The Costs and Benefits of Financial Advice*

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Abstract

We assess the value that financial advisors provide to clients using a unique panel dataset on the Canadian financial advisory industry. We find that advisors influence investors' trading choices, but they do not add value through their investment recommendations when judged relative to passive investment benchmarks. The value-weighted client portfolio lags passive benchmarks by more than 2.5% per year net of fees, and even the best performing advisors fail to produce returns that reliably cover their fees. We show that differences in clients' financial knowledge cannot account for the cross-sectional variation in fees, which implies that lack of financial sophistication is not the driving force behind the high fees. Advisors do, however, influence client savings behavior, risky asset holdings, and trading activity, which suggests that benefits related to financial planning may account for investors' willingness to accept high fees on investment advice.

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1 Introduction

Individual investors rely extensively on financial advisors to guide their investment and savings decisions. For example, in the United States roughly 40% of households that own mutual funds made purchases through an independent financial planner, and a similar proportion made purchases through a full-service investment broker (Investment Company Institute 2013). Likewise, among Canadian retail investors roughly 60% of assets are in accounts directed by financial advisors, while full-service brokers manage another 20% of assets (Canadian Securities Administrators 2012). Despite investors' widespread use of financial advisors, relatively little is known about the cost of advisors' services and the quality of their advice. This paper helps to fill that void by measuring the costs of financial advice for a large sample of advisory clients, and assessing the benefits reflected in those clients' investment and savings choices.

It remains an open question whether and to what extent financial advisors add value. Given the complexity of asset allocation, investment selection and optimal savings decisions, as well as the potential for self-directed investors to make mistakes due to lack of financial knowledge or behavioral biases, there is substantial scope for advisors to add value.[1] On the other hand, pricing for advisory services is often opaque and advisor quality is difficult to assess, which can dull the market forces that would otherwise reduce prices or improve quality. Indeed, there is evidence that competition is ineffective in reducing price mark-ups within retail asset management (Hastings, Hortaçsu, and Syverson 2013). Furthermore, the typical compensation scheme—whereby advisors

[1] There is a large literature documenting the behavioral biases of individual investors. Barber and Odean (2000, 2001, 2002) show that investors lose by trading too much, and link this tendency to overconfidence in one's own trading abilities. Grinblatt and Keloharju (2000, 2001) show that individual investors perform worse than institutional investors, and that investors exhibit a "disposition effect," a preference to sell stocks with unrealized capital gains rather than those with capital losses. Benartzi and Thaler (2001), Choi, Laibson, and Madrian (2005), and Calvet, Campbell, and Sodini (2007) show that individual investors under-diversify.

are paid through commissions on the investment products they sell—creates an agency conflict, which can harm naïve investors and limit value added even in a market populated by well-informed investors.[2] These supply-side considerations offer reasons why the value of financial advice may be limited.

To provide further evidence on the value of financial advice, we take advantage of uniquely detailed and extensive data furnished by three large financial institutions. The data include transaction-level records on over ten thousand financial advisors and these advisors' one million Canadian clients, along with demographic information on both investors and advisors. Importantly, the data cover a substantial portion—roughly 10%—of the non-bank advisory industry in Canada, which allows us to overcome a limitation of other research on this topic, which studies smaller and potentially unrepresentative groups of investors and advisors. The data also include useful individual characteristics such as age and financial knowledge, which allows us to explore differences in the costs and benefits of advice in the cross-section of households.

Our analysis proceeds as follows. First, we quantify the costs of advice and characterize the distribution of fees across investors and advisors. The investors in our sample pay an average expense ratio equal to 2.43% (1.8% at the 10th percentile versus 2.8% at the 90th percentile). The average investor pays \$1,575 per year for financial advice, but this amount varies considerably across investors because fees are proportional to assets under management. While investors in the bottom decile pay as little as \$55 per year, those in the top decile pay more than \$3,918 per year.

Next, we assess the quality of advisors' investment advice. We begin by evaluating the investment performance of advised clients. Net of fees, we find evidence of substantial underperformance

[2] In theoretical work, Inderst and Ottaviani (2009) examine the effects of such agency conflicts on household welfare. In empirical work on this topic, Hackethal, Inderst, and Meyer (2012) find that investors who rely more heavily on advice have a higher volume of security transactions and are more likely to invest in products that salesmen are incentivized to sell.

relative to passive investment benchmarks. In aggregate, advised portfolios lag passive benchmarks by 2% to 3% per year, depending on the choice of benchmark. These estimates represent economically substantial underperformance: an investor who expects to retire in 30 years gives up a quarter of potential savings in present value terms by lagging the passive benchmarks by 3% per year.

It is the performance drag from fees and not negative stock-picking or market-timing abilities that accounts for most of this underperformance. The value-weighted expense ratio of the average advisor in the sample is 2.4% per year; among the top-1% of the most expensive advisors, the expense ratios reach 3.5% per year. Across advisors, we find substantial variation in investment performance, but little evidence of value added, even among the best performing advisors. The alphas in the 5th percentile of the distribution are associated with t-values below -2.5 no matter the choice of passive benchmarks. At the same time, the alphas even in the 99th percentile of the distribution are statistically insignificant. We use the Fama and French's (2010) luck-versus-skill methodology—which they introduce to measure the proportion of skilled mutual fund managers—and find no evidence of skill (net of fees) even in the extreme right tail of the distribution.

We also use the time-series dimension of our data to study whether investors seem comfortable with their investment performance and the fees that they are charged. Though revealed preference suggests that investors expect their advisors to deliver positive net alphas when they sign up for an account, it may be that these expectations are mistaken and that after learning about fees and returns over time, they close their account.

We find that past performance affects investors asymmetrically: the likelihood of account closure increases following negative returns, but shows little relationship with performance when returns are positive. Fees, on the other hand, show little relationship with account closure on average, but do seem to be important to more financially knowledgeable clients: among clients with moderate to high financial knowledge, the likelihood of closing the account rises substantially with past fees. This quitting behavior gives advisors of more knowledgeable clients an implicit incentive to limit fees and pursue lower cost strategies. Consistent with this hypothesis, we find that more knowledgeable clients are charged lower fees. The magnitude of the difference, however, is very small, a mere 2.3 basis points. This finding suggests that lack of financial sophistication is not the driving force behind high fees.

Taken altogether the results on investment performance suggest that investment advice alone does not justify the fees paid to advisors. Nevertheless, households display a strong revealed preference for using financial advisors, which suggests that many expect the benefits to outweigh the costs. In the balance of the paper, we examine whether clients benefit in other ways from their relationship with the advisor, specifically through financial planning and advice on savings and asset allocation.

To evaluate the importance of financial planning, we examine advisors' impact on savings choices. We estimate the causal effect that advisors have on their clients' behavior by first identifying advisors who retire, quit, or die, and whose clients are subsumed by another advisor. We then measure differences in client behavior between the disappearing advisor's clients and the new advisor's existing clients both before and after the switch. Using a difference-in-difference estimator, we find significant convergence in investors' use of automatic-savings agreements. Upon losing their old advisor, clients begin to resemble their new advisor's existing clients. The impact on the utilization of automatic savings plans is economically noteworthy—the difference in these utilization rates decreases from 41.7% to 29.4% as a result of the switch. While these findings do not quantify the value of savings advice per se, they are suggestive that advisors play an important role in clients savings decisions, whether in providing a savings goal or in providing monitoring and commitment to meet that goal over time.

To complement this evidence on the benefits of advice in the last section of the paper we pull away from the transaction-level data on advised households and use data from a detailed household survey that includes both advised and unadvised households to estimate the effect that financial advisors have on households' financial decisions. In this analysis we exploit a 2001 regulatory change in most of Canada (Quebec was excluded) that imposed registration requirements for mutual fund dealers (and their financial advisors) and thereby reduced the supply of advisors. Using a differences-in-differences model to compare affected households to those in Quebec, we find that the registration requirement reduced households' likelihood of using an advisor. Exploiting this variation within an instrumental variables model, we show that financial advisors have a substantial effect on households' decisions, increasing their risky asset holdings as well as their trading activity.

Our paper contributes to the empirical literature on the quality of financial advice. Bergstresser, Chalmers, and Tufano (2009) provide indirect evidence that advised clients earn poor returns by documenting substantial underperformance of mutual funds sold exclusively by brokers or advisors. Yet their study lacks specific data on financial advisory portfolios, which prevents them from precisely quantifying the underperformance of advised clients. Mullainathan, Noeth, and Schoar (2012) evaluate the quality of advisors' recommendations in the context of a field experiment, and find evidence of poor advice; advisors encourage "return chasing" and also direct clients toward higher cost, actively managed funds. Finally, Chalmers and Reuter (2013) find that Oregon University retirement plan participants opting for financial advice underperform both passive investment benchmarks and the returns of self-directed plan participants. Qualitatively, our findings are similar to these studies, but an important contribution of our analysis is to provide evidence on a large and representative group of advised clients. We also benefit from the 10-year length of the panel by being able to examine the relation between account closures, past performance and past fees.

The rest of the paper proceeds as follows. In Sections II and III, we provide background on Canadian retail investment industry and describe our data. Section IV analyzes net and gross performance, and the role of fees. Section V studies how past performance affects investors' investment decisions, such as the decision to retain the same advisor. Section VI provides evidence that advisors influence their clients' savings and asset allocation choices. Section VII uses survey data to investigate advisors' causal effect on their clients' savings and investment decisions. Section VIII concludes.

2 The Retail Investment Industry in Canada

Canadian households purchase investment products and services through five main channels, three of which involve financial advice and two of which are client-directed. By far the most common choice is to invest with the help of an advisor: out of $876 billion of retail investment assets as of year-end 2010, roughly 80% are in accounts directed by an advisor (Canadian Securities Administrators 2012).[3] Non-bank financial advisors, which are the subject of our study, account for the largest portion of retail assets—$390 billion, or 44% of total assets.[4]

Among advisors the services vary, but the core services offered by all advisors are financial

[3] The two non-advisory channels, bank branch sales and self-directed accounts (including discount brokerage and mutual fund direct sales), account for 11% and 7% of retail investment assets, respectively.

[4] The other two types of advisors, for which we do not have data, are full-service brokers, who oversee 20% of retail assets, and financial advisors within bank branches, who oversee 17% of retail assets.

planning and investment advice. As part of financial planning, advisors help clients formulate retirement and education savings plans, first and foremost, but also arrange mortgage loans and provide insurance and estate planning in some cases. Within the scope of investment advice, advisors offer guidance on asset allocation and investment selection, and execute trades on their clients' behalf. For the accounts in our sample, discretionary trading by the advisor is not permitted; each trade must be initiated or approved by the client.

