

Costly Financial Advice: Conflicts of Interest or Misguided Beliefs?*

Juhani T. Linnainmaa

Brian T. Melzer

Alessandro Previtero

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Abstract

A commission-based compensation model incentivizes financial advisors to place their clients into expensive investments and to churn their portfolios. We use detailed data on financial advisors and their clients to show that conflicts of interest matter: advisors sometimes execute trades that serve solely their own interests. At the same time, most advisors personally invest just like their clients. They chase returns, prefer expensive, actively managed funds over cheap index funds, and trade frequently. We show that most of the cross-sectional variation in compensation emanates from differences in advisors' beliefs, not from conflicts of interest. Advisors do not change their investing behavior after leaving the industry. Advisors therefore do not trade differently because they are advising clients. Our results suggest that a switch to a fee-based compensation model may prove ineffective in improving the quality of financial advice.

*Juhani Linnainmaa is with the University of Chicago Booth School of Business and NBER, Brian Melzer is with the Northwestern University, and Alessandro Previtero is with the University of Texas at Austin and Western University. We thank Chuck Grace and Jonathan Reuter for valuable comments. We are grateful for feedback given by seminar participants at Boston College, Dartmouth College, University of Maryland, Georgetown University, HEC Montreal, Indiana University, University of Texas at Austin, and University of Colorado Boulder. We are especially grateful to Univeris, Fundata, and four anonymous financial firms for donating data and giving generously of their time. Alessandro Previtero received financial support from Canadian financial firms for conducting this research. Address correspondence to Alessandro Previtero, Western University, 1255 Western Road, London, Ontario N6G 0N1, Canada (email: aprevitero@ivey.ca).

“Jerry, just remember—it’s not a lie if you believe it.”

—George Costanza

1 Introduction

Many households let financial advisors guide their investment decisions.¹ The typical compensation scheme uses commissions, and so the advisor’s fee derives from the products he sells. This arrangement creates an agency conflict, which may bias advice. Advisors may be tempted to recommend products that maximize their fees rather than those best-suited for their clients. In this paper, we measure the importance of these conflicts of interests in shaping advisors’ recommendations. We use data that, in addition to detailing clients’ trades, also detail advisors’ own trades.

Financial advisors’ beliefs about the value of active management may also lower the quality of advice. Although academics share a near consensus about the passive vehicles being the superior choice for uninformed investors (Fama and French 2010), this view is not necessarily shared by financial advisors. In fact, a selection mechanism may steer those who hold the *opposite* view towards becoming financial advisors. An individual who chooses to become a financial advisor may not hold the view that investing is as simple as bundling together a handful of index funds. Under this explanation, financial advisors are not random draws from the population. They may therefore recommend active management and active investment strategies not because they receive higher commissions by doing so, but because they believe that active management—even after commissions—dominates passive management.

¹In 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).

Both conflicts of interest and misguided beliefs can generate “bad” advice. The econometric challenge lies in disentangling these mechanisms. We use a unique data set on Canadian financial advisors to separate advisors’ beliefs from conflicts of interest. Our data contain not only on clients’ investments but also the personal investments of the advisor. Importantly, this information about advisors is not available to clients themselves. We observe advisors’ portfolios because most advisors have accounts at the same company they work for, and they have the same identifier when they act as advisors and when they trade for themselves.

We measure trading behavior in dimensions that previous research has suggested as being possibly welfare reducing: high turnover, preference for actively managed funds, return chasing, disposition effect, home bias, and preference for growth over value.² Behaviors such as these may reduce performance both through their effects on portfolio choice and taxes—the client may not hold an efficient portfolio or he may make investments that increase taxes—and through their effects on turnover. An investor who chases returns, for example, may trade more frequently than those who believe that past returns are uninformative about future returns, and it is the high turnover that may hurt performance.³

We show that both clients and advisors display economically significant preferences for certain trading patterns. For example, the average percentile one-year return rank of the funds that clients buy is 0.59, and the average of those bought by advisors is 0.61. Both the clients and advisors

²These behavioral patterns have been studied extensively. See, for example, Nofsinger and Sias (1999), Grinblatt and Keloharju (2001), 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 (2001), 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; and (1991), Coval and Moskowitz (1999), and Grinblatt and Keloharju (01) 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.

³See, for example, Odean (1999), Barber and Odean (2001), and Grinblatt and Keloharju (2009) for analyses of how high turnover lowers the average investor’s investment performance.

therefore condition their trading decisions on past returns, and both groups prefer funds with better-than-average historical returns. Advisors and clients both display the reverse disposition effect in that they sell mutual funds that are trading below their purchase prices. This pattern holds for both retirement and non-retirement accounts, and is therefore distinct from tax-loss selling. Both clients and their advisors display a strong preference for actively managed mutual funds. Passive funds account for less than 1% of the average client’s portfolio, and even less of that of the average advisor.

We show that these measures vary considerably in the cross-section of clients, and that some of this variation stems from heterogeneity in client attributes such as age, risk tolerance, financial knowledge, and wealth. Young clients, for example, do not chase returns to the same extent as older clients, they display a stronger reverse disposition effect, and they exhibit less of a home bias in their portfolios. Nevertheless, these attributes together explain but a modest amount of total variation in client behavior. By contrast, advisor fixed effects consistently increase the model’s explanatory power considerably. Clients who have the same advisor therefore trade similarly. They condition their trading decisions in the same way on past returns and gains and losses.

We show that advisors sometimes recommend trades that are to their personal benefit.⁴ We examine client trading behavior around the expiration of deferred sales charges. Investors need to pay these charges when they purchase a back-end load fund and then sell this holding “too soon.” At the time the deferred sales charge expires, the advisor has an incentive to move the client to a different fund. He can either earn a new sales commission or increase his trailing commission, and doing something dominates staying still. We find that advisors respond to the expiration of the

⁴Under Canadian securities legislation, advisors have a duty to make suitable investment recommendations, based on their clients’ investment goals and risk tolerance. The extent of advisors’ fiduciary duty, however, is a gray area. 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).

deferred sales charge schedule by putting their clients into new investments. These trades are not motivated by clients' liquidity needs, rebalancing or asset-allocation considerations. The funds that advisors recommend to replace the old is almost always of the same style. These trades are therefore not in the clients' interests. Moreover, because the advisor benefits from the trade, an adding-up constraint—all the fees in the system are ultimately financed by the clients' investments—imply that the clients are worse off.

We find that advisors' misguided beliefs are more important than conflicts of interests in explaining clients' trading behavior. We use each advisor's total compensation as a measure of conflicts of interest. This measure represents conflicts of interest because of the same adding-up constraint: if advisors have no investment skill—and we find that their gross alphas are statistically indistinguishable from zero—then an increase in the advisor's compensation makes the clients worse off. We estimate models that explain cross-sectional variation in client behavior with advisor compensation and behavior. In a return-chasing regression, for example, we regress clients' return-chasing measures against advisors' compensation and return-chasing measures. Although compensation correlates positively with some of the behavioral biases—consistent with the conflicts of interest mechanism—these correlations are economically small. Advisors' own behavior, by contrast, is statistically and economically significant in almost every specification. In the return-chasing regression, for example, cross-sectional variation in advisors' compensation explains just 0.4% of the variation in clients' return-chasing estimates; adding advisors' own return-chasing estimates, however, increases this explanatory power to 11.2%.

Advisors could execute trades in their own portfolios that are contrary to their beliefs if they think such trades enhance their credibility in the eyes of their clients, thus making it easier to extract

value from their clients. We show that advisors do not appear to engage in such “window dressing.” We track advisors who quit and show that their trading behavior stays largely unchanged: they continue to chase returns, invest in actively managed funds, and choose funds that, in terms of their fees, are even more expensive than those bought by the average client.

Our results are related to studies of the financial advisory industry. These studies examine the behavior of financial advisors, measure their ability to add value, and explore the importance of conflicts of interest and beliefs in explaining poor advice.⁵ Gennaioli, Shleifer, and Vishny (2015), for example, develop a model in which investors prefer to hire managers because of trust and, if investors hold biased expectations, managers pander to these biases. Mullainathan, Nöth, and Schoar (2012) find that advisors encourage return chasing and recommend expensive, actively managed mutual funds even to clients who start with well-diversified, low-fee portfolios. Cheng, Raina, and Xiong (2014) find that mid-level managers in securitized finance held positive views about the state of the housing market 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.” Dvorak (2015) studies the 401(k) plans of the advisors who help design similar plans for other defined contribution plans. The contents of these plans overlap significantly—they have identical categories of funds, fund families, and funds—but when they differ, the funds specific to the clients’ plans are more expensive.

