Distrust Spillover on Banks: The Impact of Financial Advisory Misconduct*

Jaejin Lee†

Abstract

I study how the disclosure of misconduct practices by investment advisory firms affects the deposits of their affiliated banks using the unique data sets of company-level operational affiliation links and comprehensive records of enforcement actions against investment advisory firms. Using branch level data, on average, the exposed bank experience decreases in deposits after the revelation, despite full deposit insurance by government (FDIC) for average US households and no change in the price (rates) of deposit products. To establish causality, I use a difference-in-difference strategy that exploits exogenous variation in fraud revelation from mutual fund scandal in 2003. Furthermore, I find evidence that the results only hold for the banks sharing name with their affiliated investment advisory firms. Overall, my evidence implies the existence of spillover of distrust shocks on banking institutions and identifies an important source of operational risk in banking sector.

Keywords: Bank, Deposits, Risk, ESG, Investment Advisors, Misconduct, Financial Affiliation, Market Discipline.
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†Correspondce: Jaejin Lee, PhD student, Gies College of Business, University of Illinois at Urbana-Champaign; E-mail: **jaejinl2@illinois.edu**.

1. Introduction

Despite the growing interactions between investment advisors and commercial banks, relatively little is known about the potential channel through which the negative impact might transmitted to each other. Figure 1 exhibits that the size of such interconnections between banks and advisors has been significantly increased in financial advisory industry. Given that banks play a central role in economy and susceptible to any kind of (unknown) risks, for regulators and policy makers to access such risks, it is important to identify the channel through which banks might face exogenous risk occurred from different outside sectors.

{Insert Figure 1 about here.}

Prior studies show that mutual funds sponsored by financial institutions underperform than other funds due to conflict of interests (Ferreira et al. (2018), Zheng and Yan (2021), Hao and Yan (2012)) and such connection can bring benefit to mutual funds by acquiring private information from their banks (Massa and Rehman (2008)) or as a stable liquidity provider (Franzoni and Giannetti (2019)).

On the other hand, extant studies provide evidence that direct regulations on banks affect the risk policy of banks (Hirtle et al. (2020), Kandrac and Schlusche (2021), Delis et al. (2017)) and brings deposit withdrawal (Delis et al. (2019)). Other studies show that financial distress on banks might bring deposit withdrawals as market discipline (Iyer et al. (2013), Martinez Peria and Schmukler (2001), Goldberg and Hudgins (2002)) and regulatory actions on financial institutions can bring loss of potential clients (Gurun et al. (2018), Liang et al. (2020), Bertsch et al. (2020)). A broader literature on the corporate misconduct examines how *direct* regulation affect the fraudulent institutions. In this paper, I instead focus on *indirect* or *hidden* channel where exogenous risk spillover to banks. Specifically, I test whether banks affiliated with investment advisory companies experience deposit withdrawal following the revelation of fraud committed by their fraudulent affiliates.

Conceptually, bank deposits could have a positive or negative relation following the revelation of misconduct committed by their affiliated financial advisory company. As the bank deposits are the safe assets, household decision of their investment portfolio may depend on the demand of safe assets and distrust on such banks through two hypothesis — *distrust spillover* and *deposits as safe-haven* — via local community. Since investment decisions by households include social interaction and geographic proximity (Gurun et al. (2018), Giannetti and Wang (2016), Pool et al. (2015), Ivković and Weisbenner (2007), Hong et al. (2004)), I assume that households face greater exposure to frauds committed by advisors located in the county in which they live. If the distrust of depositors on bank or financial industry dominates the demand for safe asset (*distrust-spillover* hypothesis), then depositors may withdraw their deposits. On the other hand, as Gurun et al. (2018) shows, fraud committed by intermediaries who mainly play in a risky asset market may increase the demand of safe asset for depositors (*deposits as safe-haven* hypothesis). Gurun et al. (2018), for example, present the evidence of increasing local bank deposits and money outflow from investment advisers in communities who were exposed to the 'Madoff Ponzi scheme' occurred in late 2008. The *distrust spillover* hypothesis and *deposits as safe-haven* hypothesis are not mutually exclusive. If distrust on banks or whole financial industry offsets demand for safe asset, then depositors will neither change their deposit. Therefore, fraud committed by bank-affiliated financial advisory companies may have a positive, negative, or no effect on movement of bank deposits.

Thus, whether the residents of community, who are exposed to fraudulent advisers, change their deposits in affiliated bank deposits after the fraud is found is an empirical question. In this paper, I exploit variation of misconduct revelation both through comprehensive regulatory action on advisory firms and a quasi-natural experiment.

