—such as risk tolerance, investment horizon, and age—as well as geographic location (province fixed effects). The advisor fixed effects $\boldsymbol{\mu}_a$ capture common variation in the return chasing behavior among clients of the same advisor. We estimate the model using OLS, with standards errors clustered by advisor to account for arbitrary correlations in errors between clients who share an advisor.

The first model reported in Table 4 excludes the advisor fixed effects to gauge the explanatory power of investor attributes alone. This model's explanatory power is modest—the adjusted R^2 is 1.0%—but some of the covariates stand out. In particular, return chasing is more common among more risk tolerant and financially knowledgeable clients who are wealthier and report short investment horizons. The second regression adds advisor fixed effects to the first one. These fixed effects increase the model's explanatory power substantially, to 17.6%. The estimates indicate that clients who share the same advisor chase returns to a similar extent; some advisors' clients follow momentum strategies while others' clients follow contrarian strategies.

The significance of the advisor fixed effects in Table 4 could emanate from endogenous matching between advisors and clients. An investor who is predisposed to chase returns may seek an advisor who recommends such trades to all his clients. In that case, the advisor fixed effects may overstate the common input of the advisor—some of the common trading among clients may reflect trades that clients initiate themselves. Although the regressions control for many demographics that plausibly relate to the advisor-client matching, such as gender, age, and income, it is possible that advisors and clients also match with each other in some other dimension that also correlates with return chasing.

We use a two-way fixed effects approach to address this issue. In this analysis, we limit the sample to clients whose advisor dies, retires, or leaves the industry. We identify a client as having been displaced if the advisor goes from having at least ten clients to quitting within six months. By limiting the sample to clients who are advised by two advisors, we can simultaneously include both client and advisor fixed effects. The inclusion of client fixed effects flexibly controls for any observed and unobserved client-level heterogeneity. The estimates in Panel A of Table 5 show that advisors significantly influence client behavior. The regression with just client fixed effects has an adjusted R^2 of 7.5%; that with just advisor fixed effects has an adjusted R^2 of 19.8%; and the model with both client and advisor fixed effects has an adjusted R^2 of 27.1%. The F-tests at the bottom of the table indicate that both client and advisor fixed effects in the last of these regressions are statistically highly significant.

Panel B of Table 5 uses the same sample of displaced clients to estimate how a client's return chasing behavior changes when he moves from the old advisor to the new advisor. For each investor i, we measure the return chasing behavior for investments made with the old advisor (Return chasing$^{\text{pre}}_{i,a_1}$) and the new advisor (Return chasing$^{\text{post}}_{i,a_2}$). We also measure the average return chasing behavior of each advisor's other clients (excluding investor i) during the period before the old advisor stops advising clients (Return chasing$^{\text{pre}}_{-i,a_1}$ and Return chasing$^{\text{pre}}_{-i,a_2}$). We run the following cross-sectional regression:

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

This regression measures the extent to which the displaced clients' return chasing behavior converges towards that of the new advisor. The slope estimate on the new-minus-old advisor variable is 0.30, and this estimate is statistically significant with a t-value of 11.64. This estimate indicates that a client's behavior "converges" from the pre-switch behavior of the old advisor substantially towards the pre-switch behavior of the new advisor. This estimate is consistent with the two-way fixed effect estimates of Panel A. It suggests that advisors significantly influence clients' return chasing behavior.

5.2 Other trading patterns

We repeat the analysis of Section 5.1 for each measure of trading behavior and the two fee measures. After first estimating regressions of trading behavior on client attributes and advisor fixed effects, we then estimate a model with investor fixed effects in the subsample of displaced clients. Because the differences between open accounts and retirement accounts in Table 2 are relatively modest for turnover, disposition effect, and home bias, we henceforth pool these accounts when measuring behavior.

The estimates in Panel A of Table 6 show that, in most cases, the inclusion of advisor fixed effects yields a significant boost to the model's explanatory power. In the active-management regressions, for example, the client attributes explain just 0.8% of the variation in the use of passive investment vehicles. With the advisor fixed effects added into this regression, the model's explanatory power increases 18.3%.

The other columns in Panel A use displaced clients to estimate models with client fixed effects, advisor fixed effects, and both. Similar to the return-chasing regressions presented in Table 5, advisor fixed effects often increase the model's explanatory power significantly. In all six behavior regressions and two fee regressions, F-tests (not reported) reject the null that the advisor fixed effects in the full model with both sets of fixed effects are jointly zero. In the active management regression, for example, investor fixed effects alone yield a negative adjusted R^2 because the reduction in the degrees of freedom more than offsets the amount of variation they resolve.

Panel B of Table 6 reports estimates from displacement regressions similar to those reported for return chasing behavior in Table 5. The estimated slope coefficient is statistically significant for five measures of behavior and the relative fee measure; it is statistically insignificant for the disposition effect and management expense ratio. Both Panels A and B suggest that advisors have more influence over some decisions—in particular, return chasing, active management, growth tilt, and relative fees—than over others, such as disposition effect.

5.3 Explaining advisor fixed effects with advisors' own investment behavior

Table 7 reports estimates from regression of advisor fixed effects on advisor attributes and advisor behavior. The dependent variables are the estimated fixed effects from the client attributes-plus-advisor fixed effects regressions reported in Panel A of Table 6. Because of the inclusion of the client attributes, these estimated fixed effects are orthogonal to the client attributes, and so advisor attributes cannot correlate with these estimates because of client-advisor matching in observable dimensions. The key explanatory variable is the advisor's own behavior. The regression reported in the first column, for example, explains variation in the advisor fixed effects estimated from the return chasing regression with the return chasing behavior measured in the advisor's personal portfolio. We report univariate regressions with advisor behavior, as well as multivariate regressions that control for advisor attributes.

The estimates in Table 7 indicate that, in most cases, advisor's personal investment behavior correlates closely with that of his clients. In the univariate return chasing regression, for example, the slope estimate for the advisor-behavior variable is 0.22 (t-value = 13.98). This estimate indicates that if an advisor chases returns, he is more likely to advise clients who also engage in return chasing behavior—or, adopting a causal interpretation based on the displacement regressions, they are more likely to advise clients to chase returns. The slope estimates, which are approximately equal to correlations or partial correlations, range from a low of 0.09 (for disposition effect) to a high of 0.35 (for home bias), indicating some variation in which dimensions advisor behavior most closely tracks that of his clients. Advisor attributes, by contrast, do not correlate meaningfully with advisor fixed effects. The adjusted R^2 measures increase only modestly when we add the advisor attributes to the regression.

5.4 Similarity in fund purchases and timing between advisors and clients

The estimates in Table 7 suggest that an advisor's personal beliefs may be an important reason why his clients trade differently from those of other advisors. That is, clients may chase returns because the advisor advises them to do so, and he advises them to do so because he personally follows the same investment strategy.

The connection between the advisor and client behavior is even closer than what the estimates in Table 7 suggest. Advisors often personally purchase the very same funds that they recommend to their clients. That is, advisors not only condition their trades on, e.g., past returns the same way as when making recommendations; rather, they often invest in the same funds as their clients at the same time.

We measure the similarity in purchase behavior in Figure 2 as follows. First, we identify all events in which an advisor purchases a new mutual fund. By focusing on new funds, we drop all reinvestments, including those made through automatic savings plans. Second, we estimate the probability that at least one of the advisor's clients buys the same fund the same month or in the two-year window around this month. Similar to the advisor, we identify purchases in which the client also purchases the fund for the first time.

The black line in Figure 2 indicates the estimates from month $t-12$ to month $t+12$, where month t is the advisor's purchase month. Panel A uses data on all fund purchases by advisors; in Panel B, we restrict the sample to purchases made by advisors who advise at most ten clients at the time of the purchase. The dashed lines denote 95% confidence intervals. We compute these intervals by clustering the data at the advisor level. Panels A and B show a significant spike in month t, indicating that when an advisor invests in a new fund, often at least one of his clients purchases the very same fund the same month. In Panel A the estimated probability that one of the clients purchases the same fund in the same month as the advisor is 0.39. In addition to the contemporaneous spike in purchases, there is also elevated probability of client purchases in the month before and two months after the advisor's purchase. The estimates in Panel B suggest that advisors with hundreds of clients do not drive these results. When we constrain the sample to advisors with at most ten clients, the estimated proportions are approximately the same what they are in Panel A.