The range of investment products sold by an advisor depends on his securities licenses. Our analysis focuses exclusively on advisors that are licensed as mutual fund dealers, a designation which permits sale of mutual fund and deposit products, but precludes sale of individual securities and derivatives.[5] In addition to being licensed to sell mutual funds, some financial advisors in our sample also have licenses to sell segregated funds, labor funds, and principal protected notes.[6]

Financial advisors who are licensed to distribute mutual funds in Canada do so through one of two self-regulatory organizations. The first, Mutual Fund Dealers Association (MFDA), supervised 80,132 advisors at the year-end 2010 and these advisors had a combined $271 billion in assets under advisement. The second regulator, Investment Industry Regulatory Organization of Canada (IIROC), supervised 28,598 advisors. The combined number of financial advisors in Canada licensed to distribute mutual funds is thus 108,730.

Under Canadian securities legislation, advisors have a duty to make suitable investment recommendations, based on their clients' investment goals and risk tolerance. To that end, advisors are required to conduct "Know Your Client" surveys with each client at account origination and annu-

[5]Full-service brokers, who are not represented in our sample, offer access to the widest range of investment products— individual securities as well as mutual funds and deposit products—by virtue of being licensed as investment dealers and mutual fund dealers.

[6]Segregated funds are variable life insurance contracts that reimburse capital upon death. Labor funds are funds that direct (venture capital) investments to small non-public firms.

ally thereafter. The extent of advisors' fiduciary duty, however, is a gray area; it is not clear that they are required to put the client's interests before their own, though they are legally mandated to deal fairly, honestly and in good faith with their clients (Canadian Securities Administrators, 2012). This gray area is important, given the potential for agency conflicts between advisors and their clients.

Agency conflicts are a concern due to the compensation scheme for advisors. Most commonly, clients pay no direct compensation to advisors for their services. Rather, the advisor earns commissions from the investment funds in which his client invests, raising the possibility that their investment recommendations are biased toward funds that pay larger commissions without providing clients better investment returns.

The size and source of these commission payments vary depending on the asset class and load structure of the mutual fund purchased by the client. Commission payments are lowest on money market funds and highest on balanced funds and equity funds, which potentially skews advisor recommendations toward riskier funds. Across load structures, commissions are lower, on average, for no-load funds and higher for load funds. For no-load funds, which are so-named because the investor pays no explicit commission on purchases and redemptions, the advisor still collects a trailing commission of up to 1% per year from the mutual fund as long as the client remains invested. For funds with a back-end load, the investor pays a fee to the mutual fund company at the time of redemption—typically, the redemption fee declines with horizon, starting at 6% within one year of purchase and declining to zero after 5 to 7 years. The advisor, in turn, is paid by the mutual fund company in the form of a payment at the time of purchase (typically 5% of the purchase amount) as well as a trailing commission (typically 0.5% annualized) as long as the client remains invested. Finally, on purchases of front-end load funds, the advisor receives an up-front sales commission directly from the client (up to 5% of the purchase amount, but negotiable between the investor and advisor), along with a trailing commission paid by the fund company (up to 1% per year while the client remains invested). While the exact source of the commissions varies, ultimately these payments are funded by clients, whether directly or indirectly through management and operating expenses deducted from their fund investments.

After summing up these commission payments and deducting the typical share of commissions (20%) that go to their employer, the average advisor in our sample earns revenue of $80,000 to $120,000 per year.

3 Data and Summary Statistics

Three large Canadian financial advisory firms supplied the data for our study. Each firm provided a full history of client transactions over a 10-year period, from 2001 to 2010, along with background information on clients and advisors. The total value of assets under advice at the end of this period was $30.9 billion, representing 11% of the assets of Mutual Fund Dealers (MFDs). Key summary statistics of these data are provided in Table 1.

Table tbl:descriptivestatistics Panel A describes the investor side of the sample and shows that our data cover a broad swath of different types of investors both in terms of their demographics, the length of the investor-advisor relationship, financial knowledge, and wealth. Across the entire sample, we have data on 748,287 investors with 1.5 million accounts; 86% of these investors were active as of year-end 2010. Men and women are equally presented in the data. The median investor in the data is 49 years old, and the 10th and 90th percentiles of the age distribution are 32 and 68 years.

The data display considerable heterogeneity with respect to how long an investor has known his or her advisor. At the end of the sample period, over 10 percent of investors had been in the client-advisor relation for less than a year (row “investor known since”); and at the end other end of the spectrum, investors in the 90th percentile of the distribution had known their advisors for at least 7 years.

Panel A’s bottom three blocks describe self-reported financial knowledge, net worth, and salary of the investors. Financial advisors collect this information at the start of the advisor-client relationship using a “Know Your Client” form. Investors vary significantly also in these dimensions. 6% of investors report high financial knowledge, and 9% of investors report no or very low knowledge. The remaining investors either report low or moderate financial knowledge (85%). More than half of investors report a net worth over $200k while 20% report a net worth of $50k or less. Annual salaries display dispersion similar to that in net worth: 27% of the investors who provided a response reported an annual salary of less than $30k, and 10% of investors reported earning more $100k per year.

Table tbl:descriptivestatistics Panel B shows summary statistics for the advisors in our sample. The median advisor’s age is roughly the same as that of the median investor, 50 years, and the 10th and 90th percentiles are 36 years and 63 years. Just below three-quarters of the advisors in our sample were still active as of year-end 2011. The remaining advisors are either inactive (22%) or had been terminated (6%) by the end of the sample period.

Advisors differ significantly from each other in terms of their experience, the number of clients they advise, and how many different licenses they have. Over 10% of advisors have been in the job for less than a year, and another 10% have at least 8 years of experience. While the median advisor advices 18 clients with a total of 29 accounts, these numbers are very different at the 10th and 90th percentiles: advisors in the bottom decile have just one client with two accounts; those in the top decile have over 200 clients with more than 400 accounts. Over a quarter of advisors have just one license—the mutual fund license—and just over 10% have three or more licenses.

Table tbl:descriptivestatistics Panel C shows that the data are divided between different types of accounts. One-fifth of the accounts are unrestricted general purpose ("open") accounts; 71% of accounts are classified as either retirement savings or retirement income accounts that receive favorable tax treatment comparable to the 401(k) plans in the U.S.; 4% of the accounts are education savings plans; and the remaining 4% are tax-exempt accounts that face restrictions on how funds can be invested and withdrawn. The data include both open and closed accounts. As of the end-year 2010, 44% of the accounts were active; the others were either inactive or had been closed. Panel C's bottom block tabulates the self-reported time horizons of the accounts. The typical investment horizon—reported for 63% of the accounts for which this information is supplied—is six to ten years. One-fifth of accounts are associated with reported investment horizons greater than ten years, and the remaining 15% of accounts have shorter investment horizons. There are some very-short-term accounts as well. Some 3% of the accounts—or just over 30,000 accounts—are associated with an investment horizon shorter than a year.

Table 2 introduces survey data from the Canadian Financial Monitor (CFM) by Ipsos-Reid, a survey and market research firm. The data are structured as a repeated cross-section, with monthly interviews of approximately 1,000 households between January 1999 and June 2013. Some households, however, do participate repeatedly, so the total number of observations (175,000) exceeds the number of unique households (79,600). In addition to providing a wealth of demographic information, each interview measures households' stock and mutual fund holdings, and their asset allocation and savings decisions. More important for our analysis, the survey collects also information on the use of financial advisors. In Table 2 we report descriptive statistics for Canadian households based on whether they report having a financial advisor. Advised households are on average four years older (56.3 vs. 52.4), 7.5 percentage points more likely to be retired (34.7 vs. 27.2), and 14 percentage points more likely to have either a college or graduate degree (69.0% vs. 54.9%). From a financial standpoint, advised household also have higher average incomes (CND $74,900 vs. 52,400), substantially higher net worth (CND $472,300 vs. 212,500) and more financial assets (CND $221,100 vs. 71,600). Last, households that use financial advisors invest more in equity (15% vs. 6.9% of financial assets), more in mutual funds (39.7% vs. 12.7%) and less in fixed income products (45.2% vs. 80.4%).

4 Do Advisors' Investment Recommendations Add Value?

In this section we assess the quality of advisors' investment advice. In the Appendix we present evidence that trading flows are significantly correlated among investors using the same advisor. Having established that clients seem responsive to their advisors' investment recommendations, we assess here the value of advisors' investment advice by comparing their investment performance relative to passive investment benchmarks. In this analysis, since we are interested in evaluating advisors, we aggregate holdings to the advisor level in computing returns. The analysis proceeds in two stages. First, we assess advisors' skill in fund selection, asset allocation and market timing by comparing gross investment returns to a variety of passive investment benchmarks. Next, we incorporate value lost due to fees by repeating the same analysis with net returns.

4.1 Client Performance Gross of Fees

To construct gross returns, we add to each client's monthly account balance all fees paid on mutual fund investments, including management expenses.[7]

We examine risk-adjusted returns with a series of models that adjust for common equity and bond market risk factors. We begin with the CAPM, Fama and French (1993) three-factor and Carhart (1997) four-factor models. Next, we add two bond-related factors to account for the substantial non-equity allocation in most client portfolios. These fixed-income factors are the return differences between the ten-year and 90-day Treasuries and that between BAA- and AAA-rated corporate bonds. For all of these models, we estimate the asset pricing regressions over the full sample period using monthly return series.

Table 3 Panel A reports the distributions of advisor-level gross alphas and t-values associated with these alphas. The distributions of t-values are useful for assessing skill because, unlike the alpha estimates, they control for differences in sample lengths and estimation uncertainty (Fama and French 2010). In these computations we first compute an advisor-level return by value-weighting the returns earned by the advisor's all clients. We then use these advisor-level returns as dependent variables in the asset pricing regressions.

The mean and median gross alphas are close to zero across the four asset pricing model. In the four-factor model with the fixed income factors, the average alpha is -0.29% per year, and the average t-value is -0.11. There is little evidence of superior stock-picking or market-timing abilities

[7] In future versions of this paper we will also incorporate back end loads or redemption fees and all fees paid directly to the advisor, including account maintenance fees and front end loads. Those data, while they will become available, are not incorporated in this set of results. So we understate fees and overstate net returns currently.

even in the right tail of the distribution. The t-values at the 99th percentile—corresponding to just over 100 advisors with the best performance in the sample—range from 2.43 (the augmented four-factor model) to 2.86 (the CAPM). Because the t-values themselves have sampling distributions, we would observe statistically significant alphas by luck alone—in particular, even if the true alphas were identically zero, we would expect to observe t-values of 1.65 at the 95th percentile and those of 2.33 and the 99th percentile. The right-tails of the t-value distribution in Panel A exceed these reference distributions by only a small margin. We note that the t-value distributions are also symmetric—the t-values at the 1st and 5th percentiles are of the same magnitude as those at the 95th and 99th percentiles. There is little evidence of abnormal mass in the right tail of the distribution to indicate the presence of skill.