To empirically examine the causal effects of distrust against financial advisers on their affiliated banks, I exploit detailed mandatory disclosure filings made by investment advisory company (hereafter, RIA) (Dimmock et al. (2018), Dimmock and Gerken (2012), Liang et al. (2020)). These mandated filings identify comprehensive history of regulatory action on RIA as well as the detailed link of business affiliation ties to banks and the locations of office branches. Regulatory action creates a discrete jump in the reputation of RIAs. I combine these with branch-level deposit volume of each banks. Additionally, since the equilibrium of deposits is the natural outcome from the interaction between demand and supply of deposits, I collect bank branch-level of deposit rates. If deposit rate shows decreasing trend following the shock, deposit withdraw can be a natural responses to such price change of deposit products. Thus, identifying which source of channel induce the movement of deposits is important.

Identifying whether fraud revelation affect deposits of affiliated banks is complicated by possible confounding variation. A potential endogeneity concern is that local social norms may affect both fraudulent behavior of RIAs and local deposit market (Parsons et al. (2018)), making my regression results spurious. In addition, as the recession on local deposit market could induce fraudulent behavior of RIA, reverse causality concern still exists. Moreover, fraudulent RIA may mechanically withdraw their bank deposits for liquidity demand to pay penalties or clients redemption after experiencing fraud. To address these endogeneity concerns, First, I conduct event study analysis to examine the dynamic impacts. Second, I exploit exogenous variation of misconduct revelation of Mutual Fund Scandal in late 2003 and extract information on the geographic dispersion of branches of RIAs involved in the scandal. Then, I construct a measure for a communities exposure to scandalous RIAs and perform a difference-in-differences (DiD) analysis around the scandal to study the changes in deposits of branch under affiliated banks. Moreover, I exploit multiple unique fixed effects including bank branch, county-year, and bank-year fixed effects. The bank branch fixed effects remove the overall level of deposit volumes, the type of branch, as well as the product offerings. The county-year fixed effects control for any time-series change of county characteristics such as demographics (Becker (2007)), county-level economy, state-level regulation, and local culture (Parsons et al. (2018)). In the same spirit, bank-year fixed effects remove the effects of characteristics specific to bank institutions such as any bank-specific shock, asset specialization of banks, and bank culture (even if these effects are time-varying).

I find that, in the years following regulatory actions on RIA, the negative relationship between the deposit volume of bank branches and the revelation of misconduct committed by affiliated RIA, which supports the *distrust spillover* hypothesis. The event study design shows the dynamics of the effect of distrust on deposit movement. The results are, however, hard to square with Gurun et al. (2018) which show a positive relation between the Madoff Ponzi scheme revelation and local deposit volume. To understand this puzzling result with the paper, I continue by exploiting heterogenous effect of fraud on deposits at the aggregated county level.

Next, I examine cross-sectional variation in the fraud committed by different types of RIAs. I decompose the fraud into (i) *Bank-affil Fraud*, which is committed by RIA affiliated with banking institutions, and (ii) *Non Bank-affil Fruad*, which is committed by any RIAs except ones affiliated with banks. Gurun et al. (2018) document deposit inflow into local bank deposit market following the 'Madoff Ponzi scheme' — residents exposed to the scheme redeem money from RIA and increase deposit in banks as their trust on whole financial advisory industry has been collapsed after the Ponzi detection. Consistent with this intuition, I find that local community do increase their deposits in banks following the regulatory action on RIA and *Bank-affil Fraud* significantly dissipate such treatment effect. The name of RIA involved in 'Madoff Ponzi scheme' is "*Bernard L. Madoff Investment Securities LLC*" and it reports no affiliation link with banking sector. Since the Madoff fraud was the world largest Ponzi scheme, this fraud revelation might induce strong demand for safe asset and increase the local deposit supply.

An alternative channel is that regulatory penalty or financial distress might bring deposit withdrawal as depositors concern on potential risks in affiliated banking institutions. To address this concern, I conduct additional analysis exploiting heterogeneity in affiliation relationship between banks and RIAs. I show that only frauds from bank-affiliated RIAs who share common name with affiliated bank institutions show a significantly negative relationship with deposit volume, whereas fraud from other type of RIA show no significant direction of deposit movement. Additionally, the correlation with the amount of penalty fined to RIA and indicator whether the affiliation shares common brand name is only 0.07 and it suggests that liquidity concern is not the main motivation for such deposit movement. Taken together, these imply that the residents of communities reacts to the implied affiliation link via brand name, which is easy to infer the link, rather than considering the potential financial distress on banks.