The universe of mutual funds is very large—over 3,000 as discussed in Section 2.2—and so the patterns in Figure 2 are unlikely to emerge because advisors and clients invest in the same funds just by luck. Nevertheless, we implement a bootstrapping procedure to estimate the purchase probabilities under the null hypothesis that advisors' investment decisions are unrelated to those of their clients. Figure 2 shows these estimates using the red lines. We compute these probabilities by randomly matching, with replacement, a purchase of advisor a in month t against the same-month purchase of another advisor $a' \neq a$. We then compute the probability that at least one of the clients of advisor a' purchases the same fund as that purchased by advisor a. We repeat this procedure 100 times to compute the confidence intervals for the resulting probability estimates. In both Panels A and B, the estimated probability of an advisor and the client of a randomly matched advisor buying the same fund is between 0.02 and 0.04. These co-purchase probabilities are significantly lower than those between advisors and their actual clients.

6 Correlation between client and advisor performance

The fee estimates in Table 6 indicate that advisors who choose expensive mutual funds themselves tend to have clients who do the same. If advisors recommend their clients the same investments as they hold personally, then client and advisor performance will correlate in the cross section because of differences in fees and performance on the mutual funds. Advisors who pay high fees will underperform those who pay low fees, and the same will be true for their clients; and advisors whose mutual fund investments perform relatively poorly *in sample* will have clients whose returns fall short of those earned by others.

Panel A of Figure 3 plots the association in fees between advisors and clients by sorting advisors into deciles based on the average fees that they personally pay on their investments during the sample period. These fees consist of management expense ratios and deferred sales charges. We then compute the average fee paid by the clients of the advisors within each decile. In this computation, we first compute advisor-level measures of client fees—that is, we compute one average per advisor—and then take the average over the advisors. This methodology gives equal weight to all advisors within each decile independent of the number of clients they advise.

Client fees increase significantly with advisors' personal fees. Moving from the bottom decile to the top decile corresponds to an increase of 36 basis points in annualized fees. The standard deviation of fees in the cross section of clients is 76 basis points. This comparison indicates that an indirect sort on *advisor* fees generates considerable amount of dispersion in client fees.

Panels B and C of Figure 3 examine the association between client alphas and advisor fees or alphas. We construct this graph as follows. First, we estimate each advisor's gross and net alphas using a two-factor model that includes the market and term factors. We then sort advisors into deciles based on these estimated alphas, and form a time-series of client returns within each decile by taking the cross-sectional average of that month's advisor-level client return. Similar to the fee computation, we give each advisor the same weight. We normalize monthly decile returns by subtracting the average return across the deciles, and run the two-factor asset pricing regression using these normalized returns. That is, the regression we estimate is

$$r_{d,t} - \bar{r}_t = \alpha_d + \beta_{d,\mathrm{mkt}}\mathrm{MKTRF}_t + \beta_{\mathrm{term}}\mathrm{TERM}_t + e_{d,t}, \tag{3}$$

where $r_{d,t}$ is decile d's month t return and $\bar{r}_t = (1/10)\sum_{d=1}^{10} r_{d,t}$. We also estimate this regression with $\bar{r}_t - r_{f,t}$ as the dependent variable, where $r_{f,t}$ is the riskless rate, and we denote this regression's alpha with $\bar{\alpha}$. This normalization strategy gives more precise estimates for comparing performance across deciles; it removes the time-series variation in returns that is common to all clients. In Panel B of Figure 3, we plot $\hat{\alpha}_d + \hat{\bar{\alpha}}$ to restore the level of alphas, but we take the standard errors from the normalized regressions, thereby showing only the across-advisors estimation uncertainty. In terms of Panels B and C of Figure 3, the estimation uncertainty that our procedure removes is about the level of the alpha curve, which we set equal to its point estimate.[9]

[9]Because we take out the time-series variation in returns that is shared by all clients, the standard errors that we report are appropriate for comparing alpha estimates across deciles. They are not the correct standard errors for tests concerning the *level* of alphas, such as for a test of whether decile d's alpha is significantly different from zero. The estimates reported in Table 3 are appropriate for the latter test.

Panel B of Figure 3 shows that client net alphas decrease significantly in advisor fees. Likewise, Panel C shows clients' gross and net alphas increase significantly in advisor alphas. Moving from the bottom decile to the top decile, the point estimate for the gross alpha increases by 1.17% per year and the net alpha estimate increases by 1.21%. The positive association between client and advisor performance in Figure 3 is thereby consistent with advisors and clients following similar trading rules, investing in similar—and sometimes the same—funds, and paying similar amounts in fees for their holdings.

Table 8 reports cross-sectional Spearman rank correlations between advisors' alphas and fees and those of their clients. We estimate gross and net alphas for each advisor and his clients and then compute the cross-sectional correlation in these estimates. We compute the standard errors by block bootstrapping the data by calendar month 100 times. In each iteration, we resample calendar months with replacement, recompute alphas and average fees, and obtain a new set of estimates for the correlations. The correlations range between 0.26 and 0.31, and they are not sensitive to the choice of returns (gross or net) or the asset pricing model. The estimates in Table 8 are consistent with the positive association apparent in Figure 3.

An alternative method for assessing the return correlation between advisors and clients is to estimate a panel regression of client net returns on advisor net returns with month fixed effects,

$$r_{a,t}^{\text{client}} - r_{f,t} = \boldsymbol{\mu}_t + \beta(r_{a,t}^{\text{advisor}} - r_{f,t}) + \varepsilon_{a,t}, \tag{4}$$

where $r_{a,t}^{\text{advisor}}$ is the return on the advisor a's personal portfolio, $r_{a,t}^{\text{client}}$ is the return on the value-weighed portfolio of advisor a's clients, and $\boldsymbol{\mu}_t$ are the month fixed effects. The month fixed effects subsume all common shocks in the time series. That is, β measures the marginal correlation in client and advisor returns when holding constant market-wide movements. The estimate of β from equation (4) is 0.171, which is statistically significant with a t-value of 41.8 when we cluster standard errors by month. This estimate indicates that if an advisor's portfolio earns an "idiosyncratic" return of 10% (that is, a return unrelated to market-wide shocks subsumed by the month fixed effects), the average return on the client portfolio is 2%.

7 Do advisors trade contrary to their beliefs?

7.1 Post-career advisors

Advisors may trade contrary to their personal beliefs for two reasons. First, even though clients cannot observe advisors' personal portfolios, advisors could in principle voluntarily disclose this information to gain their clients' trust. For example, if an advisor personally invests in expensive actively managed funds, the client can perhaps be convinced to do the same. Although advisors could lie about their own investments, doing so might generate legal liabilities. Second, an advisor might suffer from cognitive dissonance if he advises his clients to invest differently than he invests himself.[10] In both explanations, the advisor behaves in a certain way because of the advisor-client relationships. We can therefore test these explanations by measuring how advisors behave after they stop advising clients. A change in advisor behavior after an exit from the industry would therefore suggest that advisors may alter their own trading behavior because of their clients.

Table 9 presents estimates of advisor behavior before and after advisors exit the industry. The change in behavior is a pairwise t-test, comparing the behavior of the same advisor before and after

[10]These mechanisms resemble the window-dressing literature in the asset management literature. Lakonishok, Shleifer, Thaler, and Vishny (1991) and Sias and Starks (1997) show that pension fund and mutual fund managers sell underperforming stocks from their portfolios towards the end of the quarter to create an impression that they are holding better stocks than what their past returns may suggest.

he leaves the industry. The estimates suggest that active advisors' personal investment behavior is probably not significantly affected by the presence of their clients. Among the six measures of behavior, only the reduction in return chasing behavior is statistically significant at the 5% level, and the decrease in turnover is significant at the 10% level. Advisors' annualized management expense ratios decrease by 13 basis points (t-value $= -5.27$) after they leave the industry, but this change relates to changes in asset allocation—the within-asset class fee measure remains nearly unchanged (t-value $= -1.15$) around the 44th percentile. Advisors' preference for expensive mutual funds is thus not specific to the time they advise clients—they maintain this preference even after there is no need to keep up the appearances.