The last column in Table 3 Panel A reports the estimates alphas and t-values for the average advised dollar. We compute the returns on the average advised dollar by value-weighting the returns of all investors in our sample. The last column's alpha estimates lie just below the means and medians of the advisor-level alpha and t-value distributions. In the four-factor model augmented with fixed income factors the alpha on the average advised dollar is -0.54% per year, and this estimate has a t-value of -0.40.

4.2 Client Performance Net of Fees

The gross return computations suggest that financial advisors are not able (or do not attempt) to profit by timing the market or selecting stocks. As a consequence, the fees that advisors charge result in negative net alphas. These fees are substantial. Across the 9,569 advisors, the average value-weighted management expense ratio that their clients face is 2.39%; the 1st and 99th percentiles of the fee distribution are 0.96% and 3.52%—there are no cheap advisors but an abundance of exceptionally expensive ones.

Table 3 Panel B tabulates the distributions of advisor-level net alphas from the same four asset pricing models as above. These computations subtract off management expense ratios (and any direct fees charged by advisors) but do not take into account any front- and back-load fees that investors may pay. As a consequence, the net alphas reported here overstate investors' realized alphas.

The estimates in Panel B show that much of the distributions of the realized net alphas are below zero. Under a quarter of alphas are positive in every asset pricing models. The medians range from a high of -1.86% (the CAPM) to a low of -2.52% (the augmented four-factor model). There is again no evidence of positive alphas even in the rightmost tail of the distribution. There are only marginally significant alphas at the 99th percentile—the t-values from the CAPM are the highest at this percentile, 1.90—whereas those on the other side of the distribution begin to approach statistical significance already at the 25th percentile.

The average advised dollar experiences performance comparable to the means of the distributions. Across the same four models, the alphas on the value-weighted portfolios of all investors in the sample are -2.31% ($t = -1.75$), -2.59% ($t = -1.91$), -2.74% ($t = -2.04$), and -2.91% ($t = -2.13$). Thus, whether we study the distributions of alphas across advisors or focus the performance experienced by the average dollar, the conclusion is the same. There is little evidence of any advisor adding value through superior performance. The performance lag is largely due to the fees the investors pay, not due to the poor performance of the underlying assets.

The economic significance of these negative net alphas is non-trivial. Consider, for example, the average advised dollar's net-of-MERs alpha in the four-factor model augmented with the fixed-income factors, −2.91% per year. Because investors could earn a net alpha of 0% by investing in the passive benchmarks, this estimate implies that the investors hand over a steady stream of potential savings year after year. To illustrate how much the investors give away in present value terms to financial advisors (and mutual fund companies), suppose that an investor sets aside a fixed amount every year, and will retire in 30 years. If the expected return on the investor's total portfolio—consisting of both equity and fixed income instruments—is 8%, an annual net alpha of 3% decreases the present value of the investor's savings by 26%.[8] This estimate means that the typical investor who begins saving for retirement with a financial advisor hands over a quarter of the present value of his or her retirement savings on day one. Even assuming a more "conservative" average net alpha of −2% per year, the wealth transfer to financial advisors and mutual fund companies amounts to 18% of the present value of the typical investor's retirement savings.

4.3 Performance over Retirement-date Matched Lifecycle Funds

The gross and net alpha estimates in Table 3 Panels A and B compare investors' realized performance to the performance they would have obtained by holding passive, well-diversified portfolios without incurring any fees. This comparison is challenging because, first, it assumes that if these investors were made "unadvised," they would have the knowledge to hold well-diversified benchmark portfolios and, second, because investors incur costs when making any investments.

Table 3 Panel C addresses these limitations by comparing investors' performance to the perfor-

[8] French (2008) makes a similar computation to evaluate how much active investors spend, as a fraction of the total market capitalization of U.S. equities, to beat the market. The computation here is the following. The present value of the investment described is an annuity with a present value of $\text{PV} = \left(\frac{C}{r}\right)\left(1 - \frac{1}{(1+r)^T}\right)$, where C is the annual dollar savings, r is the rate of return on the investment, and T is the investment horizon. The ratio of present values under the rates of return of r_1 and r_2 is then $\frac{\text{PV}_1}{\text{PV}_2} = \left(\frac{r_2}{r_1}\right)\left(1 - \frac{1}{(1+r_1)^T}\right)\Big/\left(1 - \frac{1}{(1+r_2)^T}\right)$. Plugging in the rates of $r_1 = 8\%$ and $r_2 = 5\%$ gives $\frac{\text{PV}_1}{\text{PV}_2} = 0.732$.

mance of retirement-date matched lifecycle funds. We assume that investors will retire at the age of 65 and then assign every investor one of the Fidelity Clearpath lifecycle funds that were available to these investors as one of the investment options—that is, it is a fund they could have held instead. The target dates of these funds range from 2005 to 2045 in five-year increments. These funds invest in other Fidelity equity and bond funds, and change the mixture of funds towards bonds as the retirement date approaches. The estimates on row "Difference in gross returns" show that, similar to Panel A's gross-alpha analysis, there is no evidence of skill in gross returns across advisors. The distribution is symmetric, and the average dollar lags the performance of the value-weighted portfolio of the lifecycle funds we assign to investors by 0.87% per year. The mean and median differences in gross returns are −0.41% and −0.47% per year. If advisors do not outperform lifecycle funds in gross returns, the (generally) higher fees of non-lifecycle funds will generate performance drag.

Row "Difference in MERs" in Panel C shows that the fees investors actually pay create a significant drag on their performance relative to the performance they would obtain by investing in lifecycle funds. The average dollar pays 1.31% per year more in management expense ratios, and the mean (median) across advisors is 1.33% (1.35%). The resulting drag on performance is statistically significant: even investors at the 1st percentile of the advisor distribution pay 3 basis points more in fees than what they would pay for the lifecycle funds. Investors are the other end of the distribution, at the 99th percentile, pay 2.48% more in fees.

4.4 Estimating the Fraction of Skilled Advisors

Table 4 uses the Fama and French (2010) bootstrapping methodology to estimate the *fraction* of advisors who can consistently outperform passive benchmarks after fees. Fama and French (2010) introduce this technique in a study of actively managed mutual funds. Because returns are very noisy, funds (and advisors) can have high or low alphas—and $t(\alpha)$s—just by luck. The empirical difficulty then is disentangling luck from skill. Fama and French assess skill using the following procedure:

1. Estimate each fund's alpha using all available data;
2. Set funds' full-sample alphas to zero by subtracting estimated alphas from monthly funds returns;
3. Resample months from the panel with replacement to preserve the covariance structure of fund returns and factors.
4. Re-estimate alphas of all funds using the resampled data; and
5. Go back to step 3 and repeat the simulation procedure 10,000 times.

By setting funds' full-sample alphas to zero, the variation in the re-estimated alphas (and $t(\alpha)$s) is due to noise. Fama and French (2010) then examine how the true distribution of $t(\alpha)$s differs from the simulated distributions. The benefit of the by-month sampling scheme is that it retains the covariance structure of fund returns and factors, so the bootstrapping procedure properly accounts for correlated observations.

Fama and French's (2010) main analysis is based on the analysis of likelihoods. They compute the percentiles of the actual $t(\alpha)$-distribution and then report the fraction of simulations in which the corresponding percentile is lower. If, for example, the simulated 90th percentile of the $t(\alpha)$ distribution is often lower than the corresponding percentile in the actual $t(\alpha)$ distribution, then fund managers at this percentile appear to have skill-that is, their $t(\alpha)$s are higher than what we would expect them to be by luck alone. Fama and French (2010) conclude that only a handful of managers have skill. In the three-factor model only at the top-2% percentiles of the actual $t(\alpha)$ distribution the t-values dominate the simulated t-values more than 50% of the time.

Table 4 shows the simulated and actual distributions of t-values using advisors' net (Panel A) and gross returns (Panel B), and reports the fraction of simulations in which the actual t-value is higher than the simulated t-value. To illustrate, consider the 10th percentile of the t-values associated with the CAPM alphas in Panel A. The actual $t(\alpha)$ at this percentile is -2.20, and this statistic is considerably lower than what it is in the average simulation, -1.04. The number 3.42 in the $\% <$ Act-column indicates that in just 3.42% of the simulations the 10th percentile of the simulated distribution lower than -2.20. That is, advisors at this percentile are considerably worse (in terms of their net alphas) than what they would be if the net alpha distribution were centered at zero and all variation in alphas was due to luck. A percentage less than 50% signifies the absence of skill.

Whereas Fama and French (2010) find that some mutual fund managers have enough skill to cover the costs they impose on their investors, the results on financial advisors in Panel A are more pessimistic. Even in the CAPM the percentage of simulations in which the actual t-value exceeds the t-value from the simulations never breaches the 50% threshold. This finding regarding the lack of skill strengthens as we move to the three- and four-factor models. In these models the fraction of simulations in which the actual t-value exceeds the t-value from the simulations hovers around 1/3 even at the 99th percentile. The reason for this downward shift in perceived skill—which is also apparent in Table 3—is that advisors overweight mutual funds that invest in small value stocks.[9]

[9] We do not implement the Fama and French (2010) methodology for the augmented four-factor model because, by doing so, we would need to increase the number of months an advisor is required to be in the sample to be included in the analysis. We require an advisor to have at least 8 months of returns to be included in the sample, which is the same threshold used by Fama and French (2010). In the four-factor model this leaves us with three degrees of freedom.

The estimates in Table 4 Panel B show that the lack of skill in advisors' net returns is due to the fees they charge. The analysis of gross returns in Panel B asks whether advisors have enough skill to cover the costs missing from mutual funds' expense ratios (Fama and French 2010). The actual-exceeds-simulated percentage climbs above 50% already at the 20th percentile of the distribution in the CAPM, and around the 40th percentile in the three- and four-factor models. These estimates suggest that if no one in the system—advisors, mutual funds, or dealers—charged any fees for the services they provide then investors could benefit from advisors' mutual fund choices. But because everyone in the chain provides their services at cost, investors lose relative to what they would earn if their money were instead invested in passive benchmarks.