Our results on the relative importance of the beliefs channel are important for policy. The distinction between the two mechanisms—the conflicts of interest and misguided beliefs—does not affect the quality of advice: the advice that clients receive is of low quality. The policy implications,

⁵See, for example, Anagol, Cole, and Sarkar (2013), Chalmers and Reuter (2015), Christoffersen, Evans, and Musto (2013), Hackethal, Inderst, and Meyer (2012), Hoechle, Ruenzi, Schaub, and Schmid (2015), and Mullainathan, Nöth, and Schoar (2012).

however, are different depending on why this quality is low. 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. If instead bad advice stems from bad beliefs, it is difficult to introduce regulation that addresses this problem without taking a stance on what constitutes “good advice.” Such regulation would be an attempt to force advisors and their clients to take actions that apparently contradict their beliefs about investing. The probable reason for why the market fails and bad advice survives even in a seemingly competitive industry is that clients are unable to distinguish between good and bad advice, and may even mistake bad for good.⁶ A potential solution is to increase transparency. If clients are provided information about the fees they pay and how their investments perform relative to reasonable passive alternatives, they may be compelled to seek and reward better advisors.

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 estimates models that explain variation in trading behavior using client attributes and advisor fixed effects. Section 4 examines conflicts of interests by analyzing trading behavior around the expiration of deferred-sales charge schedules. Section 5 measures the extent to which conflicts of interest or advisors’ misguided beliefs explain variation in client trading behavior. Section 7 concludes.

⁶The market for financial advice may resemble the “market for quacks” described in Spiegler (2006). In this model, patients are boundedly rational and choose their doctors based on anecdotal evidence. Spiegler (2006) shows that patients suffer a welfare loss and that this welfare loss cannot be addressed by market interventions that enhance competition as long as patients’ quality of reasoning remains low.

2 Data

We use the same data on financial advisors as those used in Foerster, Linnainmaa, Melzer, and Previtero (2015). These data were provided by three Canadian financial advisory firms, known as Mutual Fund Dealers (MFDs), who cover over 6% of the total assets of MFD advisors. Non-bank financial advisors such as these dealers 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). 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. Both clients and advisors are tagged by unique identifiers that are derived from their social insurance numbers, the Canadian equivalent of social security numbers. We use these identifiers to link advisors to their personal investment portfolios. Most advisors in our sample have their personal portfolios at their own firm. Importantly, advisors’ portfolios are not visible to the public or their clients, either in real time or after the fact. Our ability to link advisors to their portfolios is incidental, and so advisors’ actions should not depend on this aspect of the data.⁷

2.1 Advisors and their clients

Table 1 provides the key summary statistics for our sample for clients (Panel A) and financial advisors (Panel B). The sample includes all individual accounts held at one of the three main dealers between January 1999 and June 2012. The sample includes 5,920 advisors and 581,044

⁷In Section 6, we measure changes in advisor behavior after they stop advising clients. We find that advisors’ behavior is largely unchanged around the exit.

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 client and account characteristics. Men and women are equally represented, and client ages range from 33 years old at the bottom decile to 69 years old at the top decile. The average client has been with his current advisor for three years, has one investment plan—e.g., a retirement account or general-purpose account—and holds three mutual funds. The distribution of client assets is right-skewed: while the median client has CND 27,000 in assets, the average account size is CND 68,100. Just over 1% of clients report working in finance-related occupations.

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). In some of our analysis, we separate retirement accounts from general accounts because of the differences in their tax treatment. The bottom part of Panel A shows the distributions of risk tolerance, financial knowledge, salary, and net worth for clients. Financial advisors collect this information through “Know Your Client” forms at the start of the advisor-client relationship. 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.

Panel B displays the same information for 3,483 advisors who appear in the dealer data also as clients. Three-quarters of advisors are men, and the average advisor is of approximately the same age as the average client. Advisors’ account values are typically greater than those of their clients. The average advisor’s account value is CND 127,100, which is nearly twice that of the average client. Advisors differ from their clients also in terms of their preferences and salary. Most advisors report either moderate-to-high or high risk tolerance, whereas the average client is only moderately

risk tolerant. The distributions of salaries and net worth are also located higher than those of 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.”⁸

2.2 Investment options

The clients in the dealer data invest in 3,023 different mutual funds. The total number of mutual funds available to Canadian investors is approximately 4,000 according to Morningstar. Most of these mutual funds are offered with different load structures. The most common types are front-end load, back-end load, low load, and no load. All of these 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. The average client’s portfolio has 28.9% of the assets in front-end load funds, 64.2% in back-end load funds, 4.5% in low-load funds, and 2.4% in no-load funds.

The differences in the structures of these products affect the conflicts of interest, and we therefore briefly describe them. Every time a client buys a mutual fund, the transaction involves four parties: the client, the advisor, the mutual fund company, and the dealer firm that employs the advisor.

Mutual fund transactions can generate six types of payments:

⁸We obtain information about advisors’ risk tolerance, financial knowledge, salary, and net worth from the Know Your Client forms that the advisors need to fill out to have an account at their own company. These responses are not visible to their clients.

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 then decreases each year until disappearing after year 7. The deferred sales charge is based alternatively on the value of the initial purchase or the value of the shares at the time of the redemption.
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.
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 that are placed in clients' 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 also often free 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 each option, the client pays the mutual fund company the management expense ratio and, if applicable, an administrative fee for funds held in retirement accounts. The advisor shares the commissions with his dealer firm. A 2010 industry study of the top ten Canadian dealers reports that advisors received, on average, 78% of the commission payments (Fusion Consulting 2011).

The no-load option typically strictly dominates the other options, that is, if the client was allowed to choose between these options, the no-load option would often be superior both in terms of costs and the lack of restrictions on selling. 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.

These options behave the same way when an advisor trades for his own account. The difference is now the payments made by the mutual fund to the advisor lower the costs of ownership. The trailing commissions lowers the advisor’s effective management expense ratio, and the sales commission acts as a discount on new purchases. The same selling restrictions as above also apply to the advisor’s own trades. For example, if the advisor sells a back-end load fund too soon, he incurs the same deferred-sales charge as the one that would be incurred by a client. If an advisor buys a front-end load fund, the front-end load is zero because it is between the advisor and the client. The advisor’s optimal choice of a load type may depend on his investment horizon and the specific structure of the product. In the dealer data, the average advisor holds 44.1% of the assets in front-end load funds, 46.4% in back-end load funds, 4.6% in low-load funds, and 5.0% in no-load funds.

3 Trading behavior of clients and advisors

3.1 Defining measures of trading behavior

We define six measures of trading behavior. The first measure is **turnover**, which we define as the market value of funds bought and sold divided by the beginning-of-the-month market value of the portfolio. This measure is the same as that used in, e.g., Barber and Odean (2000). Investors may be less active in their retirement accounts than in their general-purpose (or “open”) accounts, and so we measure turnover separately for these account types. The second measure is **active management**, which we define as the fraction of (non-money market) assets invested in actively

managed mutual funds. We classify as passive those funds that are either identified as index funds in Morningstar or that call themselves index funds or target-date funds.

The third measure is **return chasing**. We rank all mutual funds each month based on their returns over the prior one year period, and then measure return chasing by computing the average percentile rank of the funds purchased by investors. This measure is the same as that used in, e.g., Grinblatt, Keloharju, and Linnainmaa (2012). A high measure implies that investors purchase funds with high prior one-year returns. The fourth measure is **disposition effect**. We use the proportion of gains realized-minus-proportion of losses realized (PGR-PLR) measure of Odean (1998). 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. Because disposition effect is related to taxes—an investor who realizes capital gains outside a retirement account may face a larger tax bill if there are no offsetting capital losses—we measure disposition effect separately within retirement accounts and open accounts. A high value of PGR-PLR implies that investors are more likely to sell funds for which they have paper gains.

The fifth measure is **home bias**, which we measure by computing the fraction of the equity holdings invested in Canadian equities. This measure is the same as that used in Foerster et al. (2015). The last measure of trading behavior is **growth tilt**, which we define as the difference between the fractions of growth funds and value funds that investors purchase.

In addition to these measures of investor behavior, we also measure the relative fees that investors pay. We rank all mutual funds each month based on their management expense ratios, and then compute the average percentile fee of the funds held by investors. We compute these percentile ranks separately for different types of funds. We use a 54-category classification scheme of Fun-

data, a company that maintains a Morningstar/CRSP-like database of mutual funds available to Canadian investors. This classification scheme identifies fund types such as “Asia Pacific Equity” and “U.S. Small/Mid Cap Equity.” A high value of percentile fee thus implies that investors hold mutual funds that are more expensive than many others in their own class.