7.2 Hypothetical investment performance of advisors: What if advisors held perfect copies of their clients' portfolios?

In addition to examining changes in advisor behavior after departures from the industry, we can compute hypothetical advisor returns to assess the plausibility of advisors holding portfolios that are contrary to their beliefs. If advisors make poor investments only to convince their clients to do the same, the "optimal" portfolio for them to hold is that of their clients. That is, if an advisor wants to use his own portfolio to convince his clients to invest in funds A and B, the best way to do so would be to invest personally in funds A and B in the desired proportions.

In Table 10, we measure the extent to which advisors enhance or hurt their investment returns by deviating from the portfolio held by their clients. We first report alphas based on advisors' actual portfolios and trades. We compute net returns after all fees and rebates on this portfolio. The six-factor model alpha for this return series is -2.46% per year (t-value of -2.53), as reported in Table 3.

We next report alphas for a hypothetical portfolio that the advisors could have held instead. This computation replaces the advisor's personal portfolio with the value-weighted portfolio of his clients. To make this return series comparable with the actual return series, we assume that the advisor would have paid the same deferred sales charges as those paid by his clients, and we credit the advisor with the sales and trailing commissions generated by this client portfolio. The six-factor model alpha for this hypothetical "perfect-copy" portfolio is -1.32% per year, and this estimate has a t-value of -1.45. This estimate is higher than the net alpha with fees estimate of -2.67% for the clients reported in Table 3 because of the sales commissions and trailing commissions that advisors would earn by serving as agent for their own purchases and holdings.

The bottom part of Table 10 measures how much advisors' alphas would change if they shifted to holding perfect copies of their clients' portfolios. In the six-factor model, the annual 1.1% increase has a t-value of 4.93. This estimate is not sensitive to the choice of the asset pricing model; the alpha estimates for the return difference range from 1.1% to 1.4% across the three models.

These estimates suggest that advisors probably do not use their personal investments to convince their clients to hold particular funds. Under this explanation, we would expect that component of the advisor's portfolio that does not overlap with the client portfolio to outperform the overlapping part. In the data, however, this non-overlapping portfolio performs significantly worse than the client portfolio. Advisors could significantly improve their performance by holding the same portfolios as those held by their clients.

8 Conclusions

Many households turn to financial advisors for guidance, and the advice they get may be of low quality. Mullainathan, Nöth, and Schoar (2012), for example, find that advisors recommend investments and trades that are contrary to the academic view that passive investment vehicles are the optimal choice for uninformed investors. Chalmers and Reuter (2015) estimate that the participants in the Oregon University System's Optional Retirement Plan would have been better off without financial advisors. A concern highlighted in these studies and in policy debates is that advisors sometimes lack fiduciary duty and receive commission-based compensation that creates a conflict of interest between advisors and their clients. Advisors may benefit from recommending expensive investments that are ill-suited for their clients when such investments pay high commissions.

Our results, however, indicate that many advisors invest personally just as they advise clients, even in the presence of a commission-based compensation scheme that creates bad incentives. Our findings do not reject the conclusions drawn in the studies referenced above, but instead provide further insight into the underlying causes of low-quality advice: advisors sincerely, but mistakenly, believe that their recommendations will outperform alternatives.

Our results are relevant both to policymakers and to financial advisory firms seeking to improve the quality of their product. Regulations that attempt to eliminate conflicts of interest—e.g., imposing fiduciary duty or eliminating commission-based compensation—may be worthwhile, but they will not resolve the problem of advisors' misguided beliefs. Our findings suggest that advisors would still recommend expensive, actively managed mutual funds to their clients. If advisors' misguided beliefs are to blame for bad advice, then the solution may involve better disclosure or correcting advisors' misguided beliefs through screening or education. Changing advisors' views about active management may, however, be difficult. Advisors are not random draws from the population. Those who believe that active management does not add value are probably less likely to pursue a career in the financial advisory industry; and those who believe the opposite may be drawn in. If so, financial advisors may pursue their vocation in part *because* of their misguided beliefs.

A Appendix

The differences in mutual fund fee structures are relevant for advisors' and clients' incentives, and we therefore briefly describe them. Every fund purchase by a client involves four parties: the client, the advisor, the mutual fund company, and the advisor's dealer firm. Mutual fund transactions can generate five types of payments:

1. **Front-end load** is a direct payment from the client to the advisor at the time of a purchase of a front-end load fund. The minimum and maximum front-end loads are set by the mutual fund company, but the mutual fund company does not receive any of this payment.

2. **Sales commission** is a payment from the mutual fund company to the advisor at the time of a purchase of a back-end load fund. The typical sales commission is 5% of the value of the purchase.

3. **Deferred sales charge** is a payment from the client to the mutual fund company at the time the client redeems his shares in a back-end load fund. The deferred sales charge typically starts at the same level as the sales commission, but the penalty is amortized: it is typically 5% of the value of the investment if the fund is sold in the first year, 6/7th of 5% if sold in the second year, continuing to decrease to 1/7th of 5% if sold in year seven. The seven-year mark for the expiration of deferred sales charge schedule is the most common, followed by eight-year schedules. Additionally, some mutual funds free 10% of the shares each year, which means that the client can sell a fraction of the shares each year without incurring a penalty.

The deferred sales charge is based either on the value of the initial purchase or the value of the shares at the time of the redemption.[11]

4. **Trailing commission** is a recurring payment from the mutual fund company to the advisor. The fund pays the trailing commission for as long as the client remains invested in the fund. Trailing commissions of 0.25% to 1% per year are standard on all funds sold by advisors.

5. **Management expense ratio** is a recurring payment from the client to the mutual fund company. These expenses are subtracted daily from the fund's net asset value.

6. **Administrative fee** is a recurring payment from the client to the mutual fund company. Some mutual funds charge this fee for shares held in retirement accounts.

These payments vary across load structures, and the load structures differ in how they restrict client behavior by imposing costs:

1. **Front-end load fund.** The advisor and client negotiate the front-end load, and the investor is free to sell the mutual fund at any time without any additional cost. The trailing commission associated with this option is typically the highest because the mutual fund company does not pay an upfront sales commission to the advisor.

2. **Back-end load fund.** The client makes no payment to the advisor at the time of the purchase, but the mutual fund company pays the advisor a sales commissions. If the client sells the mutual fund "too soon," he incurs a deferred sales charge. Back-end load funds

[11] Some mutual fund families let clients "switch" from one fund to another in the same family without triggering the deferred sales charge. The client is typically charged a 2% switching fee for this service. When we measure performance, we combine these switching fees with deferred sales charges. Similarly, some mutual funds, regardless of their type, impose restrictions on short-term trading. In the typical arrangement, a client has to pay a 2% short-term trading fee if he sells the fund within a month of the purchase. We combine also these penalties with deferred sales charges when measuring performance.

also often release 10% of the shares each year so that the client can sell these shares without incurring a sales charge. The trailing commission associated with this option is typically low because of the upfront sales commission.

3. **Low-load fund.** These investments are similar to back-end load funds, except that the sales commission is smaller and the deferred sales charge schedule shorter.

4. **No-load fund.** The client makes no payment to the advisor at the time of the purchase, and the mutual fund company does not pay the advisor a sales commission. The trailing commission is often also 0%.

In every option, the client pays the mutual fund company the management expense ratio. Advisors share their commissions with their dealer firms. A 2010 industry study of the top ten Canadian dealers reports that advisors received, on average, 78% of the commission payments (Fusion Consulting 2011).

REFERENCES

Anagol, S., S. Cole, and S. Sarkar (2013). Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market. Harvard Business School working paper No. 12-055.

Barber, B. M. and T. Odean (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance 55*(2), 773–806.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Betermier, S., L. E. Calvet, and P. Sodini (2015). Who are the value and growth investors? HEC Paris working paper.

Bhattacharya, U., A. Hackethal, S. Kaesler, B. Loos, and S. Meyer (2012). Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Review of Financial Studies 25*(4), 975–1032.