Additional concern is that fraud revelation may not occur randomly. The timing of fraud investigation might correlates with the situation in financial market. I alleviate concerns with a quasi-natural experiment. The mutual fund scandal (MFS) was occurred by the sudden detection of ongoing fraud that was wide-spread in the financial advisory industry. In September 3, 2003, NY Attorney General revealed ongoing abusive trades that allowed selected clients to profit at the expense of the rest of clients. Soon after that revelation, several regulatory agencies, including SEC, launched investigation into the whole advisory industry. The sudden fraud detection generates plausibly exogenous variation of fraud revelation independent to local deposit market or situation in RIA market and identifies the exact fraud revelation date to local communities. Using this quasi-natural experiment, I continue to find a significant negative relation between fraud revelation by RIA and the deposit level of branches under affiliated banks in the exposed community.

I further alleviate concerns related to the detailed channel of deposit movement by focusing on the rates of savings deposit. Interaction between the supply of deposits by depositors and the demand by banks determine the equilibrium of the level of deposits. The decreasing movement of deposit might be in response to supply change by banks rather than the change of demand. To address this concerns, I find evidence that treated bank branches does not significantly change the savings deposit rates after the trust shock, which implies that the movement of deposits, which is the result of equilibrium between supply and demand of deposit, is not induced from the changes of deposit demand side.

My paper is related to several strands of finance and economics literature. The first is the impact of distrust in financial industry or investment advisory companies on the behavior of investors. Empirical studies find evidence that the economic importance of trust on financial industry (Guiso et al. (2008); Kostovetsky (2016); Gennaioli et al. (2015)). Gurun et al. (2018) find that money outflows from investment advisors and inflows to bank deposits where the victims of Madoff Ponzi scheme were located. Also using corporate scandal data, Giannetti and Wang (2016) show that households decrease their stock market participation after the fraud revelation from the firms located in the same state with the households. Similarly, Georgarakos and Inderst (2014) shows the relationship between financial advice and risky asset allocation. However, this line of research examines only the direct impact of distrust on fraudulent entity, but not spillover impact on other industry or sector. My paper complements this literature by showing that those direct cost maybe just a fraction of the negative impact on financial industry. To the best of my knowledge, this is the first study that examines the spillover effects of distrust from bank-affiliated financial advisory companies to banking industry using an exogenous shock to establish a *causal* link between local deposits market and fraud from RIA industry.

Second, my study also fits in the literature on the market discipline in banking industry. A number of studies find evidence of market discipline in banking based on fundamental risk of banks (e.g., Martinez Peria and Schmukler (2001); Maechler and McDill (2006); Saunders and Wilson (1996); Schumacher (2000); Schnabel (2009)). In the same spirit, recent literature show market discipline based on other types of financial information. Iyer and Puri (2012) show local social network mitigates bank run and depositors with high uninsured deposits are more likely to run from banks. Hasan et al. (2013) examine market discipline based on bad rumors of banks. However, only a handful of paper address market discipline based on non-financial information of banks. Homanen (2022) shows the deposit withdraw through the civil protests against banks who financed a high controversial pipeline project. Unlike the focus of his paper, I focus on distrust transmission to affiliated banks as an indirect costs of fraud revelation. While Homanen (2022) only uses limited geographical location as a variation to depositors' exposure to the protest and a single event, I exploit wide dispersed location of the exposure to trust shock, which mitigates the concern for potential omitted variables related with geographical characteristics and exploit universe regulatory actions against RIAs.

Third, my paper is also related to a growing body of literature on financial misconduct in the investment advisory industry (Egan et al. (2019); Dimmock and Gerken (2012); Dimmock et al. (2018); Patel (2019); Clifford and Gerken (2017)). These studies generally suggest overall picture of fraud in financial advisory industry and major determinants of advisors being fraudulent. For example, Dimmock and Gerken (2012) examine several factors attributable to fraud of RIAs and test the predictability of fraud using the public information in SEC filings. Egan et al. (2019) show that fraudulent advisors repeat misconduct behavior and fraudulent advisory firms tend to hire fraudulent advisors. My paper contributes to this literature by showing the existence of external cost of fraud from financial advisors, impacting not only the advisory firms themselves but also on other affiliated-sector. Most importantly, my study illustrates that the traditional practice of considering the financial misconducts as *independent* trust shock in the financial industry may not adequately capture real economic costs of fraudulent behavior in current financial system. Given the substantial growth of interaction between advisory industry and banking sectors, future studies on trust shock in financial market should take into account these *indirect* spillover impact on affiliated sections.