3.2 Trading behavior in client and advisor portfolios

Table 2 shows the means of our six measures of trading behavior—and the fee measure—separately for clients and advisors. For the purposes of this table, we aggregate the data to an advisor level and display the estimates for those advisors who advice clients in the data for at least two years and whose personal portfolios are displayed in the dealer data. We aggregate the data to the advisor level by computing the average measure of each advisor’s clients. The first row, for example, shows that the average advisor has an annualized turnover of 35.7% in his personal retirement account, and that the turnover of the average client is 29.7% in these accounts. The second to the last column shows that the difference in these turnover estimates, based on 3,408 advisor-level observations, is statistically highly significant.

The average client invests almost exclusively in actively managed mutual funds. The fraction of assets in passive funds is just 1.2%. The average return-chasing measure is 59.0%, which indicates that clients invest in mutual funds that have performed well over the prior one-year period. Clients display a *reverse disposition effect* in both the retirement and open accounts, that is, they are more likely to sell mutual funds that have decreased in value after purchase. Because this pattern holds

for both retirement and open accounts—although it is more pronounced for open accounts—it is, at least in part, distinct from tax-loss trading.⁹

Clients display pronounced home bias in both their retirement and open accounts, and this pattern is consistent with that in Foerster et al. (2015). The home bias measure may be higher for retirement accounts because, before 2005, Canadian tax code set a maximum on the amount of assets that could be allocated into foreign investments for funds held in retirement accounts. Finally, clients display a substantial preference for growth funds, with a 8.6% difference in the fractions of growth and value funds purchased.

Advisors behave quite similarly to their clients in most dimensions. Advisors have a higher turnover, they chase returns to an even greater extent, they are more likely to sell losing mutual funds (reverse disposition effect), they display less of a home bias, and their portfolios are not tilted as much towards growth funds. Passive funds account for a negligible share—just 1%, below that of the average client—of the average advisor’s portfolio. Both the typical client and advisor invest almost all of their assets into actively managed funds. Some of the differences in Table 2 may be related to differences in clients’ and advisors’ preferences. Advisors may, for example, display less of a home bias because they are, on average, more risk tolerant than their clients. A desire for riskier investments, at least in the absence of cheap leverage, may therefore necessitate greater investments in non-Canadian equities. In Section 5, where we correlate an advisor’s behavior with that of his clients, we therefore use measures that adjust for differences in client attributes.

Both advisors and clients invest in expensive mutual funds. The finding that the average percentiles are close to 50% is not surprising. If we all mutual funds were of equal size, the average

⁹This reverse disposition effect pattern is consistent with the findings of Chang, Solomon, and Westerfield (2015). Chang et al. (2015) use the Odean (1999) data to measure the disposition effect in stocks and mutual funds, and find a reverse disposition effect in mutual fund transactions. They propose an explanation that combines effects emerging from delegation—that is, do investors have themselves or someone else to blame?—and cognitive dissonance.

investor’s percentile fee would have to equal 50%. The important result in Table 2 is that advisors are not meaningfully different from their clients when it comes to choosing between cheap and expensive alternatives. If anything, advisors invest in funds that are, before trailing commissions, more expensive than those held by their clients. In Section 6, we show that this pattern holds even for advisors who have exited the industry.

3.3 Explaining cross-sectional variation in client behavior

Investor trading behavior may correlate significantly with investor attributes for both rational and behavioral reasons. For example, an investor who is hit more frequently by liquidity shocks—i.e., unpredictable in- and outflows of cash—may need to trade more frequently than a retiree. An investor who believes that skill persists in the short run may be tempted to chase returns to a greater extent than an investor who believes that skill does not exist or that it is a more stable attribute of a mutual fund manager. Figure 1 demonstrates that behavior varies considerably in the cross section of clients by plotting 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.

In Table 3, we estimate the extent to which our six measures of trading behavior vary in the cross section of clients by investor attributes. We estimate panel regressions of the form:

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

where y_{iat} is the measured behavior of client i of advisor a , $\boldsymbol{\mu}_t$ and $\boldsymbol{\mu}_a$ are year and advisor fixed effects, and $\mathbf{X}_i$ is a vector of investor attributes. The investor attributes include the variables

summarized in Table 1. We also include province fixed effects to control for differences tied to geography. We estimate the panel regressions using client-year data. In the return-chasing regression, for example, we define y_{iat} as the average percentile rank of the funds bought in year t . We estimate the models using OLS and cluster the standard errors by advisor to account for correlations over time and across clients of the same advisor.

We estimate the models both with and without advisor fixed effects to measure the extent to which clients of the same advisor trade in the same way. Panel A of Table 3 summarizes the importance of the advisor fixed effects and client attributes in explaining cross-sectional variation in client behavior. In most cases, the inclusion of advisor fixed effects yields a significant boost to the model’s explanatory power. In the return-chasing regression, for example, the client attributes explain just 1.3% of the variation in the return-chasing estimates. With the advisor fixed effects in the regression, the model’s explanatory power is 9.0%.

These increases in adjusted R^2 s are not due to endogenous matching between advisors and clients. That is, advisors might appear to have a large impact on their clients simply because advisors attract similar clients, and our list of investor attributes does not include all the variables by which clients and advisors match. Foerster et al. (2015) study home bias using the same data and restrict the sample to clients whose advisors quit. Advisor fixed effects remain highly important in a regression that controls for unobserved heterogeneity using investor fixed effects.¹⁰ The coefficient estimates of the investor attributes also typically sharpen or remain unchanged when we add advisor fixed effects to the regression, which suggests that the attributes that we examine are not important because they proxy for the mechanism by which advisors and clients match.

¹⁰Foerster et al. (2015) also show that adjustment in the *adjusted* R^2 measures also works as intended. When the advisor fixed effects are replaced with randomized indicator variables that have the same frequency distribution as advisor fixed effects, the resulting adjusted R^2 from the “advisor-fixed effects” regression is almost the same as that from the no-fixed effects regression.

Panel B shows that, although the explanatory power of the client attributes is small, many patterns are economically and statistically significant. The coefficients we report in Panel B are from the full model that includes advisor fixed effects. Because of these fixed effects, these regressions measure the marginal effects of within-advisor differences in investor attributes. The turnover regressions, for example, show that clients who report higher financial knowledge and very short investment horizons (the omitted category) trade more frequently than other clients. The point estimates indicate differences in annualized turnovers that range from 1 to 4 percentage points. Although almost all clients invest solely in actively managed funds, financial knowledge is one variable that correlates with this choice. However, perhaps surprisingly, investors who report high financial knowledge invest even *less* in passive vehicles than those reporting low financial knowledge.¹¹

We observe similar patterns for most of the other measures of trading behavior. Clients who report high financial knowledge or high risk tolerance, for example, are both more likely to chase returns and invest less in Canadian equities than those who report lower levels of financial knowledge. There are also significant differences between men and women in terms of some of the measures. Women’s turnover is higher in retirement accounts, they are less likely to chase returns, and they display less of a home bias than men. In terms of the other measures, the marginal effect associated with the female-indicator variable is close to zero and statistically insignificant. We save the estimates of the advisor fixed effects from the regressions presented in Panel B of Table 3,

¹¹High financial knowledge does not have to imply that the client believes in market efficiency. In fact, the Know Your Client form characterizes a person with high financial knowledge as someone who “[follows] the financial markets closely; [is] aware of and [understands] a wide variety of investment products and strategies.” Contrary to this description, a person who believes in market efficiency would not feel compelled to follow the markets closely, and might not be familiar with a wide variety of investment products and strategies.

and later measure (in Section 5) how these fixed effects correlate with the advisor behavior and compensation.

4 Measuring conflicts of interest

4.1 Do advisors respond to incentives? Sales commissions, deferred sales charges, and advisors' incentives

The most common load structure used by financial advisors is that back-end load structure. In our sample, 64.2% of client assets are invested in back-end load funds. In this section, we examine how advisors respond to differences in the incentives generated by the front-end and back-end load fee structures.

When an advisor buys a back-end load fund for his client, the advisor earns money from both an upfront commission and a trailing commission. The typical arrangement is for the fund company to pay the advisor 5% as the upfront commission. If the investor, for example, invests \$10,000, the dealer receives \$500 at the time of the investment. The second component is the trailing commission. The typical trailing commission is 0.5% of the value of the investment for back-end load funds. If an investor invests \$10,000, and the value of the investment stays unchanged, the advisor gets \$50 per year

Back-end load funds are also known as deferred-sales charge funds because an investor incurs a penalty if he sells the fund “too soon.” This 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. In the typical arrangement, back-end loads free

10% of the shares each year, which means that the client can sell these shares without incurring a penalty.

