Out of Sight, Out of Mind: Search Frictions and Financial Adviser Misconduct

[Preliminary Draft. Please Do Not Circulate.]

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October 16th, 2022

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[1] Lawrence Zhao is with Rice University. I am very grateful to Alex Butler and Gustavo Grullon for their relentless guidance and support. I would like to thank Alan Crane, Kevin Crotty, Kunal Sachdeva, Tarik Umar, Emmanuel Yimfor, and seminar participants at Rice University and Rice University Breakfast Club PhD Workshop. The contents of the paper are solely my responsibility.

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Abstract

The misconduct records of financial advisers are public information, yet advisers that persistently engage in misconduct survive in the market. Past literature attributes this phenomenon to market segmentation caused by search frictions associated with client sophistication. I investigate this hypothesis by examining FINRA's unprecedented advertising campaign promoting BrokerCheck. Exposed advisers sustain a 9% abnormal decrease in assets under management. Advisers that primarily serve less sophisticated clients experience more severe adverse effects. Clients switch to advisers with clean records. Advisers increasingly discipline employees who engage in misconduct. My findings highlight the importance of resolving search frictions in fighting financial adviser misconduct.

JEL Codes: D14, D18, G11, G20, J64
Keywords: Financial education intervention, misconduct, information disclosure.

I. Introduction

The investment-advisory industry comprises firms called "registered investment advisers" (RIAs). American households rely on these RIAs for investment recommendations, financial planning advice, and transaction services. Approximately 40 percent of American households seek advice from brokers or financial planners when making decisions about saving and investment (Survey of Consumer Finances (2016)). As of 2019, 12,933 federally registered investment advisers, along with 436,256 investment adviser representatives, help manage over $30 trillion of assets.

RIAs owe a fiduciary duty to clients and are obligated by law to report disciplinary actions against them and their affiliates. These reports are made public by the Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA). In theory, disciplinary records can penalize perpetrators and deter misconduct (Klein and Leffler (1981) and Shapiro (1983)). Empirical studies show that even indirect exposure to misconduct destroys trust and results in nonparticipation (Giannetti and Wang (2016) and Gurun, Stoffman, and Yonker (2018)). That said, RIAs that persistently engage in misconduct survive in the market (Egan, Matvos, and Seru (2019)). Anecdotal evidence suggests that some investors do not know where to access misconduct records or whether such records even exist (The Wall Street Journal (2014)). Consistent with the anecdote, Egan, Matvos, and Seru (2019) attribute this phenomenon to market segmentation caused by search frictions associated with client sophistication.

In this paper, I investigate this hypothesis by examining FINRA's unprecedented advertising campaign promoting BrokerCheck. To improve households' awareness of misconduct records, on June 1st, 2015, FINRA launched a national advertising campaign promoting BrokerCheck, a free online tool that allows investors to access every broker's misconduct records. The $3.5 million advertising campaign, which ran for five weeks on cable channels, relevant websites, and search engines, was unexpected and unprecedented. The advertisements, featuring examples of people taking action without conducting any background research, urged viewers not to make the same type of leap-before-you-look mistakes when choosing a broker. Households rank media (television, radio, magazines, and newspapers) as the most effective way to learn about money management (Hilgert, Hogarth, and Beverly (2003)). Not surprisingly, Google trends show that search frequency for the phrase "BrokerCheck" doubled after the campaign, suggesting increased awareness and reduced search frictions among consumers.

I begin by examining whether investors become more attentive to RIA misconduct in their investment decisions after the advertising campaign. To do so, I construct a panel of U.S.-based RIA-year observations using Form ADV filings from the SEC. I focus on the sample of RIAs that have not engaged in misconduct during the two years prior to the advertising campaign but vary in historical misconduct records that date back to the more distant past. Restricting the sample to RIAs with no recent misconduct records ensures that my analysis is not confounded by the mechanical relationship between recent misconduct discoveries and investor responses. Specifically, doing so allows me to isolate the impact of revelation of historical misconduct on future investor decisions. The identifying assumption is that among the RIAs with no recent misconduct, such records in the distant past are plausibly exogenous to current clients' investment decisions.

I exploit the variations in past misconduct among RIAs to implement difference-in-differences tests that identify the causal effect of the advertising campaign on clients' investment decisions. I estimate that, after the advertising campaign, RIAs with past misconduct (henceforth misconduct RIAs) experience a 9% decrease in assets under management relative to RIAs with clean records, which is equivalent to roughly $1.04 trillion of assets. My results are robust after controlling for unobserved heterogeneity across RIAs and time-variant local economic conditions with RIA fixed effects and state-year fixed effects.

I then ask whether my findings are driven by a particular segment of the market. I explore the heterogeneous effects on RIAs with different characteristics by estimating a difference-in-difference-in-differences specification. Consistent with the hypothesis that search frictions are higher among less sophisticated investors, I find that RIAs that mainly serve less sophisticated retail customers see more severe adverse effects. In particular, misconduct RIAs whose assets are primarily from retail clients sustain an additional 14.8% decrease in assets under management relative to other misconduct RIAs.

To better understand the effect of reducing search frictions on the persistence of RIA misconduct, I examine whether the advertising campaign incentivizes labor market disciplines against the employees who engage in misconduct. After the advertising campaign, RIAs with past misconduct are two percentage points more likely to remove past misconduct records in a year by firing employees who engage in misconduct, compared to a pre-treatment average of 2.9% per year.

There is also a spillover effect on RIAs without past misconduct (henceforth clean RIAs), which is consistent with investors switching to these RIAs. In particular, clean RIAs that have offices in the neighborhood of misconduct RIAs experience positive abnormal growth in assets under management. Instead of depositing money in the bank, as shown in

Gurun, Stoffman, and Yonker (2018) when investors face industry-wide reputation shocks, investors move the assets that they withdraw to clean RIAs. These results highlight the importance of reducing search frictions in an effective reputation mechanism described in Klein and Leffler (1981) and Shapiro (1983).

One concern is that my results may not be unique to the advertising campaign and may instead by driven by trends in the financial advisory market. To ensure that the patterns I document are robust, I conduct placebo tests to investigate whether RIAs with and without historical misconduct behaved differently during periods other than the advertising campaign in 2015. These placebo tests rule out the alternative explanation that time-variant differences between the two groups of RIAs, such as investment strategies and returns, caused them to behave differently.

My paper adds to the literature on financial adviser misconduct. Qureshi and Sokobin (2015) examine the characteristics of financial advisers who engage in misconduct and the predictability of misconduct. Dimmock, Gerken, and Graham (2018) study the peer effect in brokerage fraud and find that fraud is contagious across firms through peer networks. Dimmock and Gerken (2012) show past fraud by advisers predicts future fraud. Egan, Matvos, and Seru (2019) document the economy-wide extent of misconduct among financial advisers and show that advisers that persistently engage in misconduct survive in the market. These papers and my results together suggest search frictions associated with client sophistication attribute to the persistence of financial adviser misconduct, suggesting a role for government intervention.

My paper also contributes to the literature on how trust in the financial market affects investor behavior and asset allocation. Kostovetsky (2016) shows that a decline in trust causes investors to withdraw from funds that announce ownership changes. Georgarakos and Inderst (2014) show that trust in financial advice affects stock market participation. Giannetti and Wang (2016) and Gurun, Stoffman, and Yonker (2018) show that even indirect exposure to misconduct destroys trust and results in nonparticipation. My paper contributes to this literature by highlighting the importance of information awareness in this process.

My paper relates to the literature on household financial sophistication and financial education interventions (see Lusardi and Mitchell (2014) for a survey). Facing the increasingly complex financial markets, many researchers advocate better information provision through government interventions (Hilgert, Hogarth, and Beverly (2003), Lusardi and Mitchell (2007), Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2010), and Van Rooij, Lusardi, and Alessie (2011)). Recently, many researchers draw unfavorable conclusions on financial education interventions. Hastings, Madrian, and Skimmyhorn (2013) argue that "there is at best mixed evidence that financial education leads to improved economic outcomes." Willis (2011) questions the cost-effectiveness of financial education. Fernandes, Lynch, and Netemeyer (2014) conduct a meta-analysis and show that interventions explain only 0.1% of the variance in financial behaviors studied, with weaker effects in low-income samples. I contribute to the literature by showing that even simple information provision can have significant economic impacts.

The remainder of the paper is organized as follows. Section II discusses details about FINRA's national advertising campaign. In Section III, I introduce my data and variables. In Section IV, I discuss my empirical methodology. In Section V, I present my main results. Section VII concludes the paper.