4.5 Determinants of Advisor Performance

In the analysis reported in Table 5, we examine the determinants of advisor performance. To do so, we regress the advisors' estimated alphas on their characteristics, such as age, tenure at the dealer, the number of clients, the complexity of the average investor, as determined by the number of accounts and investments per client, and the number of licenses the advisor has to sell products other than mutual funds. As a dependent variable we use each advisor's estimated net alpha, measured in standardized units (as a t-statistic), under a given asset pricing model. Due to missing data on advisor age, this analysis uses data on 2,200 advisors. Advisor characteristics explain between 12% and 15% of the cross-sectional variation in $t(\alpha)$s depending on the asset pricing model. This explanatory power is high relative to models that seek to explain cross-sectional variation in mutual fund managers' alphas. Chevalier and Ellison (1999), for example, estimate a cross-sectional regression of alphas on age, tenure, educational background, and fund style, and find report an adjusted R^2 of just 3.1%.

Table 5 shows that advisor's tenure at the dealer is the strongest correlate of net alpha. Advisors who have been with the dealer longer deliver significantly worse investment performance than those who are new to the job. Other attributes explain cross-sectional variation in performance as well. Advisors with more clients deliver worse performance, as do those whose clients have more complex portfolios. The clients of advisors who oversee a small number of investors with "simple" portfolios attain relatively better performance. The regressions also suggest that investors whose advisors have a license to sell more products other than just mutual funds lag investors whose advisors are focused on just mutual funds. This performance lag would not arise directly from these other products, such as variable life insurance contracts, because the net alphas in Table 5 only measure the performance of the mutual fund portion of the portfolio.

5 Do Clients Respond to Investment Performance?

Our analysis up to this point shows that advisors fail to add value in their investment recommendations. This lack of value added is noteworthy and raises the question of whether investors are aware of, and responsive to, investment underperformance. In this portion of the analysis, we investigate this issue by testing whether past investment performance explains net account contributions and the likelihood of account termination.

We model the probability an investor abandons his or her advisor as a function of the investor's investment performance. The idea is simple. If investors pay high fees because they receive some valuable (but unobservable) services in returns, the resulting poor performance comes as no surprise, and account closures should be unrelated to performance. But if some investors operate under the assumption that advisors offset their high fees by timing the market or selecting underpriced investments, or they do not understand a priori the magnitude of the fees they are charged, then realized poor returns may jolt some investors to revise these beliefs and close their accounts. The common element is that investors may expect equal or superior performance relative to passive benchmarks, and if their performance fails to meet this expectation, we should observe it through a correlation between account closures and past performance.

5.1 Account Closure, Past Performance, and Fees

We use a Cox proportional hazard model to measure the effect of past investment performance on the likelihood of account closure. The hazard rate of closing the account at time t conditional on being held open until time t is,

$$h(t) = h_0(t)e^{\beta_1 r_{t-12,t} + \delta_t}, \tag{1}$$

in which $r_{t-12,t}$ is the investor's return over the prior one-year period. Within this model, the coefficient β_1 measures the effect of the client's prior year investment returns on his likelihood of account closure. The model includes year-month fixed effects (δ_t) to account for common time series variation in contributions and withdrawals across all investors. Given the presence of time fixed effects, β_1 is not identified from common patterns in market returns over time. Rather, it is identified in the cross-section, from the relative hazard rates of closure for accounts that experience poor performance relative to those that experience good performance.

The first two models in Table 6 Panel A report estimates from this model with the first model omitting the year-month fixed effects. Although the hazard rate decreases significantly in returns in the first model—the coefficient on the prior one-year return is 0.76 with a t-value of -5.31—the second model with year-month fixed effects reveals that this relation is entirely due to a market-wide correlation between account closures and performance. When the entire market falls, more investors close their accounts.

The third model in Table 6 Panel A relaxes the functional form with return categories in 10% bins ranging from -30% or less to $+30\%$ or more,

$$h(t) = h_0(t)e^{\beta_1 \mathrm{I}(r_{t-12,t} \leq -30\%) + \beta_2 \mathrm{I}(-30\% < r_{t-12,t} \leq -20\%) + \beta_7 \mathrm{I}(30\% < r_{t-12,t})}, \tag{2}$$

in which the omitted return category is that between 0% and 10%.

The estimates of this model reveal a significant nonlinear relation between accounts closures and past performance. While there is no relation in the domain of positive returns, investors who experience moderately poor performance relative to the market are significantly more likely to close their accounts. The coefficient for the first negative return interval from -10% to 0% is 1.33 (t-value = 10.40); for more extreme negative returns, from -20% to -10%, it is 1.18 (t-value = 4.27). These two estimates are economically significant. The interpretation of the first estimate, for example, is that an investor who lags his or her peers up to -10% has a 33.1% higher hazard rate relative to investors who outperform their peers by up to 10% (the omitted return category). The relation between account closures and past performance disappears when moving further left in the return distribution.

The result in Table 6 Panel A that investors abandon their advisors following poor performance suggests that some investors feel that the returns they receive are unacceptably low. At the same time, the relation between account closures and performance is present only within a small segment of the return distribution. That investors overall are relatively unresponsive to past performance may make sense of advisors' persistent and significant underperformance. Advisors may lack incentives to improve performance or cut fees, even in the context of a competitive market, if their clients display little sensitivity to investment performance. In the next portion of the analysis we test directly whether the rate of account closure changes with fees.

Table 6 Panel B reports estimates from Cox proportional hazards rate models that replace past performance with the average expense ratio of the investor's holdings over the prior one-year period. Controlling for the proportion of risky assets held in the investors' account, we find that investors are more likely to quit when they are charged higher fees. The coefficient of 1.18 implies that for every 1 percentage point increase in the prior year's expense ratio—roughly a 50% increase over the average expense ratio of 2.4%—the probability of account closure increases by 18%. Interestingly, this sensitivity to the expense ratio depends on clients' self-reported financial knowledge. In the second specification, we find that within the sub-sample of investors that report low financial knowledge (roughly 50% of investors), there is no relationship between fees and account closure.[10] For investors that report moderate to high financial knowledge, on the other hand, the likelihood of account closure increases quite strongly as fees rise: for every 1 percentage point increase in the expense ratio, we estimate a 45% increase in the hazard rate of account closure.

The fact that low-knowledge investors are price insensitive suggests that advisors for this segment of the market lack an implicit incentive to compete by lowering prices. Accordingly, we would expect these investors to be charged higher prices. Though we do indeed find that they pay higher fees, the increase is only 2.3 bps over the expense ratio paid by those with moderate to high financial knowledge. This difference, while statistically significant, is very small relative to the average expense ratio of roughly 2.4% and the range of expense ratios that we observe in the data. This

[10]These investors categorize their financial knowledge as low, very low, or none. The alternative is to report moderate or high financial knowledge.

result implies that differences in financial knowledge do not explain much of the cross-sectional variation in fees across investors, and that lack of financial sophistication is not the main driver of high fees within this market.

6 Do Advisors Affect Clients' Savings Behavior and Asset Allocations?

Investment advice alone does not seem to justify the fees paid to advisors. In the remaining of the paper, we investigate if clients benefit in other ways from their relationship with the advisor. For example, advisors can add value to their clients by helping them formulate savings plans and by choosing asset allocations that best fit clients' investment horizons and preferences. In this section we test whether advisors have a causal effect on their clients' savings behavior and asset allocation choices. The idea we pursue is that advisors may differ in their personal preferences, and differences in these preferences may bleed over into the advice they give their clients.

The fact that advisors are not assigned to investors randomly hampers attempts to measure the effect advisors have on their clients. If investors are matched with advisors by any attribute correlated with preferences, such as similarity in demographics, a study of cross-sectional variation in savings behavior and asset allocation choices across advisors measures not only the influence that advisors have on their clients' behavior (if any) but also the differences created by endogenous matching

We measure the causal effect from advisors to clients by first identifying advisors who retire, quit, or die and whose clients are subsumed by another advisor. In the advisory industry one's clients are a valuable good, and upon exit advisors sell their book of clients to another advisor.

Our identification strategy is to measure the similarity between the disappearing advisor's clients and the new advisor's existing clients both before and after the switch, and to test for convergence in these groups' behavior around the switch. To illustrate, consider measuring advisors' influence over the rate at which clients utilize automatic savings plans—plans in which a fixed amount is withdrawn from the client's checking account every month and invested in mutual funds. Suppose that advisor A has 20 clients and, upon retirement, sells his clients to advisor B who, before this event, also had 20 clients. Our strategy is to examine the difference in automatic-savings-plan utilization rates between advisor A's 20 clients and advisor B's 20 clients both before and after the switch. This difference-in-difference estimator controls for the endogeneity problem—although advisor A might sell his clients to advisor B because A and B are similar in some dimension, then advisor A's and B's clients would be similar both before and after the switch—there would be no changes in their behavior relative to each other. If, however, advisors have a causal effect on their clients' decisions, then the two groups of investors should become more alike in their behavior after the switch.

The details of the test are as follows. We first identify investors who switch from old advisor A to new advisor B, and then we count the number of investors completing the same A-B switch in the same month. We require that both A and B had at least five clients six months before this event, and that A has no clients six months after the switch. We use these windows and client counts because investors do not always transition from one advisor to another in one month—this transition period can last several months. For every A-B switch that we observe, we also identify all investors who were clients of advisor B both the month of the switch as well as a year earlier. Finally, we define the pre-switch period from two years before the switch to six months before the switch, and the post-switch period from six months after the switch to two years after the switch. We leave the gap in the middle to account for the transition period from one advisor to another. These rules result in a sample of 1,048 events in which advisor B subsumes advisor A's clients and advisor A exits.

We measure advisors' impact on the utilization of automatic savings plans, fees, and asset allocation choices. We measure the utilization of automatic savings plans by computing the fraction of purchases involving these plans; fees by the average MER of the funds that investors purchase; and the asset allocation choices by the fraction of equity funds that investors purchase. We count both equity and alternative investments as being 100% equities, and balanced and target-date funds as being 50% equities. We ignore purchases emanating from automatic reinvestment of dividends and interest—which flow automatically into the same fund—to focus on discretionary decisions. We also do not examine sales because of the short-sale restrictions are binding—investors' redemption choices are limited to the funds that they hold at the time of the A-B switch. We measure fees and asset allocations separately for purchases made through automatic savings plans (conditional on the investor having one) and for one-off purchases. We examine differences in both average fees as well as fees relative to style average—if, for example, fund X is U.S. small-cap fund with an MER of 2.0% in January 2007, and the average MER of all other U.S. small-cap funds is 1.5% the same month, then fund X's MER over style average is 0.5% in January 2007.