After reaching the seven-year mark, the investor keeps paying the same management expense ratio as before and the advisor still receives the trailing commission. The difference is that, after the expiration of the deferred-sales charge, the investor is no longer locked in. At this point, the advisor has an incentive to move the investor to a different fund. If he sells the investor another back-end-load fund, he captures another 5% commission while “locking” the investor down for another seven years. Alternatively, the advisor can move the investor to a front-end-load fund, which typically means that the advisor can increase his trailing commission from 0.5% per year to 1%. An opportunistic advisor has little incentive to keep the investor in the current fund. If an investor holds a deferred-sales charge fund at the 7-year mark, he can profit by shifting the investor to a different fund.

These incentives are not lost on the Canadian media. The Globe and Mail, for example, cautioned its readers about this behavior:¹²

“Here is what to look out for...they watch the six-year or seven-year DSC schedule closely. The minute a fund is no longer on a DSC schedule (meaning that the funds can be sold without additional fee to the client), the mutual fund salesperson coincidentally decides it is time for a change in direction. They sell the fund and put the client into a new DSC fund, starting the clock all over again for the investor, and receiving a new 5 per cent upfront payment from the mutual fund company.”

¹²“Is your adviser simply churning your funds?” Globe and Mail, May 20, 2011.

Figure 2 plots the hazard rates of front-end load (dashed line) and back-end load funds (solid line) up to eight years after the purchase. The probability of selling at time t conditional on still holding the fund at time $t - 1$ stays relatively constant for both types of funds, and typically remain between 1 and 2 percent. The major difference between the two graphs is the large spike at exactly the seven year mark (84 months) observed for the back-end load funds. The presence of this spike for deferred-sales charge funds indicates that advisors often move clients to new funds as soon as they can do so without expressly harming the investor by violating the lock-up clause.

The spike in Figure 2 does not necessarily harm the investor directly. This pattern only hurts the investor through a higher tax bill (if the trade is made outside retirement accounts) and, in some cases, by locking the investor down for another 7 years. At the same time, the investor may benefit from changing his asset allocation, and prefers to do so exactly at the 7-year mark to avoid paying the deferred sales charge. The spike in the hazard rate, however, is unlikely to reflect pent up demand to trade on the part of the clients. First, the probability that the client buys into a new fund at the seven-year mark is 0.885; for other months, this probability is 0.709. This difference indicates that clients at the seven-year mark are less likely to sell funds to satisfy a liquidity need. Second, conditional on buying into another fund, the probability that the client buys a fund of the same type is 0.876; for other months, this conditional probability is 0.375. (We use the 54 Fundata categories to identify funds that are of the same type.) This difference suggests that investors trading at the seven-year mark are far less likely to do so because they want to rebalance their portfolios or to shift their asset allocations.

In spite of these findings, advisors rarely lock up their clients again for another seven years. Conditional moving the client to a new fund before the seven-year mark, the probability that an

advisor switches the investor to another deferred-sales charge fund is 0.780. For the switches at the 7-year mark, however, this probability is just 0.177. Advisors thus often move investors from a deferred-sales charge fund to a front-end-load fund at the 7-year mark. This change benefits the advisor because by doing so he often replaces the ongoing 0.5% trailing commission with a 1.0% trailing commission.

5 Conflicts of interests and misguided beliefs in advisors' recommendations

5.1 Example: Turnover and return chasing

Advisors may encourage their clients to chase returns or switch out from underperforming mutual funds to increase turnover. Advisors who predominantly place their clients into back-end load funds increase their compensation by increasing their clients' turnover. Indeed, if we estimate a cross-sectional regression of client turnover on client return-chasing,

$$\text{client turnover}_a^{\text{fe}} = \alpha + \beta \text{client return-chasing measure}_a^{\text{fe}} + \varepsilon_a, \quad (2)$$

where a indexes advisors and the superscripts fe indicate that these are the advisor fixed effects from the regressions reported in Table 3. We estimate the regression using these fixed effects so that the measures are orthogonal to investor attributes such as age, risk tolerance, and gender. The slope estimate from this regression is 0.330 (t -value = 5.37) when we measure turnover in retirement accounts, and 0.497 (t -value = 5.57) when we measure it in open accounts.¹³ Some of

¹³We restrict the sample to advisors who advise clients for at least two years in the sample. The retirement-accounts regression has 4,050 observations (i.e., advisors) and the open-accounts regression has 1,996 observations.

the patterns document in Table 2 may therefore be symptoms of advisors searching for ways to extract more value from their clients.

5.2 Cross-sectional variation in advisor compensation

If advisors pander to their clients behavioral biases to encourage trading, we expect advisors who encourage, say, return chasing to extract higher compensation. Table 4 sets the stage for our conflicts-versus-beliefs test by showing that advisors differ considerably in the cost of advice per dollar under management. We measure the three sources of compensation for advisors: front-end loads, trailing commissions, and sales commissions. We compute each month the dollar amounts of these sources of compensation and then scale it by the client assets under management at the end of month $t - 1$. We report the annualized distributions of the three components of compensation as well as the total compensation. We measure the compensation before the payments to dealer firm—each advisor’s actual compensation is therefore approximately 80% of the numbers reported in Table 4. Because compensation accrues unevenly—an advisor with a few clients does not, for example, earn front-end loads or sales commissions each month—in this table we restrict the sample to advisors who advise clients for at least five years.

Although advisors place their clients into front-end load funds in approximately one-quarter of the transactions, the front-end load is often negotiated to zero. Even the advisor at the 90th percentile earns just 2 basis points per year in front-end loads on the client assets under management. The trailing commission, on the other hand, is very stable, because these commissions lie between 25 and 100 basis points for almost all funds. The median advisor earns a trailing commission of 56 basis points on the client assets under management. The sales commissions, by contrast, vary substantially. At the one extreme are the low-turnover (and front-end-load only) advisors who do

not earn substantial compensation through sales commission; and at the other end of the distribution are advisors who extract up to 2.5% per year in sales commissions on client assets under management. Importantly, the total compensation varies significantly across advisors—the spread between the bottom and the top decile is 2.4%.

5.3 Conflicts of interest versus misguided beliefs

Advisor compensation is a measure of conflicts of interest because of the market-clearing (or adding-up) constraint. If advisors cannot identify good investments, then the total size of the pie is fixed: an increase in the compensation of the advisor lowers the client’s investment performance. All the fees in the system are ultimately paid by the client, and the investment options are structured so that the mutual fund’s compensation is approximately the same independent of which option the advisor chooses.¹⁴ Foerster et al. (2015) find that advisors’ gross alphas are statistically indistinguishable from zero. Therefore, similar to Carhart (1997), an increase in fees therefore has a one-for-one negative impact on client performance.

In Table 5 we estimate regressions that measure the extent to which differences in advisor compensation explain cross-sectional variation in client behavior. We estimate regressions of the form,

$$y_a^{\text{fe}} = \alpha + \sum_{j=2}^5 \beta_j \text{Compensation quintile } j_a + \gamma y_a^{\text{own}} + \varepsilon_a, \quad (3)$$

where y stands for one of the six measures of behavior introduced in Section 3, y_a^{fe} are the advisor fixed effects from the regressions reported in Table 3, Compensation quintile j_a is an indicator variable that takes the value of one for advisors whose total compensation—based on the computation

¹⁴For example, if the advisor places the client into a back-end load fund, the trailing commission that the advisor receives from the mutual fund is lower than that attached to a front-end load fund so that the fund makes up for the sales commission.

presented in Table 4 lies in the j th quintile, and y_a^{own} is the measure of behavior computed from advisor a 's own portfolio and trades. This regression is a horse race between the conflicts of interest and beliefs mechanisms. If advisors pander to clients' biases to increase their own compensation, we expected β_j s to increase in the quintile j . If, however, some clients trade differently from others because advisors hold different beliefs, then we expect γ to be positive and statistically significant.

The estimates in Table 5 show that although differences in advisor compensation, in some cases, correlates positively with the strength of the behavioral pattern, the advisor's own behavior is typically far more important both in its statistical and economic significance. The results can be divided into three camps. First, in the case of disposition effect, neither conflicts of interest nor beliefs explain cross-sectional variation in client behavior. Second, in the cases of active management, home bias, and growth tilt, advisors' beliefs explain a significant amount of the variation in client behavior—the adjusted R^2 s range to 7.7% to 22.5% in these regressions—but the slopes on the compensation quintiles are either statistically insignificant or they have the “wrong” sign.