II. FINRA's National Advertising Campaign

On June 1st, 2015, the Financial Industry Regulatory Authority (FINRA) announced a national advertising campaign promoting BrokerCheck (brokercheck.finra.org), FINRA's free online tool that allows investors to access information about every broker's employment history, certifications and licenses, as well as regulatory actions, violations, or complaints made against them. The campaign, announced and launched on the same day, was unexpected and unprecedented. The motivation of the campaign, as FINRA chairman and CEO Richard Ketchum said in a statement, was that "people immediately go online to check out a new restaurant where they might spend $25 for a meal, but don't think to use BrokerCheck when they're handing over $2,500 – or $25,000 of their life savings or even more – to an investment professional to invest."

The advertisements, featuring examples of people taking action without conducting any background research, urged viewers not to make the same type of leap-before-you-look mistakes when choosing a broker. In order to reach a broader public, the $3.5 million campaign spanned cable channels, websites, and search engines. In particular, the campaign ran for five weeks on cable channels, including CNBC, Bloomberg, CNN, MSNBC, Fox Business, Fox News, ESPN, Discovery, the History Channel, and HGTV. The campaign also ran digitally on relevant sites that include Bloomberg, CNBC, Fortune, Reuters, TubeMogul, the Undertone Network, the Wall Street Journal, and search engines Google, Yahoo, Bing, and YouTube.

Figure 1 shows weekly Google search frequency for the phrase “BrokerCheck” in the U.S. before and after the advertising campaign. The figure shows that search interest in the phrase “BrokerCheck” doubled after the advertising campaign was launched, suggesting that investors’ awareness of misconduct records improved substantially. The discontinuity in search frequency was statistically significant, as shown by the non-overlapping 95% confidence intervals from pre- and post-periods. A closer look at the state-level data shows that, out of the 38 states where search interest can be reliably estimated by Google, 35 saw an increase in search frequency for the phrase “BrokerCheck”, accounting for over 91 percent of the RIAs in my sample.

[Insert Figure 1 here.]

RIAs and their representatives are not necessarily brokers. Since BrokerCheck only contains misconduct records of FINRA-registered brokers, one may cast doubt on whether the advertising campaign affected the publicity of misconduct records of RIAs and their representatives. First, Egan, Matvos, and Seru (2019) document that 84 percent of active SEC-registered investment adviser representatives are also dually registered with FINRA as brokers. Second, searches for investment advisers who are not registered as brokers will be redirected to the SEC’s Investment Adviser Public Disclosure platform, which contains misconduct records for all investment advisers. Therefore, it is reasonable to believe that the advertising campaign improved the publicity of misconduct records of the vast majority of RIAs and their representatives.

III. Data

I collect data on RIAs from Part 1A of SEC form ADV. The form is also known as the Uniform Application for Investment Adviser Registration. RIAs that are regulated under the Investment Adviser Act of 1940 are mandated to file this form at initial registration, annually in the form of an annual update, and anytime there is a material change to their advisory business. The form and its schedules include detailed information about RIAs, including general information about the advisory business, ownership structure, assets under management (AUM), number of employees, client composition, locations, compensation, services provided, conflicts of interests, and disciplinary actions against the RIA and its affiliates.

To construct the sample, I keep only the "annual updating amendments" filings, which must be made within 90 days of the adviser's fiscal year-end. Many advisory firms submit more than one update throughout the year, but only the annual amendment requires them to update their assets under management. I use these filings to construct a panel of U.S.-based RIA-year observations from 2012 to 2017, which straddles FINRA's advertising campaign in June 2015. A few RIAs submitted more than one annual update for a given year, in which case I keep the one that was submitted first.

I remove filings of RIAs whose AUM do not change over time and whose AUM are missing. Given that not all RIAs manage money, I exclude RIAs who are "pure" financial planners or investment consultants by requiring RIAs to report having discretionary authority. Additional sample screenings include requiring RIAs to be based in the United States, to exist in 2014, and to survive until at least 2015. I remove outliers from the sample by purging RIAs that achieved growth in AUM that is larger than the 99th percentile of all RIA growth in any year.

I also collect ZIP-code-level demographics to compute RIA-level client characteristics. These data are the 5-year estimates as of 2014 from the American Community Survey by the U.S. Census Bureau. These data include age, population, number of persons of 65 years of age or older, number of high school graduates, number of college graduates, gender makeup, ethnic composition, and household income.

My final sample includes annual observations for 8,063 unique RIAs from 2012 to 2017, resulting in 45,142 total number of observations. Table 1 Panel A provides key summary statistics for the RIAs in my sample. The median RIA has $404 million in assets under management, one domestic office, nine non-clerical employees, and clients in two states. In an average RIA, retail investors (individuals that are not high-net-worth) and high-net-worth individuals make up roughly 14% and 27% of the assets under management, respectively. Nine percent of RIAs have misconduct records on file. Every year, about two percent of RIAs engage in new misconduct. 39% of RIAs provide financial planning services, 40% advise a private fund, 37% take custody of clients' cash or securities, and 37% charge a performance-based fee.

[Insert Table 1 here.]

Table 1 Panel B reports firm-level client demographics for RIAs as of 2014. The firm-level aggregate is computed as the weighted average of demographics in the ZIP codes where an RIA has offices. As of 2014, RIAs serve areas with a median household income of $82,321 and an average age of 39. White people, high school graduates, college graduates, and retirees make up 75%, 67%, 43%, and 15% of the potential clients of RIAs, respectively.

IV. Empirical Methodology

I estimate the causal effect of the advertising campaign on investor behaviors and RIA responses using a difference-in-differences framework. My approach exploits differences across RIAs in their misconduct records before the campaign was launched. The national advertising campaign improved the visibility of misconduct records for all RIAs. That said, there is no reason to believe that customers of RIAs that had clean records were affected by the advertising campaign in any way – these customers simply reconfirmed the quality of their RIAs. On the contrary, customers of RIAs that previously engaged in misconduct were more likely to be surprised by the true quality of their RIAs and change their behaviors accordingly. Therefore, I include RIAs that had engaged in misconduct prior to the advertising campaign as my treatment group.

I estimate regressions of the following form:

$$Outcome_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i + \sum_{m=1}^{M} (\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t},$$

where $Outcome_{i,j,k,t}$ is the outcome variable of interest for RIA i with its main office in state *j* and fiscal year-end in month *k*, in year *t*. My paper focuses on two outcome variables: $log(AUM)_{i,j,k,t}$, the natural logarithm of assets under management for the RIA, and $Record\ Removal_{i,j,k,t}$, a dummy variable that equals one if the RIA removes a misconduct record from its Form ADV filing due to job separation. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records before the campaign. The coefficient β_T on $Post_t \times Past\ Misconduct_i$ measures the effect of the advertising campaign. Investors' changing preference for products and services could affect RIAs differently over time, independent of the treatment. Therefore, I interact a number of RIA characteristics and client demographics with $Post_t$ to control for observable heterogeneity across RIAs that could result in differences in my outcome variable before and after the advertising campaign.

My main specification includes a set of RIA fixed effects, denoted by α_i, to absorb unobserved time-invariant RIA characteristics. However, time-varying heterogeneity across RIAs, such as changing local economic conditions and client demographics, could also affect my outcome variables. Therefore, I include state-year-month fixed effects, denoted by $\gamma_{j,k,t}$, in my specification, where month refers to the month of fiscal year-end of the RIA. By including interacted fixed effects, my specification is analogous to that recommended by Gormley and Matsa (2014) to control for unobserved heterogeneity. I cluster standard errors to allow correlation within an RIA.

An important assumption of my empirical strategy is that in the absence of treatment, the difference between the treatment and control group is constant over time. I verify the parallel trends assumption by plotting in Figure 2 the average cumulative change in the natural logarithm of the assets under management for the treatment and control groups. The figure shows that records of past misconduct did not affect the change in an RIA's assets under management until after the advertising campaign, which confirms the validity of the parallel trends assumption in my tests. In Section V.E, I verify the assumption for all my outcome variables using difference-in-differences regressions with a set of interaction terms between each year and the treatment variable.

[Insert Figure 2 here.]

I face two important challenges with this empirical setup. First, RIAs that engage in misconduct may be different from those with clean records in many aspects, including observable characteristics, such as compensation, services provided, locations, client base, and unobservable characteristics, such as investment strategies and returns. Because I include RIA fixed effects in my specification, this should not be a major concern unless one believes that there exists unobserved time-variant heterogeneity across RIAs, which caused investors to respond differently instead of the advertising campaign. To the extent that there is no time-variant heterogeneity across RIAs that coincides with the advertising campaign, my results are robust. Moreover, if the unobserved time-variant heterogeneity across RIAs caused the differential responses, then I might expect to see similar effects in other periods. To that end, the parallel trends graph in Figure 2 shows no unusual changes in assets under management for RIAs with past misconduct prior to the advertising campaign. Placebo tests in Section V.E further address the concern by investigating whether investors of different RIAs behaved differently during other periods.