We compute the average utilization rate, fee, and fraction-of-equity funds for the old advisor's and new advisor's clients before and after the switch. We measure convergence in client behavior as the difference in absolute differences between the two groups and over the pre- and post-switch periods:

$$\text{convergence in } y = \left|y^{\text{post}}_{\text{old advisor}} - y^{\text{post}}_{\text{new advisor}}\right| - \left|y^{\text{pre}}_{\text{old advisor}} - y^{\text{pre}}_{\text{new advisor}}\right|, \tag{3}$$

in which y is the utilization rate, fee, or fraction-of-equity funds. A negative difference-in-absolute difference estimate indicates a convergence in client behavior.

Table 7 Panel A shows the average absolute differences in both the pre-switch and post-switch periods and the t-value associated with the difference in absolute differences. The estimates on the first row show that advisors have a significant influence on the rate at which investors utilize automatic savings plans. The absolute difference in utilization rates before the switch is 39.4%, and it is 28.2% after the switch. The difference of −11.2% is significant with a t-value of −16.98. These estimates imply that if a client without an automatic savings plan is moved from an advisor who does not promote the use of such plans to one who does, the client is likely to set up the plan after the switch.

Advisors have less influence over investors' asset allocation choices, and the data show a marked difference between investments made through automatic savings plans and discretionary (one-off) purchases. The clients show no convergence in the fees they pay and their decisions to invest in equities when the sample is limited to discretionary purchases. If anything, the two groups of investors diverge from each other around the switch. By contrast, clients who have automatic savings plans in place before the switch and retain it after the switch become similar to their new advisor's existing clients after the switch. The effects are, however, economically small. The absolute difference in total annual MERs decreases from 35.4 basis points to 31.9 basis points (t-value = −3.82), the difference in MERs over style average decreases from 26.3 basis points to 21.3 basis points (t-value = −6.50), and the convergence in fraction invested in equities is just under a percentage point (t-value $= -2.85$). The difference between the results for discretionary purchases and purchases done through automatic savings plans suggest that advisors, upon acquiring new clients, redefine the set of funds into which these investors' automatic savings flow. A client moving from a low-cost advisor to a high-cost advisor begins purchasing slightly more expensive funds, and vice versa. Advisors, by contrast, have no influence—at least shortly after the switch—over the choice of funds into which their new clients direct their one-off purchases.

An alternative method for assessing the impact advisors have on individuals' savings decisions examines the probability that an investor starts or removes an automatic savings plan. We define two outcome variables, $Add\ Plan_i$ and $Remove\ Plan_i$, for every household i who switches from advisor A to B. $Add\ Plan_i$ is defined for households who do not have a plan with advisor A, and it takes the value of "1" for those who initiate a plan after the switch; $Remove\ Plan_i$ is defined for those households who have a plan with advisor A, and it takes the value of one for those who remove the plan after the switch. We examine how these choices depend on the difference between the utilization of automatic savings plans between all households (except household i) of advisors A and B in the before-switch period. This rate is ASP_{A} for other households of advisor A, and ASP_{B} for all households of advisor B. The idea here is the same as that in Panel A: if a household without a plan moves to an advisor whose clients often have automatic savings plans, we expect this household to add a plan after the switch; but if automatic savings plans are rare also among the new advisor's clients, we expect the household to remain without a plan. We use the add a plan-remove a plan specification to examine whether the decision to add or remove a plan is asymmetric, that is, that it responds differently to the differential plan usage rates between advisors A and B.

Columns 1 and 4 in Table 7 Panel B regress the decision to add or remove a plan on an indicator variable that takes the value of 1 if the average savings rate of advisor B exceeds that of advisor A, $\mathrm{I}(ASP_{\mathrm{B}} > ASP_{\mathrm{A}})$. The significantly positive coefficient in the first column indicates that when households move from a low-intensity advisor to a pre-switch high-intensity advisor, they are more likely to add an automatic savings plan after a switch. But column 4 shows that there is no similar effect for plan removals—the decision to remove a plan is unrelated to the difference in savings-plan intensities between advisors A and B. Columns 2 and 5 replace the indicator variable with a continuous variable for the difference in the savings-plan usage rates, and columns 3 and 6 let the slope on this continuous variable to differ depending on its sign. The estimates in columns 2 and 3 show that the probability of adding a plan is increasing in the usage-rate difference, and the slope does not vary significantly between the positive and negative domains. The decision to remove a plan, by contrast, is unrelated to the relative utilization rates in every specification.

7 The Effect of Financial Advisors on Households' Savings and Investment Behavior: Evidence from Survey Data

In this section we complement the previous evidence on the impact financial advisors have on their clients' financial behavior using household survey data from the Canadian Financial Monitor (CFM) by Ipsos-Reid. A fundamental challenge in measuring the impact of financial advisors is that demand for advisory services will depend on the outcomes of interest, such as the savings rate or participation in risky asset markets. For example, if individuals with high savings rates and large asset portfolios gained more from working with an advisor than clients with little savings, then we would observe a positive correlation between savings and use of an advisor even if advisors have no impact on savings.

We address this identification issue by using a regulatory change in the early 2000s that reduced the supply of financial advisors. Specifically, as of February 2001 mutual fund dealers and their agents, such as financial advisors, were required to register with the Mutual Fund Dealers Association of Canada (MFDA) and follow the rules and regulations of the MFDA. The introduction of this registration requirement meant that dealers who wished to remain in business were now subject to more stringent regulatory standards, including minimum capital levels as well as audit and financial reporting requirements. For the underlying advisors, the registration requirement also mandated securities training and established a basic standard of conduct.[11] The draft rules and bylaws were originally posted for comment on June 16, 2000. An overview of public comments given by dealers and advisors in response to the draft proposal reveals particular concern about costs imposed by the requirement, including compliance costs associated with financial reporting and capital costs created by meet minimum capital standards. To the extent that these changes reduced the supply of advisors, they are useful in identifying a change in households' use of advisors that is unrelated to their demand for advisory services. Importantly, the regulatory change did not apply to dealers and advisors in the province of Quebec, allowing us to use Quebec residents as a baseline from which to measure the impact of the registration requirement over time.

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

$$y_{ipt} = \alpha + \beta \text{Register}_p * \text{Post}_t + \gamma \text{Register}_p + \delta \text{Post}_t + \theta \mathbf{X}_{it} + \varepsilon_{ipt}, \tag{4}$$

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

in which subscripts i, p, and t index households, provinces, and months between January 1999 and January 2004, respectively. The variable *Post* is an indicator that takes the value of one for dates after June 2000, when the registration requirement was announced and draft rules were published for comment. Register is an indicator variable that takes the value of one for households located in provinces that faced the registration requirement. Through β, the coefficient on the interaction of Register and Post, we measure the impact of the registration requirement over time, taking changes in Quebec as a baseline from which to measure this effect. The vector $\mathbf{X}_{it}$ contains household-level controls for income, education, age and retirement status, each of which is predictive of household demand for advisory services.[12] In some versions of the model we include province and month fixed effects to control more flexibly for differences over time and across provinces. To estimate the model we use weighted least squares, incorporating survey weights from the CFM to provide regression estimates that reflect a nationally representative sample.

First, we estimate the impact of the registration requirement on households' use of financial advisors. Table 8 Panel A reports the regression estimates from three models in which the dependent variable is an indicator variable that takes the value of one for households who use a financial advisor at the time of the survey. The baseline probability of using an advisor in these 1999-2004 surveys is 0.38. The estimates in the three models, which differ in terms of the inclusion of household controls and fixed effects, suggest that the registration requirement had both a statistically and economically significant effect on the use of financial advisors. The point estimates in the three models place the marginal effect between -0.043 and -0.040, which translate into a

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

proportional decrease of approximately 11% in the use of financial advisors. In the first model, which excludes household controls, the coefficient on the registration-requirement indicator is positive and marginally significant at the 10% level, indicating that before the law change residents of Quebec are less likely to use advisors than their counterparts in provinces subject to the registration requirement. However, this disparity is entirely explained by differences in income and demographics; the coefficient on Register is very close to zero once household-level controls are added to the model. This evidence helps support our premise that after controlling for observable differences Quebec residents can serve as an reasonable baseline from which to measure the change in advisor usage. The substantial increase in R2 induced by the inclusion of these controls shows that income, education, age, and retirement status indeed substantially correlate with the demand for advisory services.

Next, we use the variation documented above to estimate the effect that financial advisors on households' financial choices in a two-stage least squares model:

$$\text{Use Advisor}_{ipt} = \alpha + \beta \text{Register}_p * \text{Post}_t + \eta_p + \mathbf{\Psi}_t + \theta \mathbf{X}_{it} + \varepsilon_{ipt}, \tag{5}$$

$$y_{ipt} = \alpha' + \beta' \widehat{\text{Use Advisor}}_{ipt} + \eta'_p + \mathbf{\Psi}'_t + \theta' \mathbf{X}_{it} + \varepsilon'_{ipt}. \tag{6}$$

Each regression includes both household-level controls as well as province and month fixed effects. The first stage provides an estimate of each household's predicted probability of using an advisor ($\widehat{\text{Use Advisor}}_{ipt}$), allowing for variation due to the *Register-Post* instrumental variable, and the second stage uses this predicted probability to provide an estimate of advisors' impact on a variety of financial choices. Because we measure changes in behavior following a relatively short window after the registration requirement is imposed, we expect to observe changes in behavior but not necessarily in "levels." That is, even if financial advisors, say, cause households to save more, differences in savings rates should not have a meaningful effect on the levels of wealth between advised and unadvised households immediately after the change in regulation.

The estimates from this instrument variables analysis, which are shown in Table 8 Panel B, are consistent with financial advisors affecting households' financial choices. We observe the strongest effects for households' holdings of risky assets and trading activity. The likelihood of owning any risky assets (stocks and mutual funds) increases by 0.67, or 67 percentage points, with the use of an advisor, and the proportion of risky assets in the portfolio increases by 0.39. Similarly, we find that the number of mutual funds held increases by 3.5 due to financial advice. We also find differences in transaction activity, specifically in households' sale of financial assets over the prior 12 months. The likelihood of selling assets increases by 0.34, or 34 percentage points, and the number of sales increases by 0.49. In each case, the IV estimate exceeds the OLS estimate, which suggests downward bias, perhaps because individuals that are most comfortable holding and trading risky assets are less likely to solicit an advisor's input.