In the remaining regression, both the beliefs and conflicts of interest appear to play a role. The return-chasing regression shows that advisors who earn more per each dollar in client assets under management have clients who are more active in chasing returns. The turnover regression points to the same conclusion, although these estimates must be interpreted with caution because of an endogeneity issue: high turnover is almost tautologically related to compensation. (The two measures do not *have* to be correlated. For example, the correlation between turnover and compensation would be zero for advisors who use solely front-end load funds with loads negotiated to zero.) Importantly, however, even in the case of turnover, the economic and statistical significance of the advisor's own behavior dominates those of the compensation indicator variables. For example,

in the retirement-accounts turnover regression, the adjusted R^2 increases from 1.7% to 7.4% when we move from a regression with just the compensation indicator variables to a specification that also controls for advisor’s own turnover.

5.4 Advisors’ trades

The estimates in Table 5 suggest that advisor’s personal beliefs are probably an important reason for why their clients trade differently. That is, clients may not necessarily chase returns because this allows the advisor to extract more value from them; rather, they may chase returns because the advisor believes that doing so enhances returns.

The connection between the advisor and client behavior is often even closer than what the numbers in Table 5 suggest. Advisors often *personally* purchase the very same funds that they recommend to their clients. That is, it is not only that advisors condition their trades on, e.g., past returns and gains and losses the same way as they condition when making recommendations. Rather, advisors invest in the exact same funds as their clients.

We measure this similarity in purchase behavior using a bootstrap computation. We record every instance of an advisor purchasing a new fund, and then examine whether any of the advisor’s clients make the same investment in the same month. The estimated probability of the same-month client purchase is 0.931; that is, an advisor’s fund purchase almost always coincides with at least one of his clients making the same investment. This probability might be overstated if the effective size of the universe of mutual funds is small. Advisors may recommend the same funds just by luck. We therefore repeat this computation after matching each advisor who buys a fund against the clients of a randomly drawn advisor who is also active in the same month. The probability that the advisor’s purchase matches the purchase of any of these random clients is just 0.036.

Nevertheless, the data suggest that the investment problem that the advisor solves is different from that solved by the advisor. Conditional on making an investment in the same fund as one of his clients, the probability that the advisor purchases the version with the same *load structure* is just 0.450. The reason is that the version that the advisor gives to his clients—which is often the back-end load option—is not the best option from the advisor’s viewpoint given the deferred sales charge schedule, the size of the sales commission, and the size of the trailing commission.

6 Post-career advisors

Advisors may trade contrary to their personal beliefs for two reasons. First, even though clients cannot observe advisors’ trades or portfolios, advisors could in principle voluntarily disclose this information to gain their clients’ trust. If an advisor’s invested wealth represents a small part of his total net worth, he may use his own portfolio to bias clients. If an advisor personally invests in expensive active funds, the client can perhaps be convinced to do the same. Although advisors could in principle lie about their own investments, doing so might leave them exposed to legal consequences. Second, an advisor might struggle with cognitive dissonance if he is compelled to advise his clients to behave in a certain way, but then invest differently in his own portfolio.¹⁵ What is common across these explanations is that 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. After this point in time, advisors’ trades should be more

¹⁵These 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.

reflective of their true beliefs. 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 6 presents estimates of advisor behavior before and after advisors exit the industry. We limit the sample to those advisors who advise clients for at least two years and who maintain an account at the same firm even after they no longer advise any clients. The change in behavior is therefore a pairwise t -test. This test compares advisors who appear in the sample both as active advisors and after they exit the industry.

The estimates in Table 6 suggest that active advisors' personal investment behavior is probably not significantly affected by the presence of their clients. Advisors' turnover decreases after they quit the industry, but the difference is not statistically significant. Advisors also show a moderate shift towards passive management at this point in time. The share of actively managed mutual funds falls from 99% to 96.8%, and this change is significant with a t -value of 3.5. The other measures of behavior are fairly similar—the only other statistically significant change in behavior is that associated with home bias in open accounts, which increases by 8 percentage points.

Advisors do not appear to become more cost-conscious in their personal accounts after they stop advising clients. Whereas the average advisor buys funds whose management expense ratio lies in the 46th percentile of the fee distribution (conditional on fund type), this percentile *increases* to the 53rd after advisors shed their clients. This change in the average percentile fee is statistically significant with a t -value of 2.45. Advisors' preference for expensive mutual funds is thus not specific to the time they advise clients—they keep displaying this tendency even after there is no reason for keeping up the appearances.

7 Conclusions

Many individual turn to financial advisors for guidance, and the advise they get may be of low quality. Mullainathan, Nöth, and Schoar (2012) find that advisors recommend investments and trades that are contrary to the view held by the academics 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. One of the concerns is that advisors do not give unbiased advise because they have no incentives to do so. They may recommend expensive investments that are ill-suited for their clients when such investments maximize their own compensation.

Our results suggest that most advisors probably give “bad” advice not because of conflicts of interest, but because they believe that these are reasonable investments. In a horse race between the conflicts of interests and beliefs mechanisms, we find that advisor beliefs dominate. These estimates do not affect the conclusions drawn in studies such as those reference above—the advice may be of poor quality (Mullainathan, Nöth, and Schoar 2012) and clients may overpay for this advise (Chalmers and Reuter 2015). Our results are important because of their policy implications. Regulations that attempt to eliminate conflicts of interest may prove ineffective. They merely try to force advisors to behave in ways that contradict their beliefs about the value of active management. A switch to a fee-based model, for example, might not fix the underlying problem. Our results suggest that advisors would still recommend expensive, actively managed mutual funds to their clients. If advisors’ misguided beliefs are to blame for bad advise, then the solution may involve better disclosure. If clients are provided information so that they can draw their own inferences

about the value of active management, competition may begin to crowd out expensive advisors of low quality (Spiegler 2006).

The finding that advisors' personal beliefs matter is perhaps not surprising. 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. Under this explanation, financial advisors are financial advisors *because* they hold misguided beliefs. The unfortunate consequence of this selection mechanism then is that unsophisticated investors receive financial advice by individuals who have “wrong” beliefs—they might be better served if they were advised by those who actively choose *not* to become financial advisors.

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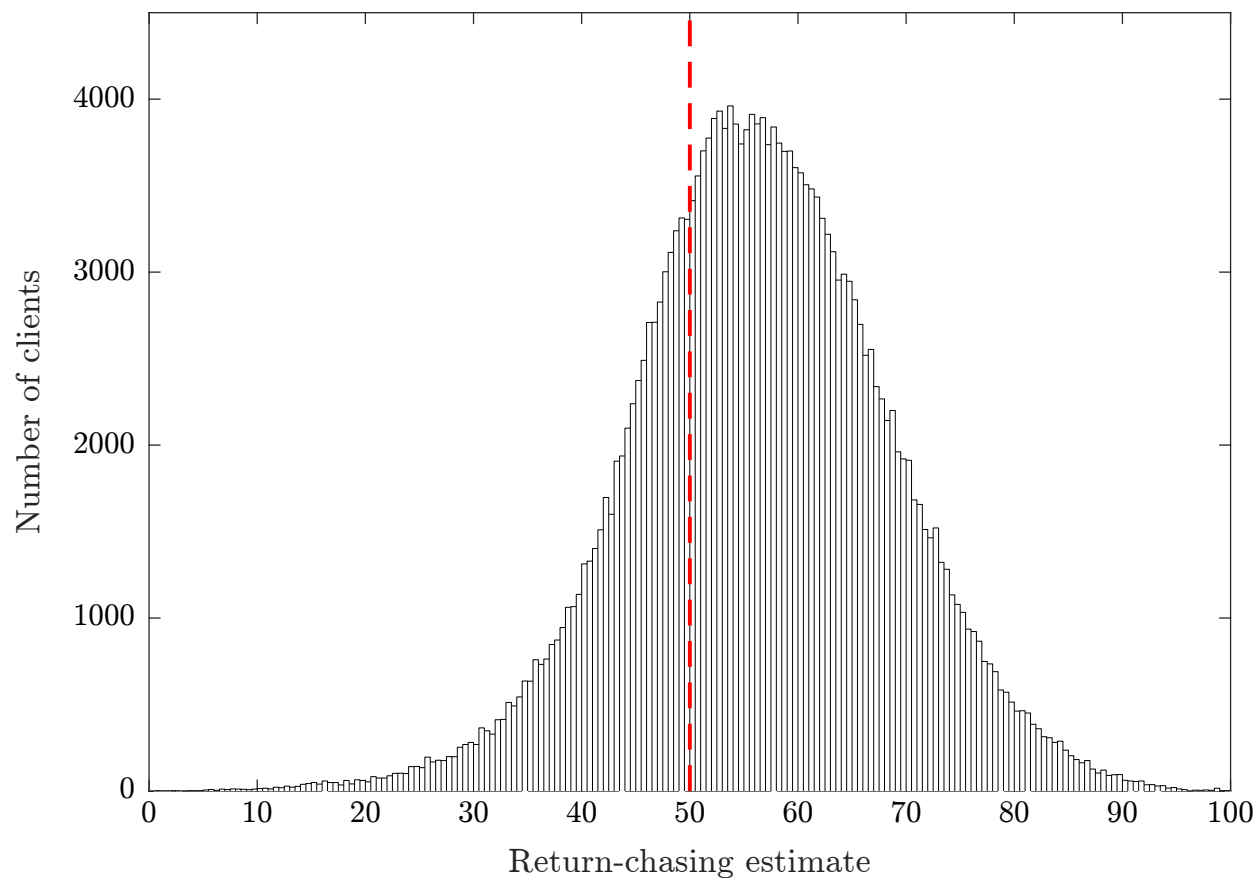