Second, past offenders are five times more likely to engage in new misconduct (Egan, Matvos, and Seru (2019)). RIAs that had misconduct records prior to the advertising campaign may engage in new misconduct during the treatment year, making it difficult to disentangle the effects of the campaign from a pure backlash triggered by the new misconduct. To address the concern, I remove RIAs that engaged in new misconduct in the year before treatment (2014) and/or the treatment year (2015). The underlying assumption is that, in my sample, investors who knew where to access misconduct records, as well as the RIAs, had already reacted to the records before 2015. Therefore, the treatment effect in

2015 can only be attributed to the advertising campaign. My results are stronger if I include these RIAs in my sample.

V. Results

A. Investor Reactions

My main empirical analysis shows that the advertising campaign was effective at raising investors' awareness of misconduct records. Investors, better informed after the campaign, withdrew assets from the RIAs that had misconduct records. Table 2 reports the results from difference-in-differences regressions. The outcome variable is the natural logarithm of one plus the assets under management of an RIA in a year. The coefficient β_T on $Post_t \times Past\ Misconduct_i$ measures the effect of the advertising campaign. If the advertising campaign improved investors' awareness of misconduct records and helped them make more-informed decisions, then β_T should be negative, which suggests that customers of RIAs that previously engaged in misconduct abnormally withdrew their investments after the advertising campaign.

[Insert Table 2 here.]

Column (1) shows a 7% decrease in assets under management for RIAs with past misconduct. In Columns (2), (3), (4), and (5) I include a number of RIA characteristics and client demographics interacted with $Post_t$ to control for observable heterogeneity across RIAs that could result in differences in my outcome variable before and after the advertising campaign. The RIA characteristics include the size of the adviser's business, fee structure, client demographics, and other characteristics. Measures of size includes the natural logarithm of one plus the number of domestic offices, the natural logarithm of one plus the number of non-clerical employees, and the natural logarithm of the RIA's beginning assets under management (measured in 2014). Fee structure variables are the dummies indicating how the RIA is compensated, including hourly fees, commission, percentage of AUM, fixed fees, and performance-based fees. RIA-level client demographics include the average household median income, average fraction of white people, average fraction of college graduates, and average fraction of retirees of the populations in ZIP codes where the RIA has offices. Other characteristics include dummy variables indicating whether more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), whether the RIA provides financial planning services, whether the RIA advises a private fund, whether the RIA takes custody of cash or securities, and whether the RIA discloses sales interest in client transactions. These controls are measured at the end of 2014, before the advertising campaign. Because I include RIA fixed effects to absorb all time-invariant heterogeneity, these variables are only included when interacted with $Post_t$. In addition, my specifications include state-year-month fixed effects to control for time-varying heterogeneity across RIAs, such as changing local economic conditions. I cluster standard errors to allow correlation within an RIA.

The estimated decline in assets under management are 11%, 10%, 9%, and 9%, in Columns (2), (3), (4), and (5), respectively. Overall, these estimates are statistically significant at the 1% level and quantitatively similar across specifications. The estimates are economically large when compared with the median growth rate in AUM of 8% in my sample. Based on the estimates from Column (5), investors of RIAs that previously engaged in misconduct withdrew approximately $1.04 trillion of assets, which is roughly 3.3% of the total assets under management for all RIAs in 2014.

I use an RIA's assets under management as a proxy for investment flows into and out of the RIA. A challenge to this proxy is that changes in assets under management are a function of both asset flows and investment returns. Note that I include RIA fixed effects and state-year-month fixed effects in my regression specifications. The RIA fixed effects control for time-invariant RIA-specific investment styles and return patterns, while the state-year-month fixed effects capture the average investment return of RIAs in each filing period. Recall in Figure 2, there is no treatment effect until after the advertising campaign. Therefore, for investment returns to confound my results, RIAs with misconduct records would have implemented investment strategies and earned returns in and only in 2015 (the year of the advertising campaign) that were systematically different from those of RIAs with clean records. To the extent that this is not the case, my results are robust. I further address this concern with a series of placebo tests in Section V.E.

B. RIA Characteristics

Certain demographic and socioeconomic groups of investors may be more susceptible to financial adviser misconduct (Egan, Matvos, and Seru (2019)). Meanwhile, RIAs that provide certain services may be able to build greater trust with their clients (Gurun, Stoffman, and Yonker (2018)). In addition, conflicts of interest and custody of assets may exacerbate the impact of the advertising campaign. The Form ADV data include detailed information on various aspects of RIAs, including client composition, fee structure, services provided, conflicts of interests, and custody of assets. In this section, I explore how these RIA characteristics affect the adverse effect following the revelation of past misconduct records. In Tables 3 and 4, I report results from difference-in-difference-in-differences regressions featuring the interaction of the post period dummy, the RIA characteristics, and the dummy for past misconduct records. The coefficient estimate on the triple interaction term estimates the extent to which the characteristic mitigates or exacerbates the effect of the advertising campaign.

Egan, Matvos, and Seru (2019) observe that RIAs that service retail customers, RIAs that charge hourly, and RIAs that charge a commission are more likely to employ an adviser who has a record of misconduct. In addition, they find that counties with a smaller share of college graduates and a large share of retirees experience more misconduct and employ more advisers with past misconduct records. They argue that there is evidence of market segmentation on misconduct, which targets unsophisticated retail investors. If their argument is valid, and retail investors are less aware of misconduct records, then the advertising campaign should impact RIAs that "specialize" in misconduct and serve unsophisticated retail investors more than those that do not.

In Table 3, I show evidence consistent with the hypothesis that RIAs that persistently engage in misconduct tend to serve less sophisticated investors. The estimates suggest that conditional on having misconduct records prior to the advertising campaign, RIAs that mainly serve retail investors, RIAs that charge hourly, and RIAs that charge a commission saw shaper decline in assets under management after the revelation of past misconduct records. Moreover, conditional of having misconduct records prior to the advertising campaign, RIAs that are located in areas with a large share of retirees sustain more severe adverse effects from the advertising campaign. The coefficient on the triple interaction between post period dummy, misconduct dummy, and more college graduates has the hypothesized sign but is not statistically significant. On the contrary, RIAs that advise private funds, such as hedge funds, private equity funds, and venture capital funds, saw fewer withdrawals after the campaign, perhaps because their investors were more financially sophisticated and had already known the misconduct records even before the campaign. All in all, these estimates suggest that retail investors were indeed reacting more strongly from the advertising campaign, indicating that they did not know about the misconduct records prior to the advertising campaign.

[Insert Table 3 here.]

Gurun, Stoffman, and Yonker (2018) suggest that RIAs could build greater trust by providing financial planning service and show that these RIAs were insulated from industry-wide reputation shocks sparked by the Madoff Ponzi scheme. That is not necessarily true when investors are informed of their own RIA's past misconduct and are directly exposed to misconduct. On the one hand, pre-existing trust built through repeated services may alleviate the adverse effects of the revelation of past misconduct. On the other hand, despite U.S. security laws and the fact that RIAs owe fiduciary duty, investors may value safety more than anything. In the latter case, the revelation of misconduct may break the previously built trust and cause a backlash. This relates to the two aspects of trust that were previously modeled: the sense of trust that stems from security from theft or expropriation (Guiso, Sapienza, and Zingales (2004, 2008) and Georgarakos and Inderst (2011)) and the sense of trust that originates from expertise and dependability (Gennaioli, Shleifer, and Vishny (2015)).

[Insert Table 4 here.]

In Column (1) of Table 4, I show results consistent with the second hypothesis. The coefficient estimate on the triple interaction between the post period dummy, past misconduct dummy, and financial planning dummy is -13% and significant at the 10% level. In particular, I show that RIAs that provide financial planning service experienced greater decline in assets under management, suggesting that they were not insulated from firm-specific reputation shocks. Instead of mitigating the impact of the revelation of past misconduct, the trust built in this way backfired at these RIAs.