We do not observe statistically significant effects for the other outcome variables, which include log income, log financial assets, log savings through automatic deposit, use of registered retirement accounts and use of life insurance. The first row, for example, shows that households' use of financial advisors does not affect their incomes.[13] This result is, in fact, comforting because although high-income households are significantly more likely to use financial advisors (there is a large positive OLS coefficient in regression of log income on *Use Advisor*), there is no obvious channel through which financial advisors should causally influence income levels. For income as well as the other outcome variables we cannot rule out the possibility that financial advisors have a substantial effect,

[13] This specification excludes the income controls.

since our tests lack the power to identify that effect. Unadvised households, for example, save more through automatic savings plans, yet the confidence interval on this point estimate is too wide to distinguish the possibility that advisors have a substantial effect on this usage rate from that that advisors have no effect at all.

8 Conclusions

We analyze comprehensive data on financial advisors and their clients to examine the amount investors pay for financial advice, and what mechanisms lead investors to tolerate these high fees. The average investor pays a substantial amount in underperformance relative to passive benchmarks for the advice and possible other services provided. The average net alphas, depending on the set of passive benchmarks, are between -3% and -2%. Although there is a wide distribution of alphas across advisors, there is scant evidence of any advisor enhancing performance enough to offset the large expenses. An investor who saves for retirement effectively gives up a quarter of his future savings (in present value terms) by lagging the benchmarks by 3%.

Our results show that investors respond to the advice they receive, yet they rarely benefit from these relationships in the form of higher returns. These findings suggest that investors receive other benefits beyond investment advice or that they are misinformed about investment performance or fees.

We find evidence that clients benefit through financial planning, as advisors seem to influence clients' savings choices. Specifically, we find that clients' use of automatic savings plans depends on their advisor. We complement this evidence using survey data on advised and unadvised clients. Exploiting a regulatory change that reduced the access to advisors, we show that financial advisors have a substantial effect on households' decisions, increasing their risky asset holdings as well as their trading activity.

Despite negative risk-adjusted investment returns, it is also possible that financial advisors add value by mitigating psychic costs, such as anxiety over investment performance or retirement preparedness (Gennaioli, Shleifer, and Vishny 2012). In future versions of this analysis we plan to test more directly whether investors are paying advisors for trust or anxiety reduction.

A Do Investors Follow Advisor Recommendations?

In this section we assess advisors impact on client portfolios. Since we do not know which trades have been explicitly recommended by the advisor, we have to infer their "recommendations" from the trades that are common across multiple clients. More specifically, we use a methodology adopted by others to measure herding among traders, by correlating the normalized monthly trading flows of each client with the trading flows of other clients that use the same advisor. For each client c, security i and month t, we compute a buy-sell ratio for all securities in which the client executes a trade in month t: $\text{BuySell}_{cit} = \frac{\text{Purchases}_{cit} - \text{Sales}_{cit}}{\text{Purchases}_{cit} + \text{Sales}_{cit}}$. This ratio varies between -1 when the client is exclusively a seller and 1 when the client is exclusively a buyer. We define $\text{BuySell}_{-c,ait}$ by aggregating the trades of co-clients, that is, other clients of the same advisor a. We use the subscript $-c$ to indicate that we exclude the clients own trades in calculating the co-clients' buy-sell ratio. We compute the buy-sell ratio in security i across all clients of other advisors ($\text{BuySell}_{-a,it}$) to get a benchmark to capture common trading patterns across all households. We then estimate the regression model:

$$\text{BuySell}_{cit} = \alpha + \beta \text{BuySell}_{-c,ait} + \gamma \text{BuySell}_{-a,it} + \varepsilon_{cit}. \tag{A-1}$$

If clients respond to advice, we expect beta to be positive and significant, and substantially larger than gamma. Given that we expect variation in trading patterns among a given advisors clients, however, we do not expect beta to be 1, even if clients follow all of their advisors recommendations.

Results from this analysis, presented in Table A1, show a robust positive correlation between the trades of a client and his or her advisor. In the first regression with no additional controls, the coefficient on the advisor buy-sell ratio is 0.16 (t-value of 27.4). This correlation does not simply capture trading patterns common to all individual investors the coefficient on the other-clients buy-sell ratio is 0.03, which, while statistically significant, is far smaller than that on co-clients buy-sell ratio. The estimates are similar in regression that control for fund fixed effects and include additional regressors for both client and advisor demographics.[14] In the regression with both fund fixed effects and controls for demographics, the slopes on co-clients and other clients buy-sell ratios are 0.14 and 0.02. The within-advisor correlations in trading flows are economically significant. A one-standard deviation shock to co-clients buy-sell ratio, for example, increases the investors buy-sell ratio by 9.3%.

These findings contrast with the results of Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012), who find that very few investors respond to advice, at least when that advice is unsolicited. The results in Table A1 show that financial advisors do not provide perfectly custom-tailored advice to every client and, whatever this advice entails, investors respond to it.

In further analysis, we examine how these trading correlations vary across client groups, dividing the sample by investor demographics and account characteristics. First, we split by the type of investment plan and investors self-reported investment horizon. As shown in Table A2, client trading correlates most strongly with co-clients for retirement savings plans, and least strongly for non-retirement accounts. Within each account type, however, there is substantially larger correlation with co-clients trades than with other clients trades. Across investment horizons, client-advisor trading correlations are quite stable; they are highest for long horizon clients (6 or more years) and lowest for medium horizon clients (1-5 years).

In unreported analyses we also divide the sample by investor demographics, and find that the buy-sell coefficient estimates vary significantly. The coefficient on the own-advisor buy-sell ratio

[14]These additional regressors consist of controls for the clients age and gender, the length of the client-advisor relationship, the time the investors account has been open, the advisors age, the time the advisor has held the license to sell mutual funds, the length of the advisors tenure, and the number of licenses the advisor holds.

is significantly larger for older investors—among 60-and-over investors the estimated coefficient is twice as large as it is for younger investors. Trading flows are also more correlated with co-clients flows for investors whose accounts have been open for a longer period of time; and investors who self-report very low financial knowledge or who have low net worth are markedly more likely to follow advice than those who report high financial knowledge.

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Table 1: Descriptive Statistics

This table reports summary statistics for investors (Panel A), advisors (Panel B), and accounts (Panel C) in a database on Canadian financial advisors and their clients. "Investor known since" is the number of years an investor has been the client of his or her current advisor. "Investor set-up since" is the number of years an investor has been the client of any advisor. Both of these durations are computed as of year-end 2010. Advisors collect information on their clients' financial knowledge, net worth, and salary using "Know Your Client" surveys. The different license types, counts of which are reported in Panel B are rights to sell mutual funds, segregated funds, labor funds, and principal protected notes. All advisors in the sample have the license to sell mutual funds.

Panel A: Investors

		Percentiles					
Variable	Mean	10th	25th	50th	75th	90th	SD
Female	0.50						
Age	49.95	32	40	49	59	68	14.01
Investor known since	4.73	0	1	3	6	12	5.92
Investor set-up since	3.18	0	1	3	5	7	3.14
Number of accounts	2.04	1	1	1	2	4	1.85
Number of investments	7.99	1	2	4	10	19	10.00
Account value, $K	57.84	1.69	6.07	20.98	62.75	142.07	399.78
Expense ratio, %	2.43	1.8	2.3	2.4	2.6	2.8	0.57
Expense ratio, $	1574.89	55	197.2	664	1843.5	3917.9	3372.94

Financial knowledge	None	Very low	Low	Moderate	High
	1.4%	7.2%	40.5%	45.3%	5.6%
Net worth	Under $50k	$50-100k	$100-200k	Over $200k	
	19.9%	11.2%	16.6%	52.2%	
Salary	Under $30k	$30-60k	$60-100k	Over $100k	
	27.0%	31.2%	31.4%	10.4%	

Panel B: Financial Advisors

Variable	Mean	Percentile 10th	25th	50th	75th	90th	SD
Age	50.09	36	43	50	57	63	10.38
Tenure	3.19	0	1	2	5	8	2.85
Number of clients	73.92	1	3	18	82	206	164.50
Number of accounts	151.15	2	5	29	139	414	371.18
Number of investments	129.39	3	11	50	165	368	192.46
Number of licenses	1.81	1	1	2	2	3	0.70
Account value, $K	3853.03	39.66	204.03	876.19	3474.42	10300.00	12000.0
Expense ratio, %	2.39	2.1	2.3	2.4	2.6	2.7	0.38

	Active	Inactive	Terminated
Advisor status	71%	22%	6%

Panel C: Accounts

Account type	Open	20%
(N = 1,530,115)	RRSP (registered retirement saving plans)	65%
	RRIF (registered retirement income funds)	6%
	RESP (registered education saving plans)	4%
	Tax-Free	4%
Account status	Active	44%
(N = 1,530,115)	Inactive	31%
	Closed	25%
Investment horizon	< 1 year	22%
(N = 1,162,890)	1 to 3 years	63%
	4 to 5 years	8%
	6 to 10 years	4%
	> 10 years	3%

Table 2: Descriptive Statistics from Survey Data

This table reports summary statistics from the Canadian Financial Monitor survey of Canadian households conducted by Ipsos-Reid. Age is that of the head of household. Education is the maximum level of education of the head of household and spouse. The indicator Retired takes the value of one if the head of household is retired. The data are from 59,250 unique households. The variable ΔFinancial Assets/Income is computed for 40,920 households.