Canadian Securities Administrators (2012). Mutual fund fees. Discussion paper and request for comment 81-407.

Chalmers, J. and J. Reuter (2015). Is conflicted investment advice better than no advice? Working paper.

Chang, T. Y., D. H. Solomon, and M. M. Westerfield (2015). Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *Journal of Finance*. Forthcoming.

Cheng, I., S. Raina, and W. Xiong (2014). Wall street and the housing bubble. *American Economic Review 104*(9), 2797–2829.

Christoffersen, S. E. K., R. Evans, and D. K. Musto (2013). What do consumers' fund flows maximize? Evidence from their brokers' incentives. *Journal of Finance 68*(1), 201–235.

Coval, J. D. and T. J. Moskowitz (1999). Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance 54*(6), 2045–2073.

Cronqvist, H., S. Siegel, and F. Yu (2015). Value versus growth investing: Why do different investors have different styles? *Journal of Financial Economics 117*(2), 333–349.

Dhar, R. and N. Zhu (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science 52*(5), 726–740.

Dvorak, T. (2015). Do 401k plan advisors take their own advice? *Journal of Pension Economics and Finance 14*(1), 55–75.

Egan, M., G. Matvos, and A. Seru (2015). The market for financial adviser misconduct. University of Chicago working paper.

Feng, L. and M. Seasholes (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance 9*(3), 305–351.

Foerster, S., J. T. Linnainmaa, B. T. Melzer, and A. Previtero (2015). Retail financial advice: Does one size fit all? *Journal of Finance*. Forthcoming.

French, K. R. (2008). Presidential address: The cost of active investing. *Journal of Finance 63*(4), 1537–1573.

French, K. R. and J. Poterba (1991). Investor diversification and international equity markets. *American Economic Review 81*(2), 222–226.

Fusion Consulting (2011). State of the industry.

Gennaioli, N., A. Shleifer, and R. Vishny (2015). Money doctors. *Journal of Finance 70*(1), 91–114.

Grinblatt, M. and M. Keloharju (2001a). How distance, language, and culture influence stockholdings and trades. *Journal of Finance 56*(3), 1053–1073.

Grinblatt, M. and M. Keloharju (2001b). What makes investors trade? *Journal of Finance 56*(2), 589–616.

Grinblatt, M. and M. Keloharju (2009). Sensation seeking, overconfidence, and trading activity. *Journal of Finance 64*(2), 549–578.

Grinblatt, M., M. Keloharju, and J. Linnainmaa (2011). IQ and stock market participation. *Journal of Finance 66*(6), 2121–2164.

Grinblatt, M., M. Keloharju, and J. Linnainmaa (2012). IQ, trading behavior, and performance. *Journal of Financial Economics 104*(2), 339–362.

Hackethal, A., R. Inderst, and S. Meyer (2012). Trading on advice. CEPR Discussion Paper 8091.

Hoechle, D., S. Ruenzi, N. Schaub, and M. Schmid (2015). Financial advice and bank profits. Swiss Institute of Banking and Finance Working paper.

Kaniel, R., G. Saar, and S. Titman (2008). Individual investor trading and stock returns. *Journal of Finance 63*(1), 273–310.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishny (1991). Window dressing by pension fund managers. *American Economic Review 81*(2), 227–231.

Levitt, S. D. and C. Syverson (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *Review of Economics and Statistics 90*(4), 599–611.

Linnainmaa, J. (2010). Do limit orders alter inferences about investor behavior and performance? *Journal of Finance 65*(4), 1473–1506.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics 47*(1), 13–37.

Mullainathan, S., M. Nöth, and A. Schoar (2012). The market for financial advice: An audit study. NBER Working Paper No. 17929.

Nofsinger, J. R. and R. W. Sias (1999). Herding and feedback trading by institutional and individual investors. *Journal of Finance 54*(6), 2263–2295.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance 53*(5), 1775–1798.

Odean, T. (1999). Do investors trade too much? *American Economic Review 89*(5), 1279–1298.

Pakula, D. C., D. J. Walker, D. T. Kwon, P. M. Bosse, V. Maciulis, and C. B. Philips (2014). Global equities: Balancing home bias and diversification—a Canadian investor's perspective. Vanguard reseach.

Roth, B. and A. Voskort (2014). Stereotypes and false consensus: How financial professionals predict risk preferences. *Journal of Economic Behavior and Organization 107*(Part B), 553–565.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19*(3), 425–442.

Shefrin, H. and M. Statman (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance 40*(3), 777–790.

Sias, R. W. and L. T. Starks (1997). Institutions and individuals at the turn-of-the-year. *Journal of Finance 52*(4), 1543–1562.

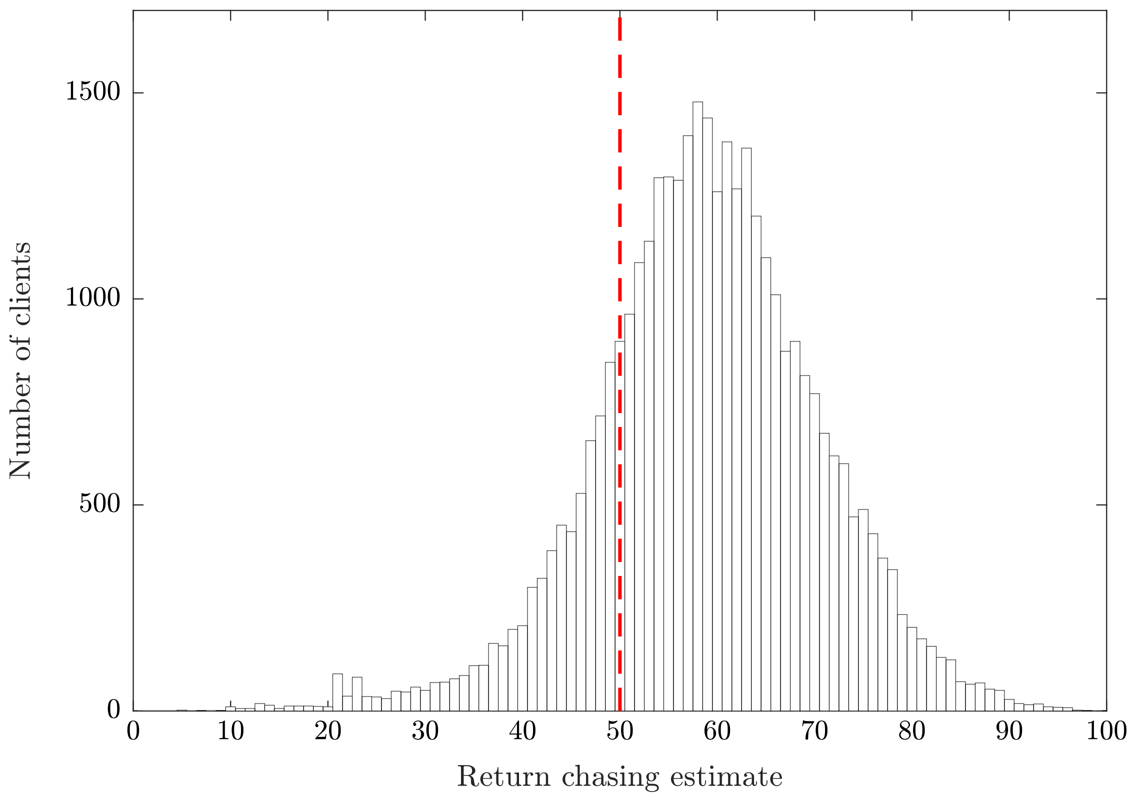


Figure 1: **Distribution of client-level measures of return chasing.** We measure return chasing by computing the average percentile return rank of mutual funds bought. This figure shows the distribution of these client-level return chasing measures for all clients with at least 10 mutual fund purchases during the sample period.