Other RIA characteristics may also mitigate or exacerbates the effect of the advertising campaign. Here I focus on whether the RIA takes custody of clients' assets and whether the RIA discloses any sales interest in client transactions and acts as a broker-dealer. Note that the sales interest here is different from commission-based fees that an RIA may charge. The sales interest refers to conflict of interest that may arise from being a broker-dealer and selling products to clients, whereas commission-based fee refers to how clients compensate an RIA. Taking custody of clients' assets or acting as a broker-dealer rewarded by sales commissions make it easier for RIAs to financially exploit their clients. Alternatively, the fact that clients allow these RIAs to take custody and/or have potential conflict of interest suggests that the clients may have a higher level of trust in these RIAs, mitigating the adverse effects of the advertising campaign. I test these hypotheses and show my results in Columns (2) and (3) of Table 4. The estimates suggest that conditional on having misconduct records, RIAs that took custody of assets or disclosed conflict of interests saw fewer withdrawals in the post period. In either case, the coefficient estimate on the triple interaction term is positive and significant, with a magnitude that almost eliminates the effects of revelation of misconduct records on asset outflows.

C. RIA Reactions

RIAs are obligated to disclose disciplinary actions against them and their affiliates, such as employees. That said, an RIA is allowed to remove disclosure reporting pages (misconduct records) from its Form ADV filings if the advisory affiliate who engaged in misconduct is no longer associated with the RIA.

As shown in the previous sections, the advertising campaign made disciplinary records more accessible for investors, making it more costly for RIAs to engage in misconduct or hire advisers with misconduct records. Therefore, there is an incentive for RIAs to fire employees who engaged in misconduct and remove misconduct records from RIA disclosure filings. In this section, I examine whether treated RIAs are more likely to remove misconduct records by firing advisers who engaged in misconduct. To test the hypothesis, I repeat the analysis in Table 2 with a different outcome variable measuring the annual probability of removing a disclosure reporting page (misconduct) due to job separation. Table 5 reports the results from difference-in-differences regressions.

[Insert Table 5 here.]

The increase in the probability of removing a misconduct record due to job separation is estimated to be 1.9, 2.2, 2.3, 2.3, and 2.4 percentage points in Columns (1), (2), (3), (4) and (5), respectively. Overall, these estimates are statistically significant at the 1% level and quantitatively similar across specifications. Given that the average probability of removing a misconduct record due to job separation is 2.9% in my treatment group prior to the advertising campaign, the estimates are economically large and meaningful.

D. Spillover Effects

Ideally, the advertising campaign should inform investors of the quality of RIAs and help investors make better investment decisions, enhancing investor welfare. However, past studies show that even indirect exposure to misconduct destroys trust and results in nonparticipation (Giannetti and Wang (2016) and Gurun, Stoffman, and Yonker (2018)). If the revelation of past misconduct destroyed investor trust to the point that it caused massive nonparticipation, it will be questionable whether the advertising campaign was enhancing investor welfare. In this section, I test whether better-informed investors switched to RIAs with clean records (henceforth clean RIAs) after the advertising campaign, causing a positive spillover effect.

I estimate the spillover effect of the advertising campaign on clean RIAs using a difference-in-differences model that resembles my specification in Table 2. I exploit the differences across clean RIAs in their proximity to RIAs with past misconduct (henceforth misconduct RIAs). Clean RIAs that were located within the neighborhoods of misconduct RIAs were more visible to the investors of misconduct RIAs who were looking for new RIAs and, therefore, were more exposed to the spillover effect upon the advertising campaign.

I estimate regressions of the following form:

$$ln(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Spillover\ Exposure_i$$
$$+ \sum_{m=1}^{M} (\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t},$$

where $ln(AUM)_{i,j,k,t}$ is the natural logarithm of the assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Control_{i,m}$ are control variables following those used in Column (4) of Table 2. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$.

I construct three measures of an RIA's exposure to investors that were shocked by their advisers' past misconduct. The first is a dummy variable that equals one if at least one of the clean RIA's offices was in the same ZIP code area as a misconduct RIA. The second equals the fraction of the clean RIA's offices that were in the same ZIP code area as a misconduct RIA. For the third measure, I compute the natural logarithm of one plus the average number of misconduct RIA offices in the same ZIP code as each office of the clean RIA.

The coefficient β_T on $Post_t \times Spillover\ Exposure_i$ measures the spillover effect of the advertising campaign on clean RIAs. If the advertising campaign enhanced investor welfare, then β_T should be positive, suggesting that better-informed investors switch to RIAs with clean records. In Table 6, I present results supporting this hypothesis.

[Insert Table 6 here.]

As shown in Table 6, all specifications consistently show greater increases in assets under management for clean RIAs located in the neighborhoods of misconduct RIAs. Overall, the estimates are statistically significant at the 5% level. In Column (1), the estimate of β_T indicates that clean RIAs that were exposed to the influx of investors saw an additional 4.9% increase in assets under management. Using the same specification with continuous measures of spillover exposure, Columns (2) shows that a one-standard-deviation increase in the fraction of exposed offices results in a 2.3% increase in assets under management. Similarly, Column (3) shows that a one-standard-deviation increase in the log average number of misconduct RIA offices per clean RIA office leads to a 3.1% increase in assets under management. Given that the median growth rate in assets under management in my sample is 8%, the magnitudes of these coefficient estimates are economically large. Using the coefficient estimates from Column (3), it is estimated that clean RIAs that were located within the neighborhoods of misconduct RIAs saw an increase in assets under management of roughly $752 billion.

E. Placebo Tests

In this section, I conduct placebo tests to address the concern that the time-variant heterogeneity across RIAs, and not the advertising campaign, caused differential outcomes that I document. In particular, I investigate whether different RIAs behaved differently during other periods. If the documented treatment effects in 2015 were due to unobserved time-variant heterogeneity across RIAs, such as systematically different investment strategies and returns, and not the advertising campaign, then I might expect to see similar effects in other periods. If that is the case, then the observed differences in 2015 may be attributed to reasons other than the advertising campaign.

I conduct placebo tests using difference-in-differences regressions with interaction terms between each year and the treatment variable. I repeat the test for my analysis on investor reaction, RIA reaction, and spillover effect in Column (4) of Table 2, Column (4) of Table 5, and Column (3) of Table 6. In particular, I estimate regressions of the following form:

$$Outcome_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \sum_{n=2012}^{2017} (\beta_{T,n} Year_{t,n} \times Treatment_i)$$

$$+ \sum_{m=1}^{M} (\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t},$$

where $Outcome_{i,j,k,t}$ is the outcome variable of interest for RIA i with its main office in state *j* and fiscal year-end in month *k*, in year *t*. $Year_{t,n}$ is a dummy variable that equals one if year *t* is equal to n. $Treatment_i$ is the variable defining treatment status following those in Column (4) of Table 2, Column (4) of Table 5, and Column (3) of Table 6. $Control_{i,m}$ are control variables following those used in Column (4) of Table 2. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$.

[Insert Table 7 here.]

Table 7 reports the coefficient estimates of $\beta_{T,n}$ for the three placebo tests. Note that the year before the advertising campaign, 2014, is used as the benchmark year for comparison. For all three tests, there were no abnormal changes in the outcome variable for misconduct RIAs during the years prior to the advertising campaign. Overall, the coefficient estimates for the year of 2015 are statistically significant at 1% level and quantitatively similar to my estimates using classic difference-in-differences regressions. Moreover, my results suggest that the effect of the advertising campaign was persistent. Taken together, these placebo tests suggest that my results are not caused by unobserved time-variant heterogeneity across RIAs.

VII. Conclusion

In this paper, I study the effect of advertising campaigns as a tool for financial education in the context of financial adviser misconduct. I exploit the variation in past misconducts among RIAs to implement difference-in-differences tests that identify the causal effect of the advertising campaign on investor behaviors and RIA responses. I show that the advertising campaign improved investors' awareness of misconduct records and helped informed investors make better investment decisions. As a result, investors withdrew assets from RIAs with past misconduct and switched to RIAs with clean records. The effects of the advertising campaign are statistically significant and economically large.

I find that the advertising campaign was successful at educating the less sophisticated investors, which were the intended audience of the intervention. Specifically speaking, using a difference-in-difference-in-differences specification, I find stronger effects among RIAs that mainly serve retail customers, which is consistent with the hypothesis that RIAs that persistently engage in misconduct tend to serve less sophisticated investors. Therefore, it is evident that investors' lack of awareness of misconduct contributes to the survival of misconduct RIAs. My paper highlights the importance of awareness in an effective reputation mechanism as described in Klein and Leffler (1981) and Shapiro (1983) and points to interventions that boost investor awareness, like the one studied in this paper, as a potential solution to the problem of persistent misconduct.