	Advised (N = 16,530; 38% of sample)			Unadvised (N = 42,720; 62% of sample)		
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
Age	56.3	14.2	58.0	52.4	16.2	53.0
Income ($C Thousands)	74.9	41.6	65.0	55.4	38.4	50.0
Net worth ($C Thousands)	472.3	413.0	372.5	212.5	290.8)	105.9
Financial assets ($C Thousands)	221.1	272.2	131.1	71.6	162.9	11.3
% equity	15.0	27.8	0.0	6.9	20.9	0.0
% mutual funds	39.7	38.4	33.2	12.7	27.7	0.0
% fixed income	45.2	38.9	32.9	80.4	34.2	100.0
ΔFinancial Assets/Income (%)†	13.5	146.4	7.7	4.4	102.8	0.6
Education, HS or less (%)	15.6	36.3	0.0	25.9	43.8	0.0
Education, some college (%)	15.3	36.0	0.0	19.1	39.3	0.0
Education, college diploma (%)	51.8	50.0	100.0	44.7	49.7	0.0
Education, graduate degree (%)	17.2	37.7	0.0	10.2	30.4	0.0
Homeowner (%)	87.4	33.2	100.0	67.8	46.7	100.0
Retired (%)	34.7	47.6	0.0	27.2	44.5	0.0

† N = 16,530 for Advised and N = 24,390 for Unadvised

Table 3: Gross and Net Alphas and Performance Relative to Lifecycle Funds

This table reports the distributions of advisor-level gross alphas (Panel A), net alphas (Panel B), and the excess returns over retirement date-matched lifecycle funds, and the t-values associated with the alpha estimates. The asset pricing models in Panels A and B are the CAPM, three-factor model, four-factor model, and four-factor model augmented with two fixed-income factors, the return difference between 10-year and 90-day Treasuries and that between BAA- and AAA-rated corporate bonds. Net returns adjust returns for management expense ratios but do not adjust for front- and back-load fees. Advisor-level alphas are computed by value-weighting returns across each advisor's all clients, and then estimating the asset pricing regressions for separately for every advisor. Column "Average dollar" reports the estimated alphas and t-values for the average advised dollar. The alphas earned by the average advised dollar are computed from the value-weighted returns of all investors in the sample. The retirement date-matched lifecycle funds in Panel C are Fidelity Clearpath funds with retirement target dates ranging from 2005 to 2045 in five-year increments. We assume that investors retire at age 65 when assigning these lifecycle funds. Row "Difference in gross returns" reports the difference between the average realized performance of an advisor's clients and the average realized performance of the value-weighted portfolio of the lifecycle funds assigned to the advisor's clients. "Difference in MERs" reports the difference between the realized management expense ratio of an advisor's clients and that of the lifecycle funds assigned to the advisor's clients.

Panel A: Gross alphas

			Percentiles							Average
Pricing Model		Mean	1%	5%	25%	50%	75%	95%	99%	dollar
CAPM	α	0.58	−10.29	−4.88	−1.03	0.53	2.12	6.28	10.89	0.06
	$t(\alpha)$	0.26	−2.89	−1.60	−0.44	0.25	0.99	2.08	2.86	0.05
Three-factor	α	0.21	−10.82	−5.27	−1.28	0.28	1.69	5.79	10.39	−0.21
	$t(\alpha)$	0.09	−3.10	−1.67	−0.56	0.13	0.78	1.77	2.60	−0.16
Four-factor	α	0.08	−10.86	−5.41	−1.33	0.17	1.51	5.63	9.87	−0.37
	$t(\alpha)$	0.05	−3.07	−1.70	−0.58	0.08	0.70	1.72	2.66	−0.28
Four-factor with	α	−0.29	−11.76	−6.26	−1.70	−0.13	1.22	5.10	10.56	−0.54
bond factors	$t(\alpha)$	−0.11	−3.09	−1.83	−0.71	−0.06	0.54	1.49	2.43	−0.40

Panel B: Net alphas (after MERs)

Pricing Model		Mean	Percentiles 1%	5%	25%	50%	75%	95%	99%	Average dollar
CAPM	α	−1.83	−13.01	−7.35	−3.40	−1.86	−0.29	3.81	8.46	−2.31
	$t(\alpha)$	−0.87	−4.31	−2.71	−1.57	−0.88	−0.12	1.15	1.90	−1.75
Three-factor	α	−2.21	−13.60	−7.73	−3.66	−2.11	−0.74	3.38	7.99	−2.59
	$t(\alpha)$	−1.02	−4.36	−2.77	−1.69	−1.03	−0.32	0.93	1.79	−1.91
Four-factor	α	−2.34	−13.59	−7.89	−3.74	−2.22	−0.92	3.19	7.47	−2.74
	$t(\alpha)$	−1.07	−4.34	−2.80	−1.73	−1.09	−0.40	0.90	1.78	−2.04
Four-factor with	α	−2.70	−14.39	−8.59	−4.08	−2.52	−1.22	2.70	8.26	−2.91
bond factors	$t(\alpha)$	−1.20	−4.43	−2.96	−1.87	−1.22	−0.51	0.69	1.58	−2.13

Panel C: Realized returns over retirement date-matched lifecycle funds

Difference in:	Mean	Percentiles 1%	5%	25%	50%	75%	95%	99%	Average dollar
Gross returns	−0.41	−20.28	−8.48	−2.36	−0.47	1.33	7.98	19.53	−0.87
MERs	1.33	0.03	0.70	1.18	1.35	1.51	1.81	2.48	1.31

Table 4: Fama and French (2010) Luck-versus-Skill Analysis of Advisors' Gross and Net Returns

We estimate advisors' alphas using the CAPM, three-factor model, and four-factor model. We record the actual distributions of $t(\alpha)$s from these models and then subtract estimated alphas from monthly advisor returns. We then resample months 10,000 times. In each simulation we re-estimate the alphas, construct the $t(\alpha)$ distribution, and compare the percentiles of each simulated distribution against the actual $t(\alpha)$ distribution. Each block in this table reports the simulated and actual distributions of $t(\alpha)$s and the fraction of simulations in which the simulated t-value at given percentile is lower than the actual t-value. Panel A (Panel B) estimates alphas from gross returns (net returns). The sample is restricted to advisors with at least 8 months of returns.

Panel A: Gross returns

	CAPM			3-factor model			4-factor model		
Pct	Sim	Act	% < Act	Sim	Act	% < Act	Sim	Act	% < Act
1	−2.11	−2.91	11.54	−2.25	−3.14	9.94	−2.40	−3.11	15.30
2	−1.79	−2.40	15.68	−1.88	−2.43	18.02	−1.98	−2.44	22.02
3	−1.61	−1.96	25.64	−1.68	−2.06	24.14	−1.75	−2.07	27.42
4	−1.48	−1.75	29.72	−1.53	−1.84	27.90	−1.59	−1.86	29.64
5	−1.37	−1.61	32.14	−1.42	−1.68	30.18	−1.47	−1.70	31.98
10	−1.04	−1.12	41.16	−1.06	−1.24	35.52	−1.09	−1.25	36.16
20	−0.66	−0.61	50.68	−0.66	−0.72	44.18	−0.68	−0.75	43.18
30	−0.39	−0.28	55.10	−0.39	−0.39	48.34	−0.40	−0.41	47.58
40	−0.17	0.01	60.18	−0.16	−0.11	52.76	−0.17	−0.15	50.42
50	0.04	0.27	64.34	0.05	0.16	56.72	0.04	0.11	54.00
60	0.25	0.55	68.70	0.26	0.42	60.14	0.25	0.36	56.98
70	0.47	0.87	73.60	0.49	0.68	62.92	0.48	0.61	59.14
80	0.74	1.23	78.36	0.76	0.98	65.76	0.75	0.90	61.10
90	1.13	1.72	83.20	1.15	1.44	70.58	1.16	1.39	67.50
95	1.48	2.14	85.58	1.51	1.86	74.52	1.53	1.83	72.06
96	1.58	2.24	85.46	1.62	1.99	75.52	1.65	1.98	73.48
97	1.72	2.38	85.58	1.77	2.16	76.60	1.80	2.16	75.20
98	1.91	2.57	85.64	1.97	2.42	79.00	2.02	2.42	77.24
99	2.23	2.94	86.22	2.33	2.83	80.20	2.41	2.88	79.70

Panel B: Net returns

	CAPM			3-factor model			4-factor model		
Pct	Sim	Act	% < Act	Sim	Act	% < Act	Sim	Act	% < Act
1	−2.11	−4.34	0.18	−2.25	−4.43	0.50	−2.40	−4.45	1.66
2	−1.79	−3.57	0.40	−1.88	−3.56	0.80	−1.98	−3.59	1.60
3	−1.61	−3.11	0.98	−1.68	−3.15	1.16	−1.75	−3.19	1.58
4	−1.48	−2.87	1.40	−1.53	−2.94	1.14	−1.59	−2.96	1.70
5	−1.38	−2.71	1.64	−1.42	−2.77	1.46	−1.47	−2.78	1.88
10	−1.04	−2.20	3.42	−1.06	−2.31	2.18	−1.09	−2.34	2.42
20	−0.66	−1.73	4.72	−0.66	−1.84	3.14	−0.68	−1.86	3.14
30	−0.39	−1.39	6.22	−0.39	−1.51	3.88	−0.40	−1.56	3.78
40	−0.17	−1.13	6.84	−0.16	−1.24	4.54	−0.17	−1.29	4.30
50	0.04	−0.84	8.46	0.05	−0.99	5.10	0.04	−1.04	4.72
60	0.25	−0.57	10.32	0.26	−0.71	5.84	0.25	−0.79	5.02
70	0.47	−0.24	13.66	0.48	−0.42	6.88	0.48	−0.49	5.80
80	0.74	0.16	19.38	0.76	−0.02	9.90	0.75	−0.10	7.76
90	1.13	0.80	32.50	1.15	0.59	18.42	1.16	0.55	15.92
95	1.48	1.26	39.42	1.51	1.11	28.18	1.53	1.07	24.40
96	1.58	1.39	41.06	1.62	1.23	27.98	1.65	1.20	25.16
97	1.72	1.51	40.36	1.77	1.39	29.40	1.80	1.37	26.50
98	1.91	1.69	40.68	1.97	1.62	31.64	2.02	1.64	30.72
99	2.23	2.01	40.74	2.34	1.94	29.90	2.42	2.05	33.12

Table 5: Net Alphas and Advisor Characteristics

This table reports coefficient estimates from regressions of advisors' estimated net alphas on advisor characteristics. The alpha estimates are measured in standardized units, as t-statistics, under the specified asset pricing model.

Regressor	CAPM	Three-factor	Four-factor	Four-factor with bond factors
ln(Age)	0.168	0.154	0.145	0.137
	[0.120]	[0.112]	[0.111]	[0.106]
ln(Tenure at dealer)	-0.326^{***}	-0.321^{***}	-0.316^{***}	-0.293^{***}
	[0.035]	[0.034]	[0.034]	[0.033]
ln(Number of investors)	-0.137^{***}	-0.162^{***}	-0.168^{***}	-0.172^{***}
	[0.024]	[0.023]	[0.022]	[0.022]
ln(Number of accounts per investor)	-0.368^{***}	-0.346^{***}	-0.35^{***}	-0.296^{***}
	[0.087]	[0.087]	[0.086]	[0.084]
ln(Number of investments per investor)	-0.103^{*}	-0.13^{**}	-0.139^{***}	-0.149^{***}
	[0.056]	[0.055]	[0.053]	[0.051]
I(Number of licenses=2)	-0.105^{*}	-0.112^{**}	-0.123^{**}	-0.142^{***}
	[0.056]	[0.055]	[0.055]	[0.053]
I(Number of licenses=3)	-0.027	-0.058	-0.057	-0.046
	[0.076]	[0.074]	[0.074]	[0.072]
N	2,200	2,200	2,200	2,200
R^2	12.1%	14.0%	14.8%	14.6%

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

Table 6: Account Closure and Past Performance

This table reports estimates from Cox proportional hazards rate models with time-varying covariates that examine how the probability that an investor closes his account is related to her past performance over the prior one-year period (Panel A) or the average expense ratio of the investors holding over the prior one-year period (Panel B). The first model has only the prior one-year return (or expense ratio) as the covariate; the second model adds year-month fixed effects; and the third model replaces the prior one-year return (or expense ratio) with dummy variables to represent different intervals of performance or fees. t-values are reported in parentheses. The data used for estimation contain 64,750 investors, 19,977 account closures, and 3,542,907 investor-month observations.