Figure 1: **Distribution of client-level measures of return chasing.** We measure return chasing by computing the average percentile return rank of mutual funds bought. This figure plots the distribution of these return-chasing measures for all clients with at least 10 mutual fund purchases during the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

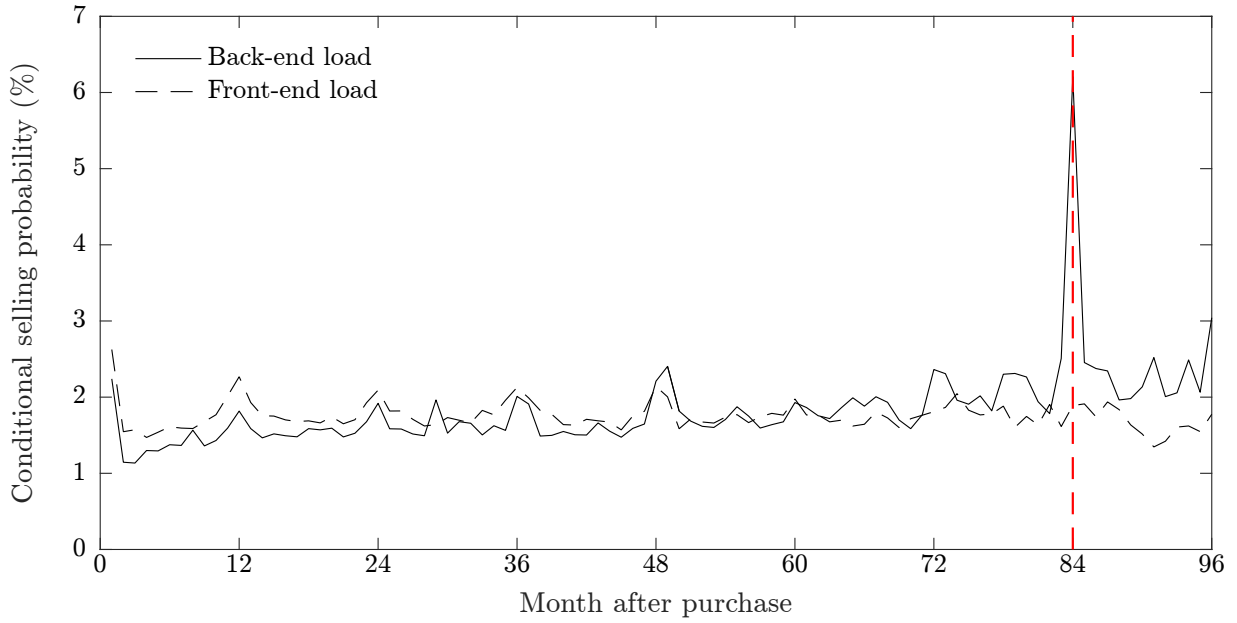


Figure 2: **Conditional probability of selling around the expiration of the deferred-sales charge schedule.** This figure plots the conditional probability of selling a fund in month t conditional on holding the fund in month $t - 1$. The solid line reports the estimated probability for back-end-load funds, and the thin line is for front-end-load funds. The sample includes all positions that are opened after the beginning of the sample period in 1999. The vertical line denotes the expiration of the typical deferred-sales charge schedule at the seven-year (84-month) mark.

Table 1: Descriptive statistics from dealer data

This table reports summary statistics for clients (Panel A) and financial advisors (Panel B). “Account age (years)” is the number of years an investor has been with any advisor. Panel B includes those advisors who appear in the dealer data also as clients. All variables are measured as of June 2012.

Panel A: Clients ($N = 581,044$)

Variable	Mean	Percentiles				
		10th	25th	50th	75th	90th
Female (%)	51.4					
Age	51.2	33	41	51	61	69
Account age (years)	3.6	1	1	3	6	7
Number of plans	1.9	1	1	1	2	4
Number of funds	5.2	1	2	3	7	12
Account value, \$ thousands	68.1	2.1	8.1	27.3	75.6	161.2
Finance professional	1.1%					

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 ($N = 3,483$)

Variable	Mean	Percentiles				
		10th	25th	50th	75th	90th
Female (%)	27.9					
Age	48.5	32	40	49	57	64
Account age (years)	3.8	1	2	3.5	6	7
Number of plans	3.2	1	1	3	4	6
Number of funds	9.6	1	3	7	13	21
Account value, \$ thousands	127.1	3.6	16.7	60.4	158.6	308.0
Tenure	4.4	1	2	4	6	8
Number of clients	74.3	1	3	24	100	217
Number of plans/client	1.7	1	1.1	1.6	2.0	2.5
Number of funds/client	4.2	1	2.0	3.7	5.6	7.5
Client assets, \$ thousands	5064.0	5.2	55.4	916.9	5,493.6	14,575.3

Account types		Time horizon	
General	32.5%	1–3 years	3.7%
Retirement savings or income	54.0%	4–5 years	7.5%
Education savings	8.1%	6–9 years	67.6%
Tax-free	5.3%	10+ years	21.2%
Others	0.1%		

Risk tolerance		Salary	
Very low	1.0%	\$30-50k	19.9%
Low	2.7%	\$50-70k	27.9%
Low to Moderate	3.1%	\$70-100k	19.7%
Moderate	30.1%	\$100-200k	30.3%
Moderate to High	20.7%	\$200-300k	1.6%
High	42.3%	Over \$300k	0.8%

Financial knowledge		Net worth	
Low	3.4%	Under \$35k	2.8%
Moderate	19.1%	\$35-60k	5.0%
High	77.6%	\$60-100k	8.1%
		\$100-200k	12.8%
		Over \$200k	71.4%

Table 2: Measures of trading behavior: Clients versus advisors

This table reports advisor-level estimates of how clients and advisors trade. The measures are defined as follows: (i) Turnover is the market value of purchases and sales divided by the beginning of month market value of holdings. This measure is annualized by multiplying by 12; (ii) Active management is the portfolio share of index funds and target-date funds; (iii) Return chasing is the average percentile rank of funds bought based on prior one-year returns; (iv) Disposition effect is the proportion of gains realized (PGR) minus the proportion of losses realized (PLR), computed using data on those months when the investor sells something; (v) Home bias is the fraction of equity invested in Canadian equity mutual funds; 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 advisor level. The last row reports the average percentile fee rank of the funds that clients and advisors purchase. We compute the percentile rank separately within each fund type using the 54-category classification of Funddata. The sample includes those advisors who also appear as clients in the dealer data, and who advise clients for at least two years.