An important policy implication of my paper is that even simple information provision, such as the advertising campaign studied here, can have large economic impacts and enhance investor welfare. That said, the success documented in this paper may not necessarily apply to other scenarios. First, the intended audience of the advertising campaign are the clients of investment advisers and brokers, who are relatively rich and more financially sophisticated to begin with. Second, the content of this advertising campaign is simpler than most other financial education interventions. Nonetheless, my paper highlights the potential of advertising campaigns as a tool for financial education, especially in a situation where the information content is simple. Ultimately, our goal is to understand which tools are most cost effective at improving certain financial outcomes, and my paper is one step towards that goal.

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Figures and Tables

Figure 1
Google Search Frequency for "BrokerCheck"

This figure shows the weekly index of Google search frequency for the phrase "BrokerCheck" in the U.S. from February 2015 to September 2015, which straddles the advertising campaign. The index is scaled based on the highest level of search frequency during this period, which occurred in the week of June 21st, 2015. The red lines are the fitted values using quadratic equations. Shaded areas represent the 95% confidence intervals of the fitted quadratic equations.

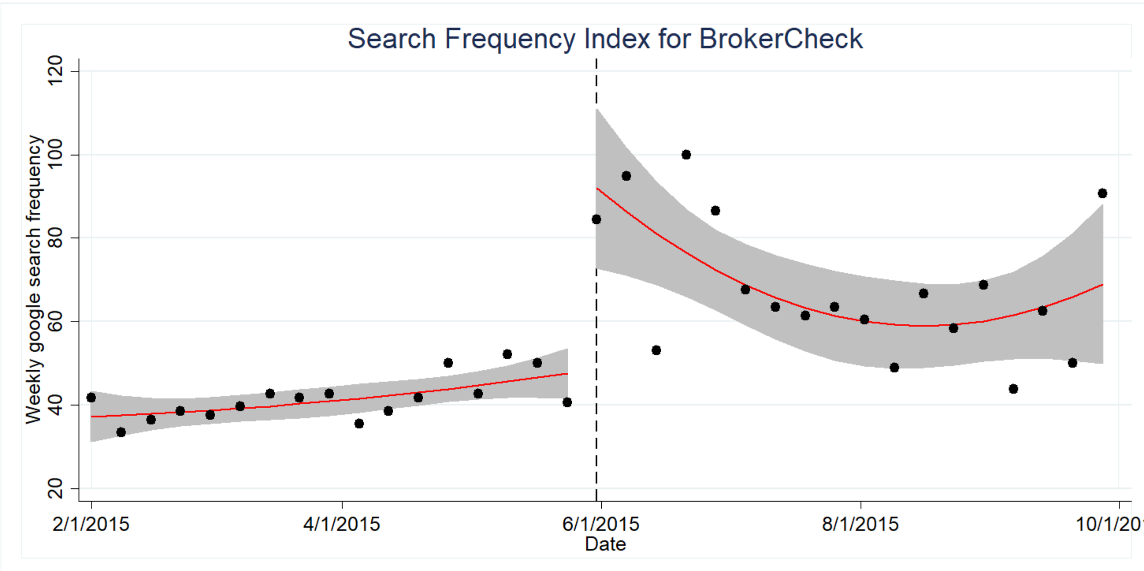

Figure 2

Average cumulative change in RIA log(AUM) by group

This figure shows the average change in the natural logarithm of the assets under management for RIAs in the treatment and control groups. RIAs that had misconduct records prior to the advertising campaign are considered the treatment group. All other RIAs are labeled the control group.

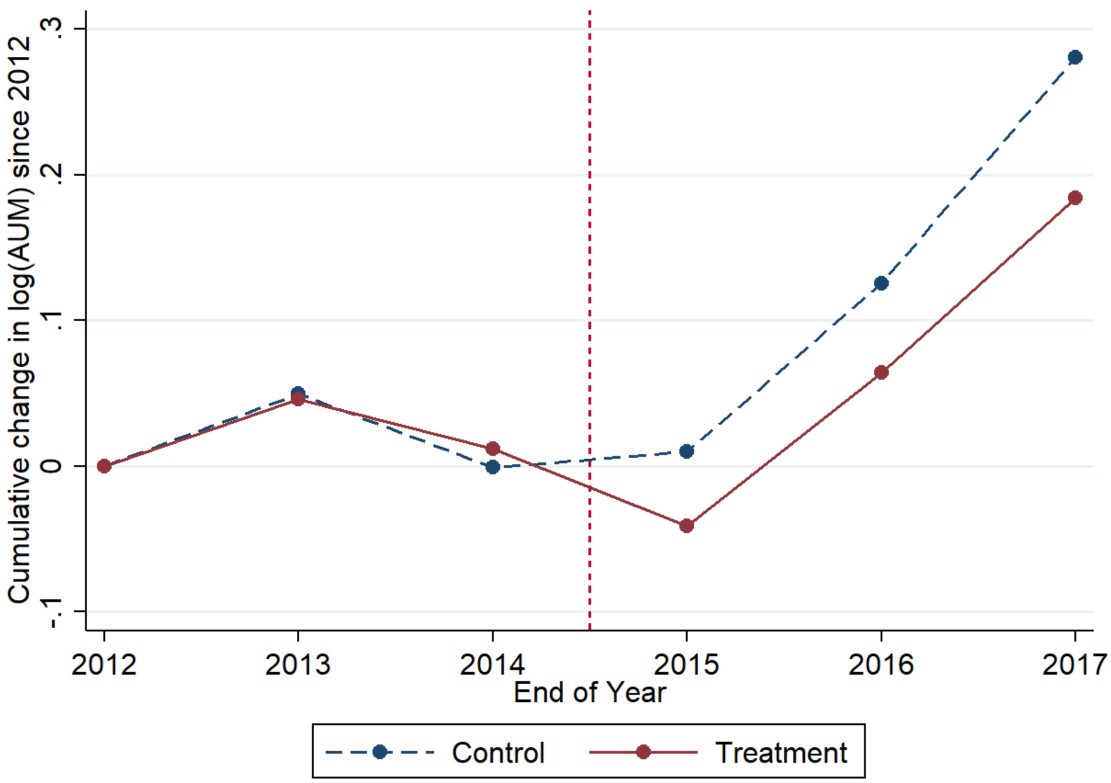

Table 1
This table presents the summary statistics for the registered investment adviser data (Panel A) and firm-level client demographics for advisory firms as of 2014 (Panel B) used in the paper. Panel A includes data for 8,063 unique RIAs from the years 2012 to 2017. Panel B reports data for the 8,063 RIAs as of 2014. The firm-level aggregate is computed as the weighted average of demographics in the ZIP codes where an RIA has offices. RIA characteristics and office locations are from annual amendments to SEC form ADV. ZIP-code-level demographics are the 5-year estimates from American Community Survey by the U.S. Census Bureau.

	(1)	(2)	(3)	(4)
VARIABLES	Mean	Median	SD	N
A. Registered Investment Adviser Characteristics				
AUM (millions)	4,170.04	403.94	23,866.91	45,142
Log(AUM)	20.11	19.82	1.80	45,142
Number of accounts	1,422.55	183.00	20,591.72	45,142
Number of client states	7.27	2.00	12.00	45,142
Number of domestic offices	1.89	1.00	3.40	45,142
Number of non-clerical employees	35.27	9.00	265.69	45,142
Share of AUM – retail investors	14.31	12.50	20.45	45,142
Share of AUM – high net worth individuals	26.98	12.50	30.66	45,142
Compensation – percentage of AUM	0.98	1.00	0.14	45,142
Compensation – hourly fees	0.30	0.00	0.46	45,142
Compensation – fixed fees	0.43	0.00	0.50	45,142
Compensation – commission	0.04	0.00	0.19	45,142
Compensation – performance-based fees	0.37	0.00	0.48	45,142
Dummy – provide financial planning services	0.39	0.00	0.49	45,142
Dummy – advise a private fund	0.40	0.00	0.49	45,142
Dummy – custody of cash or securities	0.37	0.00	0.48	45,142
Dummy – sales interest	0.36	0.00	0.66	45,142
Dummy – have misconduct records	0.09	0.00	0.29	45,142
Dummy – engage in new misconduct	0.02	0.00	0.14	45,142
Dummy – remove record due to separation	0.01	0.00	0.07	45,142
Misconduct (stock)	0.28	0.00	2.60	45,142
Misconduct (flow in 1 year)	0.04	0.00	0.50	45,142
B. Client Demographics				
Median household income	82.32	81.19	34.50	8,063
Average age	38.84	39.55	7.96	8,063
Percent - male	0.48	0.49	0.09	8,063
Percent - white	0.75	0.79	0.18	8,063
Percent - high school graduates	0.67	0.68	0.15	8,063
Percent - college graduates	0.43	0.43	0.17	8,063
Percent - age 65 or up	0.15	0.15	0.07	8,063