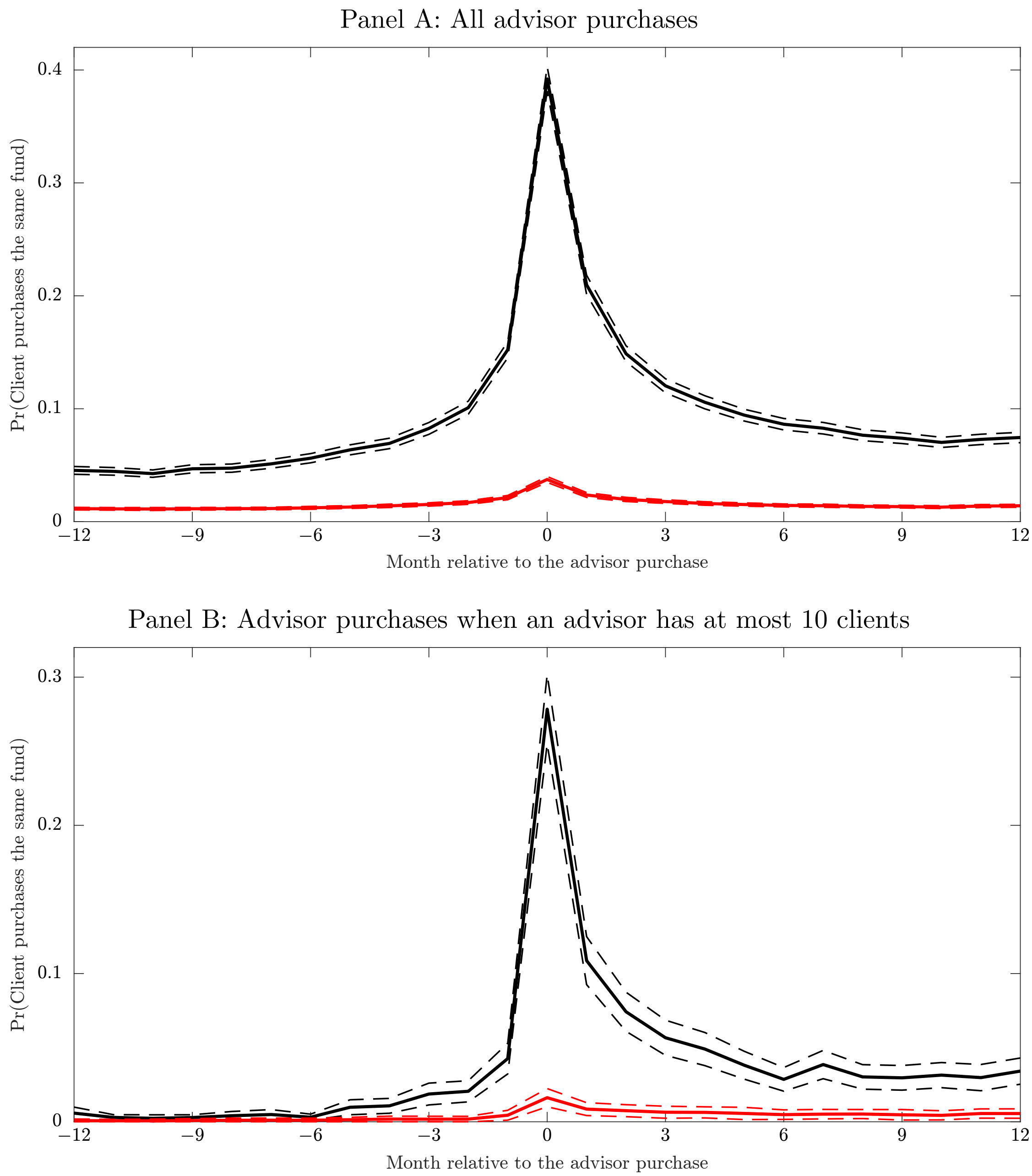
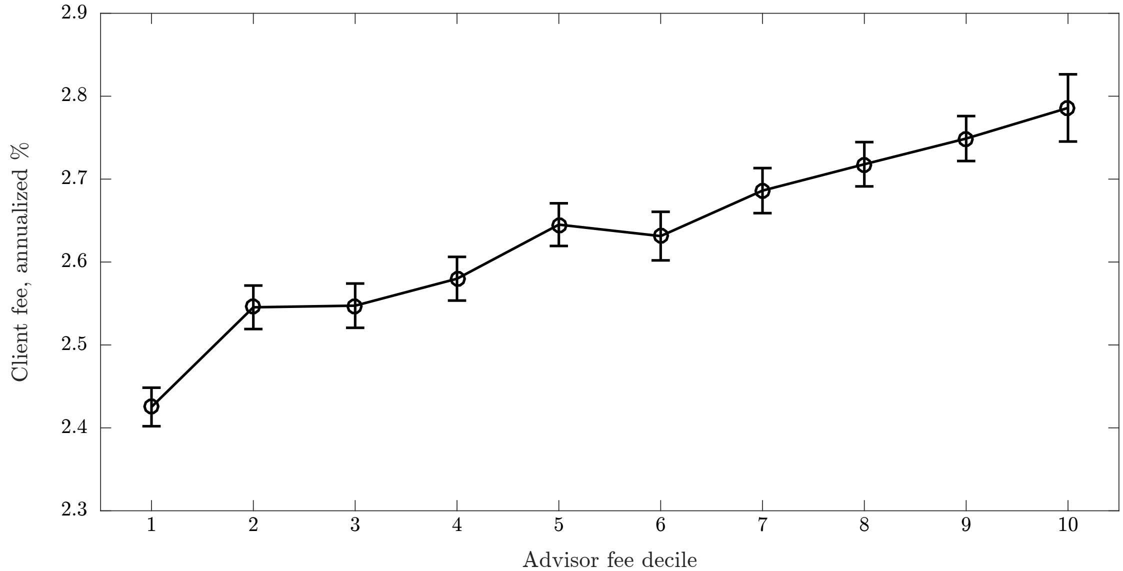
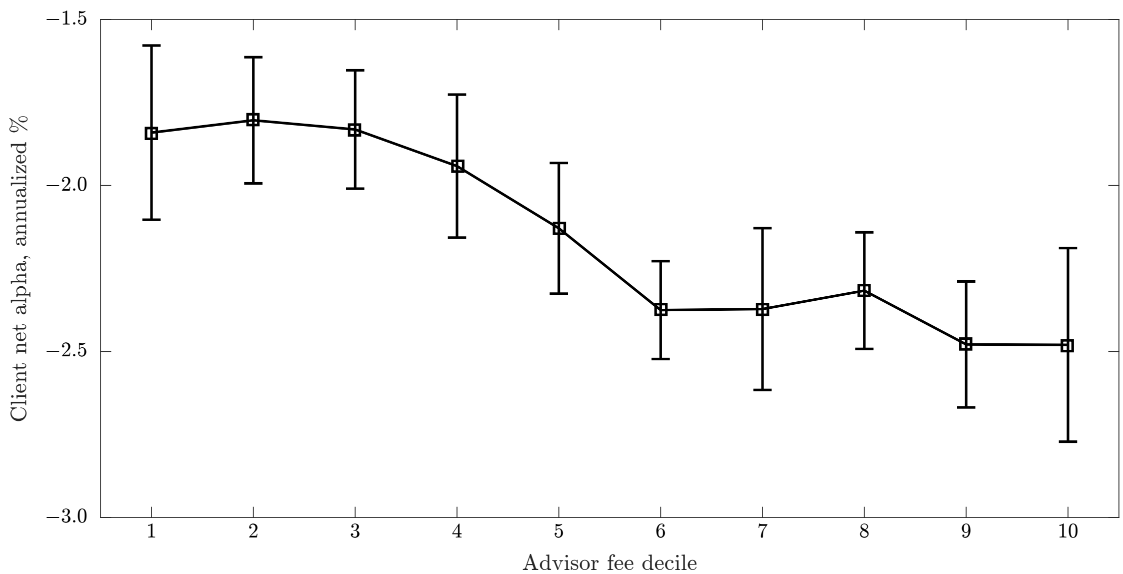


Figure 2: **Similarity in fund purchases and timing between advisors and their clients.** We identify personal purchases of new funds by advisors and measure the probability that at least one of the advisor's clients purchases the same fund for the first time during a two-year period surrounding the month of the advisor's purchase. Panel A includes all purchases; Panel B restricts the sample to purchases made by advisors who have at most 10 clients at the time of the purchase. The black lines indicate the actual purchase probabilities by the clients and the 95% confidence intervals associated with these probabilities. The red lines indicate purchase probabilities simulated under the null hypothesis that advisors' purchases are independent of those of their clients. We resample the data 100 times with replacement and randomly match an advisor with another advisor (and his clients) who also purchases a new fund in the same month.