Behavior	Clients		Advisors		Difference, <i>t</i> -value	<i>N</i>
	Mean	SE	Mean	SE		
Turnover						
Retirement accounts	29.7%	0.5%	35.7%	0.8%	7.01	3,408
Open accounts	29.4%	0.7%	51.9%	1.5%	14.47	2,154
Active management	98.8%	0.1%	99.0%	0.1%	1.49	3,421
Return chasing	59.0%	0.2%	61.4%	0.3%	9.20	3,132
Disposition effect						
Retirement accounts	−6.2%	0.3%	−7.2%	0.6%	−1.47	2,600
Open accounts	−11.6%	1.0%	−15.0%	1.9%	−1.65	505
Home bias						
Retirement accounts	56.4%	0.4%	46.1%	0.5%	−19.90	2,977
Open accounts	50.3%	0.6%	42.6%	0.9%	−8.85	1,590
Growth tilt	8.6%	0.2%	6.9%	0.3%	−5.04	3,391
Percentile fee						
within fund type	46.3%	0.2%	47.8%	0.4%	4.04	1,987

Table 3: Explaining cross-sectional variation in client behavior with client attributes and advisor fixed effects

This table reports estimates from panel regressions of client behavior on client attributes, advisor fixed effects, year fixed effects, and province fixed effects. The measures of behavior are described in text and summarized in Table 2. Each measure is computed at the client-year level. We omit the indicator variables for the lowest categories. Turnover, disposition effect, and home bias regressions are estimated separately using data on retirement accounts and open accounts; the other regressions pool trades and holdings across all accounts. Panel A summarizes the explanatory powers of the models with and without advisor fixed effects. Panel B reports coefficients estimates and t -values of models that include advisor fixed effects. The mean of the dependent variable ($\bar{y}$) in the panel is reported at the top of each regression. Each model includes (unreported) year and province fixed effects. Standard errors are clustered by advisor.

Panel A: Model explanatory power (adjusted R^2) with and without advisor fixed effects

Behavior	Model	
	Client attributes	Client attributes + advisor FEs
Turnover		
Retirement accounts	0.9%	3.4%
Open accounts	0.9%	3.7%
Active management	1.0%	7.8%
Return chasing	1.3%	9.0%
Disposition effect		
Retirement accounts	1.5%	3.6%
Open accounts	2.7%	6.4%
Home bias		
Retirement accounts	3.8%	18.9%
Open accounts	6.9%	27.5%
Growth tilt	0.6%	7.5%

Panel B: Coefficient estimates

Account type → Mean → Regressor	Turnover				Active management	
	Retirement		Open		All	
	$\bar{y} = 28.2\%$		$\bar{y} = 26.9\%$		$\bar{y} = 99.3\%$	
	$\hat{b}$	t	$\hat{b}$	t	$\hat{b}$	t
Age, 30–34	−6.0	−14.4	−1.2	−2.5	0.00	−0.1
35–39	−7.9	−17.3	−3.0	−6.3	0.10	2.4
40–44	−8.2	−17.0	−3.1	−6.8	0.14	3.2
45–49	−7.5	−15.4	−2.8	−6.2	0.13	3.0
50–54	−6.4	−12.9	−1.0	−2.2	0.12	2.5
55–59	−5.5	−11.0	−0.2	−0.5	0.16	3.1
60–64	−5.5	−10.6	0.0	0.0	0.30	5.2
65–69	−5.5	−10.7	−1.1	−2.2	0.41	6.1
70–74	−9.6	−17.5	−2.5	−5.0	0.46	6.7
75–80	−9.8	−17.6	−2.9	−6.2	0.58	8.2
Risk tolerance						
Low	2.7	2.7	0.3	0.3	−0.01	−0.2
Low to Moderate	1.9	2.0	−1.5	−1.5	−0.59	−5.4
Moderate	−2.1	−2.4	−6.3	−7.1	−0.21	−2.9
Moderate to High	−2.3	−2.5	−6.6	−7.2	−0.11	−1.6
High	−1.4	−1.4	−4.4	−4.4	0.18	2.4
Fin. knowledge						
Moderate	0.3	2.1	0.9	4.1	0.05	2.1
High	1.6	5.1	2.6	4.9	0.10	2.1
Time horizon						
Short	−3.4	−5.8	−4.4	−5.3	−0.26	−4.0
Moderate	−2.2	−3.9	−3.5	−5.0	−0.41	−6.6
Long	−2.2	−3.8	−2.0	−2.6	−0.58	−8.3
Female	0.8	7.3	0.9	5.1	0.04	2.3
French speaking	0.7	1.2	2.3	2.4	−0.23	−1.8
Salary						
\$30-50k	−0.5	−3.4	−0.2	−0.8	0.05	2.4
\$50-70k	0.4	2.1	0.7	2.5	0.02	0.8
\$70-100k	0.9	4.6	2.2	6.1	0.02	0.6
\$100-200k	1.3	1.0	6.2	2.3	0.01	0.1
Over \$200k	2.3	1.7	9.9	4.3	0.22	1.5
Net worth						
\$35-60k	−1.1	−2.8	1.6	2.5	0.04	0.6
\$60-100k	−0.7	−1.5	1.8	2.9	−0.08	−1.2
\$100-200k	−0.5	−1.1	2.2	3.4	−0.03	−0.6
Over \$200k	1.4	3.2	4.3	7.0	−0.02	−0.3
Finance professional	−0.2	−0.3	0.8	0.6	−0.05	−0.4

Panel B: Coefficient estimates (continued)

Account type → Mean → Regressor	Return chasing		Disposition effect			
	All		Retirement		Open	
	$\bar{y} = 57.9\%$		$\bar{y} = -4.2\%$		$\bar{y} = -10.2\%$	
	$\hat{b}$	t	$\hat{b}$	t	$\hat{b}$	t
Age, 30–34	−1.3	−11.2	0.9	2.0	0.8	0.6
35–39	−1.8	−14.6	1.3	3.0	1.5	1.4
40–44	−1.6	−13.7	2.1	5.1	1.4	1.3
45–49	−1.5	−11.9	2.3	5.5	1.1	1.1
50–54	−1.2	−9.5	2.6	6.2	0.9	0.9
55–59	−0.8	−6.3	2.8	6.8	1.7	1.6
60–64	−0.7	−5.3	3.1	7.4	3.5	3.2
65–69	−0.5	−3.0	3.5	8.0	3.1	2.8
70–74	−0.3	−1.9	4.0	8.9	4.5	3.6
75–80	−0.5	−2.4	4.2	9.1	4.6	3.3
Risk tolerance						
Low	−0.7	−1.8	0.7	0.8	3.4	1.2
Low to Moderate	0.9	2.5	0.8	1.1	1.9	0.6
Moderate	0.7	2.0	1.0	1.4	3.4	1.3
Moderate to High	1.0	2.7	1.2	1.8	4.5	1.6
High	0.9	2.1	−0.6	−0.8	2.8	1.0
Fin. knowledge						
Moderate	0.3	5.1	0.0	−0.4	0.6	1.7
High	0.9	7.7	0.0	−0.1	1.5	1.8
Time horizon						
Short	0.9	3.3	−0.6	−1.2	2.4	1.2
Moderate	1.0	3.7	−0.4	−1.0	1.7	0.9
Long	1.6	5.7	0.2	0.4	1.4	0.6
Female	−0.1	−3.2	−0.2	−1.7	−0.1	−0.4
French speaking	−0.1	−0.7	0.2	0.3	0.1	0.0
Salary						
\$30–50k	−0.1	−1.2	−0.1	−1.0	−1.4	−2.3
\$50–70k	0.0	0.1	−0.1	−0.7	−0.6	−0.8
\$70–100k	0.1	1.0	−0.2	−1.1	−1.3	−1.5
\$100–200k	−0.9	−1.9	−0.2	−0.3	1.6	0.4
Over \$200k	−0.4	−1.0	−0.6	−0.8	−0.9	−0.2
Net worth						
\$35–60k	0.2	1.1	−0.5	−0.9	−1.6	−1.1
\$60–100k	0.3	1.7	−0.2	−0.4	−0.6	−0.4
\$100–200k	0.5	3.1	0.0	0.1	−2.7	−2.1
Over \$200k	0.9	5.6	0.6	1.2	−1.0	−0.8
Finance professional	0.6	1.6	−1.5	−2.1	−2.2	−0.8

Panel B: Coefficient estimates (continued)