Table 2
Investor Reactions

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. In Columns (2) to (5), I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. Size includes the natural logarithm of one plus the number of domestic offices, the natural logarithm of one plus the number of non-clerical employees, and the natural logarithm of the RIA's beginning assets under management (measured in 2014). Fee structure variables are the dummies indicating how the RIA is compensated, including hourly fees, commission, percentage of AUM, fixed fees, and performance-based fees. RIA-level client demographics include the average household median income, average fraction of white people, average fraction of college graduates, and average fraction of retirees of the populations in ZIP codes where the RIA has offices. Other characteristics include dummy variables indicating whether more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), whether the RIA provides financial planning services, whether the RIA advises a private fund, whether the RIA takes custody of cash or securities, and whether the RIA discloses sales interest in client transactions. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level. Coefficient estimates for additional controls are reported in Table A.1 of the Appendix.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)	(4) Log(AUM)	(5) Log(AUM)
Post * Past misconduct	-0.071***	-0.108***	-0.099***	-0.093***	-0.092***
	(0.025)	(0.031)	(0.031)	(0.031)	(0.031)
Post * RIA size		Y	Y	Y	Y
Post * Fee structure			Y	Y	Y
Post * Other characteristics				Y	Y
Post * Client demographics					Y
Observations	44,652	44,652	44,652	44,652	44,652
R-squared	0.895	0.904	0.904	0.905	0.905
RIA FE	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.

Table 3

RIA Characteristics - Do retail investors react more strongly to the advertising campaign?

The table displays regression results of difference-in-differences regressions estimating the differential impact of the advertising campaign on RIA asset flows based on different RIA characteristics. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i \times Characteristic_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. $Characteristic_i$ include *Retail investors*, which equals one if more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), *Hourly fees*, which equals one if the RIA charges an hourly fee, *Commission*, which equals one if the RIA charges a commission, *More college graduates*, which equals one if the RIA's clients are in the top quintile in terms of fraction of college graduates as of 2014, *More retirees*, which equals one if the RIA's clients are in the top quintile in terms of fraction of retirees as of 2014, and *Private fund*, which equals one if the RIA advises a private fund. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. Control variables that are interacted with $Post_t$ include size, fee structure, client demographics, and other characteristics, as described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level. Coefficient estimates for additional controls are reported in Table A.2 of the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(AUM)	Log(AUM)	Log(AUM)	Log(AUM)	Log(AUM)	Log(AUM)
Post * Past misconduct	-0.064*	-0.053	-0.079**	-0.101***	-0.054*	-0.136***
	(0.036)	(0.041)	(0.033)	(0.034)	(0.031)	(0.040)
Post * Past misconduct * Retail investors	-0.148**					
	(0.072)					
Post * Past misconduct * Hourly fees		-0.123*				
		(0.063)				
Post * Past misconduct * Commission			-0.117*			
			(0.070)			
Post * Past misconduct * More college graduates				0.055		
				(0.079)		
Post * Past misconduct * More retirees					-0.196**	
					(0.095)	
Post * Past misconduct * Private fund						0.109*
						(0.066)
Post * Control	Y	Y	Y	Y	Y	Y
Observations	44,652	44,652	44,652	44,652	44,652	44,652
R-squared	0.905	0.905	0.905	0.905	0.905	0.905
RIA FE	Y	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4
RIA Characteristics – Service provided

The table displays regression results of difference-in-differences regressions estimating the differential impact of the advertising campaign on RIA asset flows based on different RIA characteristics. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i \times Service_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. $Service_i$ include *Financial planning service*, which equals one if the RIA provides financial planning service, *Custody of assets*, which equals one if the RIA takes custody of clients' cash or securities, and *Sales interest*, which equals one if the RIA also acts as a broker-dealer and discloses sales interest in client transactions. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. Control variables that are interacted with $Post_t$ include size, fee structure, client demographics, and other characteristics, as described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level. Coefficient estimates for these controls are reported in Table A.3 of the Appendix.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)
Post * Past misconduct	-0.043	-0.144***	-0.136***
	(0.046)	(0.042)	(0.040)
Post * Past misconduct * Financial planning service	-0.126*		
	(0.066)		
Post * Past misconduct * Custody of assets		0.136**	
		(0.063)	
Post * Past misconduct * Sales interest			0.105*
			(0.062)
Post * Control	Y	Y	Y
Observations	44,652	44,652	44,652
R-squared	0.905	0.905	0.905
RIA FE	Y	Y	Y
State-year-filing month FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5
RIA Reactions

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $Record\ Removal_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $Record\ Removal_{i,j,k,t}$ is a dummy variable that equals one if RIA i, with its main office in state j and fiscal year-end in month k in year t, removes a misconduct record from its Form ADV filing due to job separation. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. In Columns (2) to (5), I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. Size includes the natural logarithm of one plus the number of domestic offices, the natural logarithm of one plus the number of non-clerical employees, and the natural logarithm of the RIA's beginning assets under management (measured in 2014). Fee structure variables are the dummies indicating how the RIA is compensated, including hourly fees, commission, percentage of AUM, fixed fees, and performance-based fees. RIA-level client demographics include the average household median income, average fraction of white people, average fraction of college graduates, and average fraction of retirees of the populations in ZIP codes where the RIA has offices. Other characteristics include dummy variables indicating whether more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), whether the RIA provides financial planning services, whether the RIA advises a private fund, whether the RIA takes custody of cash or securities, and whether the RIA discloses sales interest in client transactions. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level. Coefficient estimates for additional controls are reported in Table A.4 of the Appendix.

VARIABLES	(1) Record Removal	(2) Record Removal	(3) Record Removal	(4) Record Removal	(5) Record Removal
Post * Past misconduct	0.019***	0.022***	0.023***	0.023***	0.024***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Post * RIA size		Y	Y	Y	Y
Post * Fee structure			Y	Y	Y
Post * Other characteristics				Y	Y
Post * Client demographics					Y
Observations	44,652	44,652	44,652	44,652	44,652
R-squared	0.313	0.314	0.314	0.314	0.314
RIA FE	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6

Spillover Effects – Do investors switch to RIAs with clean records?

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Exposure_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA *i* with its main office in state *j* and fiscal year-end in month *k*, in year *t*. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Exposure_i$ measures the RIA's exposure to new investors who were shocked by their pervious advisers' past misconduct. In particular, *Exposure dummy* equals one if at least one of the RIA's offices was in the same ZIP code area as an RIA with misconduct, *Fraction of offices exposed* equals the fraction of the RIA's offices that were in the same ZIP code area as an RIA with misconduct, *Log(average number of misconduct RIA offices in ZIP)* is the natural logarithm of one plus the average number of misconduct RIA offices in the same ZIP code as each office of the clean RIA. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. These control variables are described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level. Coefficient estimates for additional controls are reported in Table A.5 of the Appendix.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)
Post * Exposure dummy	0.049**		
	(0.025)		
Post * Fraction of offices exposed		0.057**	
		(0.025)	
Post * Log(average number of misconduct RIA offices in ZIP)			0.025**
			(0.011)
Post * Control	Y	Y	Y
Observations	40,938	40,938	40,938
R-squared	0.895	0.895	0.895
RIA FE	Y	Y	Y
State-year-filing month FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7
Placebo Tests

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $Outcome_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \sum_{n=2012}^{2017}(\beta_{T,n} Year_{t,n} \times Treatment_i) + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $Outcome_{i,j,k,t}$ and $Treatment_i$ for Columns (1), (2), and (3) are defined following Column (4) of Table 2, Column (4) of Table 5, and Column (3) of Table 6. In Columns (1) and (2), $Treatment_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. In Column (3), $Treatment_i$ is the natural logarithm of one plus the average number of misconduct RIA offices in the same ZIP code as each office of the clean RIA. $Year_{t,n}$ is a dummy variable that equals one if year t is equal to n I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. These control variables are described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Log(AUM)	(2) Record Removal	(3) Log(AUM)
Placebo test for	Column (4) of Table 2	Column (4) of Table 5	Column (3) of Table 6
Year2012 * Treatment	0.024	-0.010	-0.010
	(0.024)	(0.008)	(0.009)
Year2013 * Treatment	0.010	-0.001	-0.010
	(0.018)	(0.007)	(0.010)
Year2015 * Treatment	-0.063**	0.025***	0.034***
	(0.026)	(0.009)	(0.010)
Year2016 * Treatment	-0.072**	0.016*	0.021**
	(0.029)	(0.009)	(0.010)
Year2017 * Treatment	-0.114**	0.018*	0.016
	(0.047)	(0.010)	(0.011)
Post * Control	Y	Y	Y
Observations	44,652	44,652	40,938
R-squared	0.905	0.315	0.895
RIA FE	Y	Y	Y
State-year-filing month FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A.1
Investor Reactions