Panel A: Client fees conditional on advisor fees



Panel B: Client net alpha conditional on advisor fees



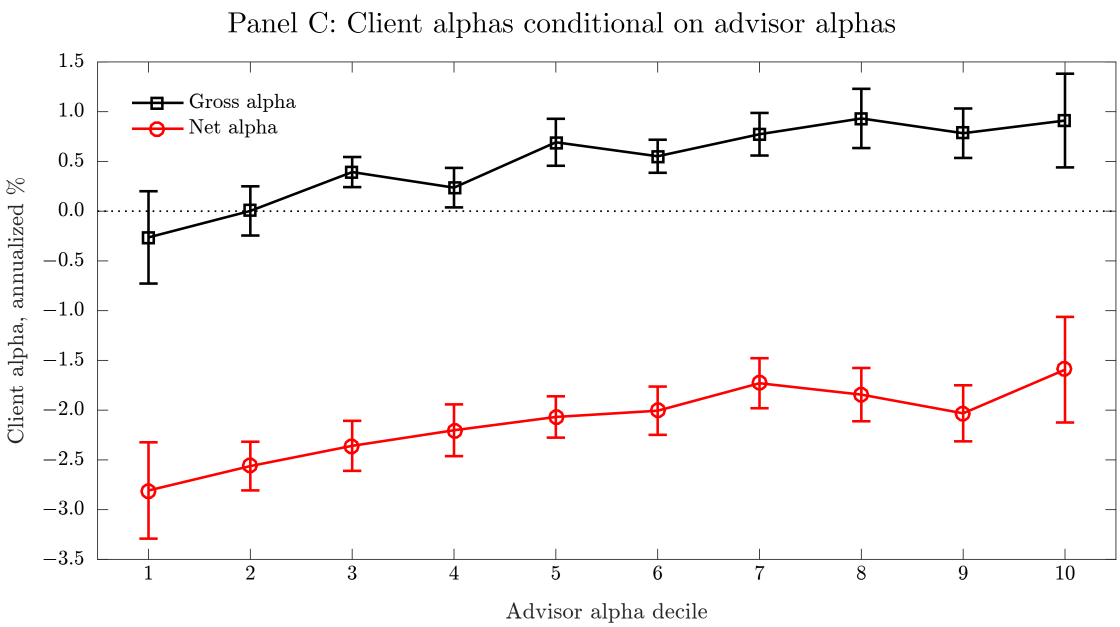


Figure 3: **Client performance conditional on advisor performance.** This figure sorts advisors into deciles based on their personal fees (Panels A and B) and alphas (Panel C) and reports the average fees and alphas of the clients of these advisors. The fees consist of management expense ratios, front-end loads, and deferred sales charges. The alphas in Panels B and C are estimated using a two-factor model with the market (equity) and term (fixed income) factors. We compute the 95% confidence intervals after removing the variation in the time series of fees and returns that is shared by all clients; see the text for details.

Table 1: Descriptive statistics from dealer data

This table reports demographics and portfolio information for clients and financial advisors, and client information for financial advisors. "Account age (years)" is the number of years an investor's account has been open. "Experience" is the number of years since the advisor obtained a license or, if not available, the number of years after becoming an advisor in the dealer data. "Risky share" is the fraction of assets invested in equities. In computing the risky share, we assume that balanced funds invest 50% in equities. In Panel A, we first compute the distributions for each calendar month and then average these distributions over time. Time horizon, risk tolerance, financial knowledge, income, and net worth information, reported in Panel B, is collected on the "Know-Your-Client" forms.

Panel A: Demographics, portfolio characteristics, and client accounts

		Percentiles				
Variable	Mean	10th	25th	50th	75th	90th
				Clients (N = 565,780)		
Demographics						
Female (%)	51.6					
Age	49.2	32.0	39.6	48.4	58.1	67.3
Investment portfolio						
Account age (years)	4.5	0.8	2.2	4.4	6.6	7.8
Number of plans	1.7	1.0	1.0	1.0	2.0	3.0
Number of funds	4.1	1.0	1.5	2.8	5.5	9.1
Account value, $K	48.2	1.7	5.8	19.3	54.8	120.1
Risky share (%)	74.1	46.8	57.2	78.3	98.1	100.0
				Financial advisors (N = 4,733)		
Demographics						
Female (%)	27.5					
Age	48.2	35.2	40.9	47.9	55.6	61.9
Investment portfolio						
Account age (years)	4.8	0.9	2.4	4.6	7.1	8.3
Number of plans	2.4	1.0	1.0	1.8	2.9	4.9
Number of funds	6.4	1.0	1.9	4.2	9.0	14.7
Account value, $K	80.0	1.5	6.6	28.3	90.7	200.7
Risky share (%)	81.2	49.2	69.9	91.2	100.0	100.0
Client accounts						
Experience	5.5	1.8	3.7	6.4	7.0	7.0
Number of clients	98.4	1.9	8.5	43.5	133.8	265.6
Client assets, $ thousands	4,889.1	53.2	292.2	1,514.3	5,765.2	14,210.5

Panel B: Account and client characteristics

Account types	Clients	Advisors	Time horizon	Clients	Advisors
General	28.8%	44.3%	1–3 years	2.6%	2.6%
Retirement	75.4%	64.9%	4–5 years	8.7%	6.5%
Education savings	8.3%	17.8%	6–9 years	70.2%	68.9%
Tax-free	3.7%	5.3%	10+ years	18.4%	21.9%
Other	0.5%	0.0%			

Risk tolerance	Clients	Advisors	Salary	Clients	Advisors
Very low	4.2%	1.0%	$30–50k	35.5%	15.9%
Low	4.3%	2.7%	$50–70k	34.3%	25.2%
Low to Moderate	8.5%	3.1%	$70–100k	16.8%	20.1%
Moderate	51.5%	30.1%	$100–200k	13.0%	36.5%
Moderate to High	19.7%	20.7%	$200–300k	0.2%	1.5%
High	11.9%	42.3%	Over $300k	0.3%	0.9%

Financial knowledge	Clients	Advisors	Net worth	Clients	Advisors
Low	41.0%	2.1%	Under $35k	3.5%	1.1%
Moderate	53.7%	16.4%	$35–60k	6.0%	2.4%
High	5.3%	81.4%	$60–100k	8.9%	6.0%
			$100–200k	17.5%	11.1%
			Over $200k	64.1%	79.4%

Table 2: Measures of trading behavior: Clients versus advisors

This table reports estimates of how clients and advisors trade. The measures are defined as follows: (i) Return chasing is the average percentile rank of prior one-year returns for funds bought; (ii) Active management is the proportion of index funds and target-date funds bought; (iii) Turnover is the market value of purchases and sales divided by the beginning of month market value of holdings, annualized by multiplying by 12; (iv) Disposition effect is the proportion of gains realized (PGR) minus the proportion of loses realized (PLR), computed using data on those months when a client or an advisor sells something; (v) Home bias is the fraction of Canadian equity mutual fund purchases out of all equity fund purchases; and (vi) Growth tilt is the fraction of growth funds bought minus the fraction of value funds bought. We compute these measures for each client and then aggregate the data to the advisor level. The bottom two rows report two measures of fees. "Total MER" is the average management expense ratio of the funds bought by clients and advisors. "Percentile within asset class" is the average percentile fee rank of funds bought. We compute percentile ranks within five asset classes: equity, balanced, fixed income, money market, and alternatives. We include clients' and advisors' open and retirement accounts, and in the case of turnover, disposition effect, and home bias, also report the measures separately for the two account types.