Account type → Mean → Regressor	Home bias				Growth tilt	
	Retirement		Open		All	
	$\bar{y} = 55.8\%$		$\bar{y} = 47.3\%$		$\bar{y} = 7.9\%$	
	$\hat{b}$	t	$\hat{b}$	t	$\hat{b}$	t
Age, 30–34	−1.3	−3.6	−1.3	−2.4	−0.2	−1.1
35–39	−1.9	−4.8	−2.0	−3.6	−0.2	−0.8
40–44	−2.2	−5.1	−2.8	−5.2	−0.4	−1.5
45–49	−2.0	−4.7	−2.5	−4.8	−0.6	−2.3
50–54	−1.7	−3.9	−1.5	−2.8	−0.7	−2.6
55–59	−1.0	−2.3	−0.7	−1.3	−1.2	−3.9
60–64	0.2	0.4	0.5	0.9	−1.6	−5.0
65–69	1.8	3.7	2.1	3.5	−1.9	−5.7
70–74	4.0	7.1	3.4	5.3	−1.7	−4.5
75–80	6.9	10.7	5.8	9.0	−1.6	−3.6
Risk tolerance						
Low	0.5	0.4	3.9	2.1	−0.4	−0.9
Low to Moderate	1.2	1.2	4.4	2.6	3.6	7.0
Moderate	1.0	1.1	−1.0	−0.7	2.5	5.4
Moderate to High	−2.9	−3.3	−5.5	−3.5	2.1	4.5
High	−15.5	−14.7	−12.9	−7.9	1.3	2.5
Fin. knowledge						
Moderate	−0.8	−4.9	−0.3	−0.9	−0.1	−0.7
High	−1.9	−5.3	−1.8	−2.9	−0.2	−0.9
Time horizon						
Short	0.5	0.8	−0.8	−1.0	0.9	2.4
Moderate	1.1	2.0	−1.6	−2.0	0.9	2.4
Long	1.0	1.6	−0.9	−1.0	0.9	2.2
Female	−0.8	−6.2	−1.3	−5.2	0.0	0.5
French speaking	0.4	0.7	2.9	2.4	−0.9	−1.8
Salary						
\$30–50k	−0.5	−3.3	−0.4	−1.4	0.0	−0.1
\$50–70k	−1.3	−7.6	−0.8	−2.1	−0.1	−0.8
\$70–100k	−1.6	−8.0	−0.2	−0.6	−0.4	−2.8
\$100–200k	−1.3	−1.1	−1.2	−0.6	−0.2	−0.2
Over \$200k	−3.7	−3.2	−0.8	−0.5	−0.6	−0.9
Net worth						
\$35–60k	−0.2	−0.4	0.1	0.1	−0.5	−1.5
\$60–100k	−0.8	−1.8	0.2	0.3	−0.7	−2.2
\$100–200k	−1.0	−2.3	−0.2	−0.3	−0.8	−2.4
Over \$200k	−1.3	−3.1	−0.4	−0.5	−1.1	−3.4
Finance professional	−0.6	−0.7	−1.8	−1.3	0.1	0.2

Table 4: Advisor compensation

Financial advisors are compensated in front-end loads, trailing commissions, and sales commissions. We measure percentage compensation by dividing the dollar amount of compensation by the total client assets under management. We compute compensation before subtracting the transfer to the dealer firm. This table reports the distributions of the annualized compensation estimates for 4,700 advisors who advise clients in the dealer data for at least five years.

Source	Mean	Percentile					
		10th	25th	50th	75th	90th	95th
Front-end load	0.017	0.000	0.000	0.000	0.002	0.019	0.064
Trailing commission	0.578	0.445	0.494	0.556	0.643	0.755	0.825
Sales commission	0.931	0.007	0.117	0.487	1.308	2.482	3.265
Total	1.526	0.575	0.757	1.105	1.889	3.032	3.866

Table 5: Regressions of client behavior on advisor compensation and behavior

This table reports estimates from cross-sectional regressions of advisor fixed effects on advisor compensation and behavior. The fixed-effect estimates are from the regressions reported in Table 3. The estimates of advisor compensation are from row Total in Table 2. Advisor compensation consists of front-end loads, trailing commissions, and sales commissions. Advisor's estimate is the estimate of advisor's behavior. For example, in the turnover regression, the dependent variable is the advisor fixed effect from the client turnover regression and advisor's estimate is the turnover of the advisor's own portfolio. The regressions include advisors who advise clients in the dealer data for at least five years. We report standard errors in square brackets for the constant and t -values in parentheses for the explanatory variables.

Account type → Regressor	Turnover				Active management	
	Retirement		Open		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.15 [1.30]	−5.59 [1.32]	2.81 [1.81]	−1.80 [1.87]	99.78 [0.23]	65.39 [1.12]
Compensation, Q_2	−0.52 (−0.31)	0.13 (0.08)	−1.29 (−0.56)	−0.42 (−0.19)	0.17 (0.58)	−0.08 (−0.31)
Q_3	−0.19 (−0.11)	0.61 (0.37)	−3.33 (−1.43)	−2.31 (−1.01)	−0.24 (−0.80)	−0.31 (−1.16)
Q_4	3.23 (1.90)	3.11 (1.88)	0.00 (0.00)	0.55 (0.25)	0.27 (0.90)	0.13 (0.48)
Q_5	9.72 (5.71)	8.77 (5.30)	8.25 (3.58)	9.12 (4.01)	−0.79 (−2.64)	−0.77 (−2.91)
Advisor's estimate		0.15 (14.54)		0.08 (8.13)		0.35 (31.13)
N	3,387	3,387	2,147	2,147	3,400	3,400
Adjusted R^2	1.7%	7.4%	1.5%	4.4%	0.4%	22.5%

Account type → Regressor	Return chasing		Disposition effect			
	All		Retirement		Open	
	(5)	(6)	(1)	(2)	(3)	(4)
Constant	−0.04 [0.56]	−15.98 [0.92]	−2.79 [1.54]	−2.59 [1.54]	6.79 [6.43]	7.09 [6.42]
Compensation, Q_2	0.69 (0.99)	0.53 (0.82)	3.40 (1.84)	3.34 (1.81)	−13.84 (−1.52)	−13.22 (−1.46)
Q_3	1.29 (1.81)	1.20 (1.84)	1.51 (0.81)	1.50 (0.80)	−13.39 (−1.67)	−11.92 (−1.48)
Q_4	2.17 (3.08)	2.16 (3.36)	1.76 (0.96)	1.78 (0.97)	−11.02 (−1.52)	−10.94 (−1.51)
Q_5	1.75 (2.43)	1.34 (2.06)	−0.73 (−0.38)	−0.56 (−0.29)	−12.36 (−1.75)	−12.12 (−1.72)
Advisor's estimate		0.26 (20.67)		0.03 (1.60)		0.06 (1.38)
N	2,069	2,069	1,034	1,034	171	171
Adjusted R^2	0.4%	17.5%	0.4%	0.5%	−0.3%	0.3%

Account type → Regressor	Home bias				Growth tilt	
	Retirement		Open		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.42 [0.71]	−11.75 [1.08]	3.77 [0.96]	−10.97 [1.86]	0.54 [0.62]	−0.33 [0.60]
Compensation, Q_2	−2.90 (−2.99)	−2.09 (−1.79)	−3.06 (−2.42)	−1.81 (−0.86)	−1.21 (−1.50)	−1.60 (−2.07)
Q_3	−4.54 (−4.66)	−1.94 (−1.65)	−1.49 (−1.17)	1.35 (0.64)	1.16 (1.44)	0.47 (0.61)
Q_4	−2.29 (−2.33)	−0.35 (−0.30)	−0.01 (−0.01)	3.03 (1.41)	0.08 (0.10)	−0.52 (−0.68)
Q_5	−5.31 (−5.29)	−2.47 (−2.02)	0.28 (0.21)	6.28 (2.83)	0.92 (1.14)	0.28 (0.37)
Advisor's estimate		0.30 (25.98)		0.28 (17.07)		0.20 (16.48)
N	5,653	2,963	4,886	1,587	3,367	3,367
Adjusted R^2	0.5%	18.9%	0.1%	16.9%	0.3%	7.7%

Table 6: 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. The sample includes those advisors who also appear as clients in the dealer data, who advise clients for at least two years, and who keep an account at the firm after they stop advising clients.

Behavior	Active advisors		Post-career		Difference, <i>t</i> -value	<i>N</i>
	Mean	SE	Mean	SE		
Turnover						
Retirement accounts	27.4%	1.8%	23.8%	3.1%	−1.11	318
Open accounts	39.1%	4.3%	27.5%	6.6%	−1.55	139
Active management	99.0%	0.5%	96.8%	0.9%	−3.50	277
Return chasing	60.3%	1.1%	60.4%	1.5%	0.10	166
Disposition effect						
Retirement accounts	−8.6%	2.0%	−7.7%	2.5%	0.27	200
Open accounts	−5.0%	8.3%	−12.3%	7.2%	−0.85	20
Home bias						
Retirement accounts	46.2%	1.8%	45.2%	2.2%	−0.58	275
Open accounts	49.9%	3.6%	58.5%	3.8%	3.03	105
Growth tilt	6.2%	1.1%	6.9%	1.3%	0.49	331
Percentile fee						
within fund type	45.8%	2.0%	53.0%	2.8%	2.45	61