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. In Columns (2) to (5), I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, other characteristics, and client demographics, respectively. Size includes the natural logarithm of one plus the number of domestic offices, the natural logarithm of one plus the number of non-clerical employees, and the natural logarithm of the RIA's beginning assets under management (measured in 2014). Fee structure variables are the dummies indicating how the RIA is compensated, including hourly fees, commission, percentage of AUM, fixed fees, and performance-based fees. RIA-level client demographics include the average household median income, average fraction of white people, average fraction of college graduates, and average fraction of retirees of the populations in ZIP codes where the RIA has offices. Other characteristics include dummy variables indicating whether more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), whether the RIA provides financial planning services, whether the RIA advises a private fund, whether the RIA takes custody of cash or securities, and whether the RIA discloses sales interest in client transactions. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)	(4) Log(AUM)	(5) Log(AUM)
Post * Past misconduct	-0.071***	-0.108***	-0.099***	-0.093***	-0.092***
	(0.025)	(0.031)	(0.031)	(0.031)	(0.031)
Post * Number of domestic offices		-0.013	-0.009	-0.000	0.009
		(0.022)	(0.019)	(0.019)	(0.019)
Post * Log(Number of non-clerical employees)		0.315***	0.321***	0.326***	0.324***
		(0.052)	(0.051)	(0.052)	(0.052)
Post * Log(Beginning AUM)		-0.271***	-0.275***	-0.280***	-0.281***
		(0.045)	(0.047)	(0.048)	(0.048)
Post * Hourly fees			-0.086***	-0.072**	-0.067**
			(0.031)	(0.028)	(0.028)
Post * Commission			-0.164***	-0.149***	-0.145***
			(0.036)	(0.033)	(0.033)

	(1)	(2)	(3)	(4)	(5)
Post * Percentage of AUM			-0.043	-0.040	-0.040
			(0.064)	(0.064)	(0.064)
Post * Fixed fees			0.073***	0.070***	0.072***
			(0.019)	(0.020)	(0.021)
Post * Performance-based fees			-0.040*	-0.053*	-0.056*
			(0.023)	(0.031)	(0.031)
Post * Retail investors				-0.148***	-0.140***
				(0.039)	(0.038)
Post * Financial planning service				0.000	0.004
				(0.029)	(0.029)
Post * Private fund				-0.013	-0.020
				(0.033)	(0.033)
Post * Custody of cash or securities				0.012	0.011
				(0.021)	(0.021)
Post * Sales interest				-0.000	-0.001
				(0.026)	(0.026)
Post * Median household income					-0.000
					(0.000)
Post * Percent white					-0.108
					(0.088)
Post * Percent college graduates					0.232**
					(0.091)
Post * Percent age 65 and up					0.041
					(0.166)
Observations	44,652	44,652	44,652	44,652	44,652
R-squared	0.895	0.904	0.904	0.905	0.905
RIA FE	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2
RIA Characteristics - Do retail investors react more strongly to the advertising campaign?

The table displays regression results of difference-in-differences regressions estimating the differential impact of the advertising campaign on RIA asset flows based on different RIA characteristics. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i \times Characteristic_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. $Characteristic_i$ include *Retail investors*, which equals one if more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), *Hourly fees*, which equals one if the RIA charges an hourly fee, *Commission*, which equals one if the RIA charges a commission, *More college graduates*, which equals one if the RIA's clients are in the top quintile in terms of fraction of college graduates as of 2014, *More retirees*, which equals one if the RIA's clients are in the top quintile in terms of fraction of retirees as of 2014, and *Private fund*, which equals one if the RIA advises a private fund. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. Control variables that are interacted with $Post_t$ include size, fee structure, client demographics, and other characteristics, as described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)	(4) Log(AUM)	(5) Log(AUM)	(6) Log(AUM)
Post * Past misconduct	-0.064*	-0.053	-0.079**	-0.101***	-0.054*	-0.136***
	(0.036)	(0.041)	(0.033)	(0.034)	(0.031)	(0.040)
Post * Past misconduct * Retail investors	-0.148**					
	(0.072)					
Post * Past misconduct * Hourly fees		-0.123*				
		(0.063)				
Post * Past misconduct * Commission			-0.117*			
			(0.070)			
Post * Past misconduct * More college graduates				0.055		
				(0.079)		
Post * Past misconduct * More retirees					-0.196**	
					(0.095)	
Post * Past misconduct * Private fund						0.109*
						(0.066)
Post * Number of domestic offices	0.009	0.010	0.008	0.008	0.007	0.009
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Post * Log(Number of non-clerical employees)	0.324***	0.324***	0.323***	0.323***	0.322***	0.323***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Post * Log(Beginning AUM)	-0.282***	-0.282***	-0.281***	-0.281***	-0.281***	-0.281***

	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Post * Hourly fees	-0.066**	-0.057**	-0.066**	-0.066**	-0.065**	-0.066**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Post * Commission	-0.142***	-0.141***	-0.120***	-0.146***	-0.146***	-0.141***
	(0.032)	(0.032)	(0.031)	(0.033)	(0.033)	(0.032)
Post * Percentage of AUM	-0.047	-0.046	-0.046	-0.046	-0.043	-0.045
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Post * Fixed fees	0.075***	0.076***	0.075***	0.075***	0.075***	0.074***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Post * Retail investors	-0.124***	-0.138***	-0.139***	-0.139***	-0.139***	-0.137***
	(0.036)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Post * Financial planning service	0.010	0.009	0.009	0.010	0.009	0.009
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Post * Private fund	-0.051*	-0.050*	-0.052*	-0.052*	-0.050*	-0.061**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Post * Median household income	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post * Percent white	-0.104	-0.102	-0.101	-0.102	-0.100	-0.104
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)
Post * Percent college graduates	0.109	0.111	0.111	0.111	0.111	0.111
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Post * Percent age 65 and up	0.221	0.214	0.211	0.217	0.202	0.218
	(0.214)	(0.214)	(0.214)	(0.215)	(0.213)	(0.214)
Post * Custody of cash or securities	0.008	0.007	0.008	0.008	0.008	0.008
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Post * Sales interest	-0.002	-0.002	-0.001	-0.001	-0.001	-0.000
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Post * More college graduates	0.071**	0.071**	0.071**	0.066*	0.070*	0.070*
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Post * More retirees	-0.044	-0.043	-0.043	-0.044	-0.028	-0.044
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Observations	44,652	44,652	44,652	44,652	44,652	44,652
R-squared	0.905	0.905	0.905	0.905	0.905	0.905
RIA FE	Y	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.3
RIA Characteristics – Service provided

The table displays regression results of difference-in-differences regressions estimating the differential impact of the advertising campaign on RIA asset flows based on different RIA characteristics. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i \times Service_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA *i* with its main office in state *j* and fiscal year-end in month *k*, in year *t*. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. $Service_i$ include *Financial planning service*, which equals one if the RIA provides financial planning service, *Custody of assets*, which equals one if the RIA takes custody of clients' cash or securities, and *Sales interest*, which equals one if the RIA also acts as a broker-dealer and discloses sales interest in client transactions. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. Control variables that are interacted with $Post_t$ include size, fee structure, client demographics, and other characteristics, as described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)
Post * Past misconduct	-0.043	-0.144***	-0.136***
	(0.046)	(0.042)	(0.040)
Post * Past misconduct * Financial planning service	-0.126*		
	(0.066)		
Post * Past misconduct * Custody of cash or securities		0.136**	
		(0.063)	
Post * Past misconduct * Sales interest			0.105*
			(0.062)
Post * Number of domestic offices	0.009	0.008	0.009
	(0.019)	(0.019)	(0.019)
Post * Log(Number of non-clerical employees)	0.324***	0.323***	0.321***
	(0.052)	(0.052)	(0.052)
Post * Log(Beginning AUM)	-0.282***	-0.281***	-0.281***
	(0.048)	(0.048)	(0.048)
Post * Hourly fees	-0.066**	-0.066**	-0.066**
	(0.028)	(0.028)	(0.028)
Post * Commission	-0.140***	-0.142***	-0.148***
	(0.031)	(0.032)	(0.033)