	Clients		Advisors		Difference,	
Behavior	Mean	SE	Mean	SE	t-value	N
Return chasing	60.21	0.17	62.98	0.27	−10.39	3,489
Active management	98.57	0.10	98.89	0.12	−2.52	3,579
Turnover						
Retirement accounts	29.51	0.70	29.07	0.69	0.47	3,442
Open accounts	27.52	0.86	40.45	1.24	−9.42	2,255
All	29.36	0.64	31.12	0.68	−2.17	3,752
Disposition effect						
Retirement accounts	−4.98	0.54	−4.65	0.84	−0.69	2,240
Open accounts	−9.44	1.02	−8.48	1.52	−1.05	1,057
All	−5.72	0.50	−5.16	0.79	−1.17	2,497
Home bias						
Retirement accounts	53.48	0.39	44.44	0.49	17.80	3,256
Open accounts	49.55	0.61	41.62	0.77	10.14	1,915
All	52.74	0.37	44.34	0.46	17.96	3,517
Growth tilt	11.00	0.29	8.65	0.36	5.97	3,579
Fees						
Total MER	2.36	0.00	2.41	0.01	−6.56	3,548
Percentile within asset class	43.72	0.19	45.11	0.25	−6.25	3,544

Table 3: Investment performance of clients and advisors

This table reports annualized percentage alphas (Panel A) and factor loadings (Panel B) for clients' and advisors' portfolios. We measure gross returns, net returns, and net returns adjusted for fees and (advisor) rebates for value-weighted client and advisor portfolios. Gross return adds back the management expense ratio; net return is the return on the investment portfolio without additional fees or rebates; net return with fees and rebates subtracts off front-end loads and deferred sales charges and, for advisors, adds back rebates earned through sales commissions on personal purchases and trailing commissions earned on funds held. We measure alphas using three asset pricing models. Model I is the Sharpe (1964)-Lintner (1965) capital asset pricing model with the excess return on the Canadian equity market as the market factor; Model II adds the return difference between the long-term and short-term Canadian government bonds (the term factor); and Model III adds the return difference between high-yield Canadian corporate debt and investment grade debt (the default factor) and the North American size, value, and momentum factors. In Panel B, t-values are reported in parentheses.

Panel A: Annualized alphas (%)

Asset pricing model	Gross return		Net return		Net return with fees and rebates	
	EST	t-value	EST	t-value	EST	t-value
			Clients			
I (CAPM)	0.32	0.34	−2.07	−2.21	−2.36	−2.53
II (CAPM + term factor)	0.51	0.54	−1.87	−1.99	−2.17	−2.30
III (4 factors + bond factors)	0.01	0.01	−2.37	−2.61	−2.67	−2.94
			Advisors			
I	−0.72	−0.70	−3.15	−3.05	−2.44	−2.36
II	−0.43	−0.42	−2.86	−2.75	−2.14	−2.06
III	−0.75	−0.77	−3.17	−3.27	−2.46	−2.53
			Difference: Advisors minus clients			
I	−1.04	−3.17	−1.08	−3.32	−0.07	−0.22
II	−0.94	−2.87	−0.99	−3.01	0.03	0.09
III	−0.76	−3.31	−0.81	−3.52	0.21	0.88

Panel B: Factor exposures and model fit

Asset pricing model	Factor exposures: Equity factors: Market	Size	Value	Momentum	Bond factors: Term	Default	Adjusted R^2
				Clients			
I	0.57						84.4%
II	0.57				−0.05		84.5%
III	0.50	0.06	0.01	−0.02	0.08	0.12	86.3%
				Advisors			
I	0.66						85.5%
II	0.65				−0.08		85.7%
III	0.57	0.10	−0.04	−0.01	0.06	0.12	88.1%
				Difference: Advisors minus clients			
I	0.09						51.8%
	(13.86)						
II	0.09				−0.03		52.5%
	(13.14)				(−1.94)		
III	0.07	0.04	−0.05	0.01	−0.02	0.00	78.0%
	(11.29)	(5.05)	(−9.51)	(1.78)	(−1.68)	(0.17)	

Table 4: Explaining cross-sectional variation in return chasing behavior with client attributes and advisor fixed effects

This table evaluates the importance of client attributes, advisor fixed effects, and province fixed effects in explaining cross-sectional variation in clients' return chasing behavior. Return chasing is the average percentile rank of prior one-year returns of funds bought. The unit of observation is a client-advisor pair. The first regression includes the client attributes. The second regression adds advisor fixed effects. The age fixed effects are based on the client's average age during the time the client is active, measured in five-year increments.

Independent	Regression 1		Regression 2	
variable	EST	t-value	EST	t-value
Constant	55.69	56.05	56.47	81.26
Risk tolerance				
Low	−0.74	−1.16	−0.53	−1.01
Low to Moderate	−0.14	−0.26	−0.11	−0.25
Moderate	1.48	2.79	1.16	2.65
Moderate to High	1.86	3.37	1.40	3.13
High	1.45	2.19	0.41	0.82
Financial knowledge				
Moderate	0.85	4.91	0.39	4.88
High	1.60	5.10	1.27	6.46
Time horizon				
Short	1.39	3.16	1.36	3.66
Moderate	1.17	2.81	1.39	3.98
Long	0.52	1.17	1.22	3.40
Female	−0.02	−0.19	0.17	2.81
French speaking	0.03	0.06	−0.08	−0.27
Salary				
$30-50k	−0.01	−0.13	−0.07	−0.99
$50-70k	0.22	1.42	0.15	1.63
$70-100k	0.19	1.13	0.18	1.68
$100-200k	−2.54	−1.91	−1.38	−1.20
Over $200k	0.04	0.06	−0.22	−0.44
Net worth				
$35-60k	0.69	2.94	0.48	2.41
$60-100k	0.62	2.64	0.33	1.73
$100-200k	1.02	4.77	0.66	3.60
Over $200k	1.48	6.42	0.85	4.71
Advisor FEs	**No**		**Yes**	
Age FEs	Yes		Yes	
Province FEs	Yes		Yes	
N	380,458		380,458	
Adjusted R^2	1.0%		17.6%	

Table 5: Explaining cross-sectional variation in return chasing behavior with advisor and client fixed effects

Panel A evaluates the importance of advisor and client fixed effects in explaining cross-sectional variation in clients' return chasing behavior. The sample consists of clients who are forced to switch advisors when their old advisor dies, retires, or leaves the industry. The unit of observation is a client-advisor pair. Panel B reports estimates from a regression

$$\text{Return chasing}^{\text{post}}_{i,a_2} - \text{Return chasing}^{\text{pre}}_{i,a_1} = \alpha + \beta(\text{Return chasing}^{\text{pre}}_{-i,a_2} - \text{Return chasing}^{\text{pre}}_{-i,a_1}) + \varepsilon_i,$$

where Return chasing$^{\text{pre}}_{i,a_1}$ and Return chasing$^{\text{post}}_{i,a_2}$ are client i's return chasing measures for investments made with the old and the new advisor, and Return chasing$^{\text{pre}}_{-i,a_1}$ and Return chasing$^{\text{pre}}_{-i,a_2}$ are the average return chasing measure of each advisor's other clients (excluding client i) during the period before the old advisor stops advising clients.

Panel A: Regressions with advisor and client fixed effects

Advisor FEs	Client FEs	Adjusted R^2
Yes	No	19.8%
No	Yes	7.5%
Yes	Yes	27.1%
Test: Client FEs jointly zero	$F(24113, 6392) = 1.29$	
Test: Advisor FEs jointly zero	$F(154, 1402) = 4.19$	
Number of observations	31,385	

Panel B: Change in client return chasing behavior after displacement

Regressor	EST	t-value
Intercept	−3.27	−9.23
New advisor − old advisor	0.30	11.64
Number of observations	5,236	
Adjusted R^2	2.7%	

Table 6: Explaining cross-sectional variation in client behavior with client attributes, advisor fixed effects, client fixed effects, and advisor behavior

Panel A evaluates the importance of client attributes, advisor fixed effects, client fixed effects, and province fixed effects in explaining cross-sectional variation in client behavior. The measures of behavior are described in text and summarized in Table 2. The unit of observation is a client-advisor pair. The estimates reported in Panel A are the models' adjusted R^2s. The measures pool trades and holdings across open and retirement accounts. The displaced-clients sample includes clients who are forced to switch advisors when their old advisor dies, retires, or leaves the industry. Panel B reports estimates from regressions that explain changes in displaced clients' behavior around the switch from the old advisor to the new advisor. The explanatory variable is the difference in the average behavior of the new and old advisor's other clients' behavior during the pre-switch period.