Panel A: One-year returns as time-varying covariates

	Model		
Covariate	(1)	(2)	(3)
Realized return$_{t-12,t}$	0.76	0.98	
	(-5.31)	(-0.23)	
Return-category dummy variables:			
Realized return$_{t-12,t}$ $\leq$ -30%			1.05
			(0.73)
-30% $<$ Realized return$_{t-12,t}$ $\leq$ 20%			1.09
			(1.64)
-20% $<$ Realized return$_{t-12,t}$ $\leq$ 10%			1.18
			(4.27)
-10% $<$ Realized return$_{t-12,t}$ $\leq$ 0%			1.33
			(10.40)
0% $<$ Realized return$_{t-12,t}$ $\leq$ 10%			*Omitted*
10% $<$ Realized return$_{t-12,t}$ $\leq$ 20%			1.03
			(1.23)
20% $<$ Realized return$_{t-12,t}$ $\leq$ 30%			0.97
			(-0.71)
30% $<$ Realized return$_{t-12,t}$			1.13
			(2.11)
Year-month FE	No	Yes	Yes

Panel B: One-year expense ratios as time-varying covariates

	Sample		
		Low financial knowledge	High or moderate financial knowledge
	All clients		
Regressor	(1)	(2)	(3)
Expense ratio$_{t-12,t}$	1.18	0.97	1.45
	(3.13)	(−0.33)	(4.46)
Control for risky asset share?	Yes	Yes	Yes

Table 7: Advisors Influence on Client Savings Behavior and Asset Allocation Choices

This table reports estimates on advisors influence on their clients savings behavior and asset allocation choices. We identify 1,048 events in which an advisor retires, quits, or dies, an event upon which the disappearing advisors clients are subsumed by another advisor with existing pool of clients. Panel A measures the convergence in behavior between the old advisors clients and the new advisors existing clients around the switch. We measure advisors impact on the utilization of automatic savings plans, annual management expense ratios (MERs) of purchases, and the fraction of purchases involving equity funds. We compute the absolute difference in each of these response variables both before and after the switch. This table reports these averages, their difference, and the t-value associated with this difference. A negative difference indicates convergence in behavior. The fee and equity-fund computations are done separately for purchases completed through automatic savings plans (conditional on investors having them both before and after the switch) and for discretionary purchases. "Fees, excess over style average" are computed as the difference between a funds MER and the average MER over all funds of the same style in the same month. Funds are classified into 54 style categories using classifications provided by Fundata. Panel B examines households decisions to add or remove an automatic savings plan. "*Add plan*" is defined for households without a plan before the switch and takes the value of "1" for those who add a plan after the switch. "*Remove plan*" is defined for households with a plan before the switch and takes the value of "1" for those who remove the plan after the switch. ASP_{A} is the fraction of advisor As clients (excluding household i) with an automatic savings plan before the switch. ASP_{B} is the fraction of advisor Bs clients with an automatic savings plan before the switch. t-values are based on errors clustered at a switch-event level.

Panel A: Convergence in behavior

	Absolute difference			
Client behavior	Pre	Post	Diff-in-diff	t-value
Utilization of automatic savings plans	0.394	0.282	−0.112	−16.98
Fees, total				
Discretionary purchases	0.406	0.450	0.045	1.93
Automatic savings plans	0.354	0.319	−0.035	−3.82
Fees, excess over style average				
Discretionary purchases	0.226	0.242	0.016	1.23
Automatic savings plans	0.263	0.213	−0.050	−6.50
Fraction invested in equities				
Discretionary purchases	0.261	0.268	0.007	0.72
Automatic savings plans	0.250	0.242	−0.008	−2.85

Panel B: Decision to add or remove an automatic savings plan

	Dependent variable					
	Add plan			Remove plan		
$\mathrm{I}(ASP_{\mathrm{B}} > ASP_{\mathrm{A}})$	0.017			0.002		
	(2.91)			(0.52)		
$ASP_{\mathrm{B}} - ASP_{\mathrm{A}}$		0.033	0.026		-0.002	-0.002
		(3.31)	(2.88)		(-0.37)	(-0.19)
$\mathrm{I}(ASP_{\mathrm{B}} > ASP_{\mathrm{A}}) * (ASP_{\mathrm{B}} - ASP_{\mathrm{A}})$			0.018			-0.001
			(0.57)			(-0.05)
Adjusted R^2	0.20%	0.26%	0.27%	0.00%	0.00%	0.00%

Table 8: The Effect of Financial Advisors on Households Savings and Investment Behavior

Mutual fund dealers and their agents, financial advisors, were required to register with the Mutual Fund Dealers Association of Canada (MFDA) as of February 2001 to continue operating. This registration requirement, which forced dealers to follow the rules and regulations of the MFDA, did not apply to the province of Quebec. This table uses Ipsos-Reid household survey data on investors use of financial advisors and asset allocation and savings decisions along with a differences-in-differences model to examine financial advisors impact on these outcomes. Panel A uses monthly data from January 1999 through January 2004 and estimates the effect of the registration requirement on the households likelihood of using financial advisor. Household-level controls consist of control variables for income, education, age, and retirement status. Panel B measures the effect of financial advisors on household log-income, log-amount of financial assets, investment in risky assets, number of mutual funds held, propensities to buy and sell assets, log-amount saved via automatic savings plans, use of registered retirement savings plans, and use of life insurance. The Log(income) regression in Panel B excludes income controls from the set of household-level controls. Robust standard errors, clustered at the household level, are reported in parentheses.

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

	Dependent variable (mean): Use Advisor (0.38)		
Regressor	(1)	(2)	(3)
Register * Post	-0.040^{***}	-0.043^{***}	-0.043^{***}
	(0.013)	(0.012)	(0.012)
Register	0.020^{*}	-0.002	
	(0.0100)	(0.0100)	
Post	-0.024^{**}	-0.023^{**}	
	(0.011)	(0.011)	
Observations	62,683	62,683	62,683
R^2	0.00	0.06	0.06
Household-level controls?	N	Y	Y
Province and month FEs?	N	N	Y

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

Panel B: The effect of the Registration requirement on financial choices

Dependent variable	Sample	The Effect of Financial Advisors OLS	The Effect of Financial Advisors IV	N	R^2	HH-level controls?	Province and month FEs?
Log(Income)	All	0.246***	−0.172	62,683	0.24	Y	Y
		(−0.010)	(0.448)				
Log(Fin'l Assets)	All	0.659***	1.027	60,374	0.38	Y	Y
		(−0.023)	(1.078)				
Any Risky Assets?	All	0.142***	0.667**	59,033	0.22	Y	Y
		(−0.006)	(0.296)				
Pct Risky Assets	All	0.095***	0.387*	59,033	0.20	Y	Y
		(−0.005)	(0.210)				
Number of Funds	All	0.835***	3.405**	59,650	0.15	Y	Y
		(−0.037)	(1.422)				
Bought Assets?	w/Inv.	0.100***	0.352	42,979	0.05	Y	Y
	Acct.	(−0.007)	(0.316)				
Sold Assets?	All	0.045***	0.339**	46,932	0.04	Y	Y
		(−0.005)	(0.157)				
Number of Sales	All	0.028***	0.486**	48,872	0.02	Y	Y
		(−0.005)	(0.190)				
Log(Amt. Auto	w/Inv.	0.400***	0.446	42,988	0.17	Y	Y
Deposit)	Acct.	(−0.035)	(1.571)				
Use RRSP?	w/Inv.	0.078***	0.388	42,987	0.21	Y	Y
	Acct.	(−0.006)	(0.298)				
Life Insurance?	All	0.059***	0.181	61,511	0.13	Y	Y
		(−0.006)	(0.272)				

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

Table A1: Correlations in Trading Flows

This table reports estimates from regressions of investors buy-sell ratios on the buy-sell ratios of all other clients of the same advisor ("co-clients buy-sell ratio") and the clients of all other advisors ("other clients buy-sell ratio"). Buy-sell ratio is as the value of purchases minus the value of sales divided by the total value of purchases and sales. Each observation is an investor-month-fund triplet. t-values are reported in parentheses.

	Dependent variable: Buy-sell ratio		
	(1)	(2)	(3)
Co-clients' buy-sell ratio	0.158	0.142	0.140
	(27.39)	(27.28)	(26.09)
Other clients' buy-sell ratio	0.030	0.018	0.019
	(18.47)	(19.26)	(15.42)
Additional client controls (age, gender, relationship longevity, account longevity)	No	No	Yes
Additional advisor controls (age, license longevity, tenure, number of licenses)	No	No	Yes
Fund fixed effects	No	Yes	Yes
N	78,215,376	78,215,376	14,276,642
Adjusted R^2	6.7%	6.7%	10.2%

Table A2: Correlations in Trading Flows by Plan Type and Investment Horizon

This table reports estimates from regressions of investors buy-sell ratios on the buy-sell ratios of all other clients of the same advisor ("co-clients buy-sell ratio") and the clients of all other advisors ("other clients buy-sell ratio"). Each model is estimated on a separate sub-sample of client accounts, splitting first by the investment plan type and then by the clients self-reported investment horizon. All models include fund fixed effects and the full set of controls for investor and advisor demographics.

Plan type	Co-clients	Other clients	N
Open	0.073***	0.024***	2,099,735
Registered retirement saving plans	0.140***	0.028***	10,002,536
Registered retirement income plans	0.110***	−0.003	1,937,611
Registered education savings plans	0.087***	0.019***	481,360
Tax-free	0.110***	0.035***	113,845

Investment horizon	Co-clients	Other clients	N
Less than a year	0.140***	0.013***	504,516
1-3 years	0.110***	0.025***	227,250
4-5 years	0.110***	0.021***	561,575
6-10 years	0.140***	0.020***	11,339,404
Over 10 years	0.130***	0.022***	900,165

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