Post * Percentage of AUM	-0.046	-0.044	-0.046
	(0.065)	(0.065)	(0.065)
Post * Fixed fees	0.076***	0.074***	0.075***
	(0.021)	(0.021)	(0.021)
Post * Retail investors	-0.137***	-0.138***	-0.137***
	(0.038)	(0.038)	(0.038)
Post * Financial planning service	0.018	0.010	0.010
	(0.028)	(0.028)	(0.028)
Post * Private fund	-0.049*	-0.052*	-0.048*
	(0.028)	(0.028)	(0.028)
Post * Median household income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Post * Percent white	-0.102	-0.103	-0.103
	(0.088)	(0.088)	(0.088)
Post * Percent college graduates	0.108	0.112	0.110
	(0.101)	(0.101)	(0.101)
Post * Percent age 65 and up	0.219	0.221	0.218
	(0.214)	(0.214)	(0.214)
Post * Custody of cash or securities	0.007	-0.004	0.008
	(0.021)	(0.022)	(0.021)
Post * Sales interest	-0.002	-0.000	-0.012
	(0.026)	(0.026)	(0.027)
Post * More college graduates	0.071**	0.070*	0.071**
	(0.036)	(0.036)	(0.036)
Post * More retirees	-0.044	-0.044	-0.044
Observations	44,652	44,652	44,652
R-squared	0.905	0.905	0.905
RIA FE	Y	Y	Y
State-year-filing month FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4
RIA Reactions

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $Record\ Removal_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Past\ Misconduct_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,m}) + \epsilon_{i,j,k,t}$, where $Record\ Removal_{i,j,k,t}$ is a dummy variable that equals one if RIA i, with its main office in state j and fiscal year-end in month k in year t, removes a misconduct record from its Form ADV filing due to job separation. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Past\ Misconduct_i$ is a dummy variable that equals one for the RIAs that had misconduct records (stock) prior to the advertising campaign but no new misconduct (flow) in two years. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. In Columns (2) to (5), I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. Size includes the natural logarithm of one plus the number of domestic offices, the natural logarithm of one plus the number of non-clerical employees, and the natural logarithm of the RIA's beginning assets under management (measured in 2014). Fee structure variables are the dummies indicating how the RIA is compensated, including hourly fees, commission, percentage of AUM, fixed fees, and performance-based fees. RIA-level client demographics include the average household median income, average fraction of white people, average fraction of college graduates, and average fraction of retirees of the populations in ZIP codes where the RIA has offices. Other characteristics include dummy variables indicating whether more than half of the RIA's AUM are from retail investors (individuals that are not high-net-worth), whether the RIA provides financial planning services, whether the RIA advises a private fund, whether the RIA takes custody of cash or securities, and whether the RIA discloses sales interest in client transactions. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Record Removal	(2) Record Removal	(3) Record Removal	(4) Record Removal	(5) Record Removal
Post * Past misconduct	0.019***	0.022***	0.023***	0.023***	0.024***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Post * Number of domestic offices		0.001	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Post * Log(Number of non-clerical employees)		-0.003**	-0.004**	-0.003**	-0.003**
		(0.002)	(0.002)	(0.002)	(0.002)
Post * Log(Beginning AUM)		-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Post * Hourly fees			0.002	-0.000	-0.000
			(0.002)	(0.002)	(0.002)
Post * Commission			-0.006	-0.006	-0.006
			(0.006)	(0.006)	(0.006)

	(1)	(2)	(3)	(4)	(5)
Post * Percentage of AUM			-0.003	-0.003	-0.004
			(0.003)	(0.003)	(0.003)
Post * Fixed fees			0.000	-0.001	-0.001
			(0.001)	(0.002)	(0.002)
Post * Performance-based fees			0.003*	0.005**	0.005**
			(0.002)	(0.002)	(0.002)
Post * Retail investors				-0.000	-0.000
				(0.003)	(0.003)
Post * Financial planning service				0.004**	0.004**
				(0.002)	(0.002)
Post * Private fund				-0.002	-0.002
				(0.003)	(0.003)
Post * Custody of cash or securities				0.003	0.003
				(0.002)	(0.002)
Post * Sales interest				-0.003	-0.003
				(0.002)	(0.002)
Post * Median household income					-0.000
					(0.000)
Post * Percent white					0.000
					(0.005)
Post * Percent college graduates					0.002
					(0.005)
Post * Percent age 65 and up					0.006
					(0.009)
Observations	44,652	44,652	44,652	44,652	44,652
R-squared	0.313	0.314	0.314	0.314	0.314
RIA FE	Y	Y	Y	Y	Y
State-year-filing month FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5

Spillover Effects – Do investors switch to RIAs with clean records?

This table presents difference-in-difference estimation results. I estimate regressions of the following form: $log(AUM)_{i,j,k,t} = \alpha_i + \gamma_{j,k,t} + \beta_T Post_t \times Exposure_i + \sum_{m=1}^{M}(\beta_{C,m} Post_t \times Control_{i,j,k,m}) + \epsilon_{i,j,k,t}$, where $log(AUM)_{i,j,k,t}$ is the natural logarithm of assets under management for RIA i with its main office in state j and fiscal year-end in month k, in year t. $Post_t$ is a dummy variable that equals one for the years following the advertising campaign in 2015. $Exposure_i$ measures the RIA's exposure to new investors who were shocked by their pervious advisers' past misconduct. In particular, *Exposure dummy* equals one if at least one of the RIA's offices was in the same ZIP code area as an RIA with misconduct, *Fraction of offices exposed* equals the fraction of the RIA's offices that were in the same ZIP code area as an RIA with misconduct, *Log(average number of misconduct RIA offices in ZIP)* is the natural logarithm of one plus the average number of misconduct RIA offices in the same ZIP code as each office of the clean RIA. I include RIA fixed effects, denoted by α_i, and a set of interacted fixed effects between RIA home state, RIA fiscal year-end, and year, denoted by $\gamma_{j,k,t}$. I interact a number of RIA characteristics and client demographics with $Post_t$, including size, fee structure, client demographics, and other characteristics. These control variables are described in Table 3. The standard errors are in parentheses. They are robust to heteroskedasticity, and I cluster them at the RIA level.

VARIABLES	(1) Log(AUM)	(2) Log(AUM)	(3) Log(AUM)
Post * Exposure dummy	0.049**		
	(0.025)		
Post * Fraction of offices exposed		0.057**	
		(0.025)	
Post * Log(average number of misconduct RIA offices in ZIP)			0.025**
			(0.011)
Post * Number of domestic offices	-0.009	0.002	-0.005
	(0.021)	(0.021)	(0.021)
Post * Log(Number of non-clerical employees)	0.365***	0.365***	0.364***
	(0.057)	(0.057)	(0.057)
Post * Log(Beginning AUM)	-0.316***	-0.316***	-0.317***
	(0.051)	(0.051)	(0.051)
Post * Hourly fees	-0.069**	-0.068**	-0.067**
	(0.029)	(0.029)	(0.029)
Post * Commission	-0.131***	-0.131***	-0.131***
	(0.033)	(0.032)	(0.032)

Post * Percentage of AUM	-0.075	-0.075	-0.074
	(0.071)	(0.071)	(0.070)
Post * Fixed fees	0.074***	0.074***	0.074***
	(0.022)	(0.022)	(0.022)
Post * Performance-based fees	-0.051	-0.051	-0.053
	(0.034)	(0.034)	(0.034)
Post * Retail investors	-0.142***	-0.141***	-0.141***
	(0.038)	(0.038)	(0.038)
Post * Financial planning service	0.001	0.002	0.003
	(0.030)	(0.030)	(0.030)
Post * Private fund	-0.013	-0.013	-0.015
	(0.036)	(0.036)	(0.036)
Post * Custody of cash or securities	0.002	0.001	0.000
	(0.022)	(0.022)	(0.022)
Post * Sales interest	-0.005	-0.005	-0.005
	(0.029)	(0.029)	(0.029)
Post * More college graduates	0.085**	0.083**	0.064*
	(0.034)	(0.034)	(0.036)
Post * Median household income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Post * Percent white	-0.054	-0.052	-0.049
	(0.092)	(0.092)	(0.092)
Post * Percent age 65 and up	0.056	0.057	0.013
	(0.178)	(0.178)	(0.176)
Observations	40,938	40,938	40,938
R-squared	0.895	0.895	0.895
RIA FE	Y	Y	Y
State-year-filing month FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1