2. Hypothesis Development

My main hypothesis is that distrust on bank-affiliated RIA spillovers to their affiliated banks and the residents of communities who are exposed to the distrust decreases deposits from affiliated bank relative to other banks, which is *distrust-spillover* hypothesis. When RIA affiliated with bank industry commit fraud, affiliation may play a bridge role for investors negative perception of the banking sector. Although *distrust-spillover* may happen when non-bank-affiliated RIA commit fraud, they stand out more sharply when banks are affiliated with the fraudulent RIA. For instance, 18% of retail mutual fund holders purchased mutual funds through bank or savings institution representative in 2021 (ICI Fact Book (2021)). Bankers may refer their affiliated RIA to their depositors, which would make depositors perceive the bank and the advisory firms as a same entity. Moreover, similar to Gurun et al. (2018), investors direct damage by fraud from financial advisors may damage their trust on financial industry and make them to alter their portfolios, especially assets trusted on financial institutions.

Since local communities affects investors behavior through social connections or words-of-mouth channel (Ivković and Weisbenner (2007); Pool et al. (2015); Pool et al. (2015); Hong et al. (2004)), I assume that local communities are more exposed to fraud conducted by RIAs or their branches located in the county of residence. Moreover, there might exist more news coverage by local media in areas with more RIAs involved in fraud scandal. Therefore, communities in these areas may therefore have been more aware of the fraud and experience severe burst of their trust on the fraudulent RIAs and its related third parties.

An alternative hypothesis, *deposits as safe-haven*, is that fraud in a risky asset market may increase the demand of safe asset for depositors. For example, fraud victims may shift their portfolio to safe assets, including bank deposits, after experiencing fraud and it can affect the investment behavior of their neighbors or local communities, through word-of-mouth or local media. Gurun et al. (2018) documents the money outflow from RIA industry and inflow to bank deposits in local communities, that were exposed to a notorious Ponzi scheme ('Madoff Ponzi scheme'), following the detection of the fraud.

It is worth pointing out that I do not claim that distrust transmission from bank-affiliated financial advisor firms is the only reason for such deposit movement in banking sector. Deposit rates may impact deposit supply and specific bank shock may change deposit demand. I thus emphasize that, affiliation, while by no means the only reason for deposit movement, may play an important channel for market discipline.

The null hypothesis of my paper is that the fraud committed by RIAs do not influence the affiliated banks. Local communities have limited effectiveness in sharing the distrust on local depositors or because depositors do perceive banks and affiliated financial advisory firms as perfectly separated entity.

3. Data and Sample Construction

Three types of data sources are used for the analysis: mandatory disclosure filings from RIA, deposit amount in bank branch level, rate of retail deposit products in bank branch level and the list of RIAs involved in *Mutual Fund Scandal* occurred in late 2003. In this section I describe these sources and outline my sample construction.

3.1 Mandatory filings from RIA

Information regarding RIAs comes from Form ADV, which is the mandatory annual report submitted from RIAs to SEC. Form ADV includes general information about the business, ownership, clients, and affiliations. I hand-collect historical Form ADV filings made by every SEC-registered RIAs for SEC. The information about branch office location is collected from *Schedule D* in Form ADV. One of main purpose of Form ADV is to provide information about conflict of interest to protect investors. In that sense, any RIA must disclose relevant information about their financial industry affiliation at *Schedule D* of Form ADV. It requires to report if the RIA has a *related person* conducting business in a specific financial industry and the definition of *related person* in Form ADV is any employee (except employees related to clerical or administrative functions), director, partner or firms under the same financial group. I further match with Summary of Deposits from FDIC by the name and address of banking institutions. As the *Schedule D* of Form ADV is available from 2012, my sample comprise RIAs during the period 2012-2021.

The historical disciplinary action against RIAs is collected from *Regulatory Action Disclosure Reporting Page* in Form ADV. This part includes the name of regulatory agency, initiation date of sanctions, amount of penalty and brief summary of alleged misconduct. It covers universal regulatory actions against RIAs and includes any malfeasant behaviors detected. Forms of fraud by RIA include but are not limited to fee overcharging, intentional misinformation and sub-optimal investment advice. The main explanatory variable *Fraud* for banks is a dummy variable that equals to one following the allegation against the banks' affiliated RIA filed.