Panel A: Regressions with client attributes and advisor and client fixed effects

	Sample: All clients			Sample: Displaced clients			
Behavior	Client attributes	Client attributes + advisor FEs	N	Client FEs	Advisor FEs	Both FEs	N
Return chasing	1.0%	17.6%	380,458	7.5%	19.8%	27.1%	31,385
Active management	0.8%	18.3%	401,067	−7.5%	29.6%	31.5%	33,620
Turnover	1.1%	10.8%	472,103	6.9%	13.5%	19.9%	52,685
Disposition effect	0.2%	6.4%	154,108	33.0%	9.9%	39.1%	13,963
Home bias	2.8%	26.9%	383,166	28.7%	30.5%	43.5%	31,815
Growth bias	0.7%	16.4%	401,067	27.0%	18.3%	39.0%	33,620
Fees							
Total MER	7.6%	27.5%	397,355	39.4%	30.5%	53.1%	33,293
Percentile within asset class	2.8%	26.5%	394,998	25.3%	27.2%	42.2%	33,103

Panel B: Displacement regressions

Behavior	Intercept EST	Intercept t-value	New advisor − old advisor EST	New advisor − old advisor t-value	Adjusted R^2	N
Return chasing	−3.27	−9.23	0.30	11.64	2.7%	5,236
Active management	−1.18	−7.60	0.73	5.90	10.1%	6,101
Turnover	−1.31	−3.74	0.09	5.79	0.2%	20,828
Disposition effect	−1.50	−1.05	0.06	1.32	0.1%	1,574
Home bias	2.39	4.25	0.16	7.28	1.0%	5,371
Growth bias	−1.45	−3.20	0.21	7.20	1.3%	6,101
Fees						
Total MER	−0.12	−15.77	0.03	1.83	0.1%	5,975
Percentile within asset class	−1.44	−5.55	0.17	7.73	1.3%	5,871

Table 7: Explaining advisor fixed effects with advisor attributes and investment behavior

This table reports estimates from regressions of advisor fixed effects on advisor attributes and investment behavior. These advisor fixed effects are from Table 6's all-clients regressions of client behavior on client attributes and advisor fixed effects.

		Active		Dispo-			Fees	
	Return	manage-		sition	Home	Growth	Total	Cond.
Regressor	chasing	ment	Turnover	effect	bias	bias	MER	percentile
				Univariate regressions				
Advisor behavior	0.22	0.25	0.22	0.09	0.35	0.21	0.13	0.25
	(13.98)	(4.39)	(4.15)	(5.26)	(22.17)	(9.07)	(5.26)	(14.15)
Adjusted R^2	11.8%	9.3%	4.4%	2.1%	19.8%	6.3%	5.5%	9.9%
N	2,618	2,816	3,015	1,326	2,610	2,816	2,751	2,722
			Multivariate regressions with advisor attributes					
Advisor behavior	0.21	0.25	0.21	0.09	0.35	0.20	0.12	0.23
	(12.91)	(4.26)	(3.59)	(4.61)	(20.02)	(8.67)	(4.57)	(12.15)
Log(Age)	3.65	0.83	−20.92	−2.06	2.38	−0.31	0.09	0.79
	(4.12)	(1.61)	(−5.41)	(−0.60)	(1.31)	(−0.20)	(4.01)	(0.90)
Female	1.45	−0.03	−0.51	−1.70	0.71	0.30	0.01	0.08
	(3.14)	(−0.11)	(−0.28)	(−0.99)	(0.74)	(0.35)	(0.45)	(0.14)
French speaking	−1.04	−1.27	−7.03	3.96	2.73	0.16	0.06	3.80
	(−2.41)	(−4.06)	(−4.79)	(2.16)	(2.88)	(0.20)	(4.78)	(6.17)
Log(# of clients)	−0.38	0.00	−2.22	−0.19	−0.45	0.05	0.01	−0.49
	(−2.57)	(0.06)	(−3.40)	(−0.36)	(−1.50)	(0.16)	(1.29)	(−3.05)
Risk tolerance								
Moderate	−0.48	0.02	4.46	−1.28	2.18	−0.25	0.05	2.23
	(−0.38)	(0.03)	(1.62)	(−0.36)	(1.02)	(−0.12)	(1.44)	(1.54)
Moderate to High	−0.36	0.15	8.35	−0.93	2.84	−0.52	0.02	1.40
	(−0.29)	(0.23)	(2.77)	(−0.27)	(1.33)	(−0.26)	(0.51)	(0.99)
High	0.55	−0.04	6.76	−3.16	3.99	−1.68	0.03	2.08
	(0.45)	(−0.06)	(2.42)	(−0.94)	(1.87)	(−0.83)	(0.82)	(1.48)
Adjusted R^2	13.1%	10.2%	7.4%	2.0%	19.8%	5.6%	5.9%	10.6%
N	2,369	2,534	2,685	1,208	2,353	2,534	2,479	2,452

Table 8: Correlations between advisors' and their clients' alphas and fees

This table reports Spearman rank correlations between advisors' and their clients' gross and net alphas and fees. The gross and net alphas are estimated using three asset pricing models that are described in Table 3. The fees consist of management expense ratios, front-end loads, and deferred sales charges. We block bootstrap the data by calendar month 100 times to compute the standard errors. We include advisors and clients with at least one year of returns.

		Correlation	
Measure	Asset pricing model	EST	Bootstrapped SE
Gross alphas	Stock market	0.31	0.04
	+ Bond market	0.30	0.03
	+ SMB, HML, WML, and default	0.26	0.03
Net alphas	Stock market	0.30	0.03
	+ Bond market	0.29	0.03
	+ SMB, HML, WML, and default	0.26	0.03
Fees	None	0.28	0.01

Table 9: Change in advisor behavior after the end of the career

This table reports estimates how advisor behavior changes after the advisor stops advising clients. The measures are defined in Table 2. We include advisors who execute trades suitable for computing the six measures of behavior and the two fee measures both before and after they stop advising clients.

	Active advisors		Post-career advisors		Difference		
Behavior	EST	SE	EST	SE	EST	SE	N
Return chasing	63.23	0.70	60.85	0.87	−2.38	1.06	491
Active management	99.08	0.23	98.76	0.26	−0.32	0.23	547
Turnover	27.81	1.53	23.81	1.71	−4.00	2.20	793
Disposition effect	−3.74	1.98	−3.37	2.55	0.37	2.97	259
Home bias	46.97	1.26	47.41	1.50	0.44	1.46	503
Growth bias	8.77	1.02	9.51	1.06	0.74	1.16	547
Fees							
Total MER	2.41	0.02	2.28	0.02	−0.13	0.02	524
Percentile within asset class	44.47	0.64	43.61	0.78	−0.86	0.74	521

Table 10: Hypothetical advisor returns from holding perfect copies of client portfolios

This table reports actual and hypothetical annualized net alphas for the advisors' value-weighted aggregate portfolio. The hypothetical net alphas are computed by assuming that the advisors hold perfect copies of their clients' portfolios. The return on this portfolio equals the net return earned by the clients, adjusted for the sales commissions that advisors earn on their personal purchases and for the trailing commissions that they earn on their personal holdings. In this computation, advisors pay the same deferred sales charges as those paid by the clients. The net alphas are computed using the three asset pricing models described in Table 3.

Return measure	Asset pricing model	Annualized percentage alpha EST	Annualized percentage alpha t-value	Adjusted R^2
Actual	Stock market	−2.44	−2.36	85.5%
	+ Bond market	−2.14	−2.06	85.8%
	+ SMB, HML, WML, and default	−2.46	−2.53	88.1%
Hypothetical	Stock market	−1.03	−1.11	84.4%
	+ Bond market	−0.82	−0.87	84.5%
	+ SMB, HML, WML, and default	−1.32	−1.45	86.2%
Hypothetical minus actual	Stock market	1.40	4.26	51.7%
	+ Bond market	1.32	3.98	52.2%
	+ SMB, HML, WML, and default	1.13	4.93	78.0%