3.2 Branch-level deposit volume data

To measure depositor movement, I collect data from the FDIC Summary of Deposits database. It measures aggregated branch office deposits and other branch characteristics for all offices of FDIC-insured banks and thrift institutions as of June 30th of each year through annual survey.

To shed light on the mechanisms under the movement of deposits, I use two levels of deposits for the analysis to measure the impact on the level of deposit at banks affiliated with fraudulent RIAs whose illegal behavior is revealed in the market. First, I use individual branch deposits for the main analysis and exploit the geographic dispersion of branches of banks and its affiliated RIAs. This provides opportunity to focus on hyperlocal effects among same regional communities and make able to sort out any confounding effect attributable to any local factors even in time-varying impacts (Parsons et al. (2018)).

To gauge the macro effects of the impact, I aggregate deposits across all branches in a given county-year to conduct the analysis on local deposit market. Similar to Gurun et al. (2018), I test whether the RIA fraud affect local deposit market and exploits heterogeneous characteristics within such fraud. My final sample contains 27,978 county-year observations.

3.3 Branch-level deposit rate data

To shed light on whether the deposit movement is from demand side or supply side, I use granular branch level deposit rate quotes provided by RateWatch. Ratewatch collects weekly branch-level deposit rates on different type of products through weekly surveys. The data cover 54% of all U.S. branches as of 2013 (Drechsler et al. (2017)). As this paper examine the movement of deposit level, I focus on general retail deposit products of 6-month, 12-month maturity of $10K certificate of deposit (CD) and money market (MM) of $10k and $25k since it is the most widely used retail deposit rates in literature (Drechsler et al. (2017), Ben-David et al. (2017), Cortés and Strahan (2017), Jacewitz and Pogach (2018)). Because my deposit sample is annual level, I aggregate the weekly deposit rate for each branch.

3.4 Additional data sources

I collect county-level demographic information from U.S. Census to construct control variables, including median age, household median income, and population.

3.5 Summary Statistics

{Insert Table 1 about here.}

Summary statistics for the analysis can be found in Table 1. Panel A summarize the characteristics of sample bank branch-years. The average branch-level deposits of my sample is $132,915 thousands and shows considerable variation in the variable, as indicated by a standard deviation of $2,425 millions. Most of branch service type is in the form of brick & Mortar office. About 6% of sample observation experience of fraud-revelation by their co-located affiliated RIAs. Moreover, 92% of bank branches who exprienced affiliates' fraud revelation share the common brand name.

The next panel B, summarize the characteristics of county-year sample. Average county population is 103,687. The average median income is $50,372 for a single household in a county and average median age is 41.28 years. About 16% of county-year sample experience fraud revelation committed by RIA operates in the same county and about 20% of county-year fraud revelation is committed by bank-affiliated RIA.

4. Identification Strategy

4.1 Event study design

Identifying whether the revelation of fraud committed by bank-affiliated RIA to affiliated banks who located at the same county with the RIA is complicated as various unobservable factors might affect both deposit volumes and misconduct. To remove such potentially confounding variation, I use granular multiple fixed effects.

I estimate following Poisson regression design:

$$y_{i,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \sum_{\tau=-4}^{4} \phi_\tau D_{i,t}^{\tau} + \boldsymbol{X'_{i,t}}\gamma + \varepsilon_{i,t}\,, \tag{1}$$

where $D_{i,t}^{\tau}$ is a relative event-time dummy that equals to 1 if bank branch i received the affiliated-RIA fraud revelation shock exactly τ years ago if $\tau > 0$ or τ years after if $\tau < 0$. Following the recent event study analysis (e.g., McCrary (2007); Atkin et al. (2018); Borusyak and Jaravel (2017)); Higgins (2019)), I do not drop observations that are further than 4 years prior or 4 years after the shock, but rather binning the endpoints by setting $D_{i,t}^{-4} = 1$ if $\tau \leq -4$ and $D_{i,t}^{4} = 1$ if $\tau \geq -4$. The specification also includes bank branch, county $\times$ year, and bank institution $\times$ year fixed effects.

Recent econometric literature has raised concerns about the using constant-adding log-linear estimation when working with count-based outcome variables and shows that fixed-effects Poisson model produces unbiased estimates (Cohn et al. (2021)). As some bank branches show zero volume of deposits sometimes and the deposits is positive integer, I conduct specification through Poisson regression in this paper for main specification related to deposit movement analysis.

The description of variation used in the main methodology is summarized in Figure 3. First, the bank branch fixed effects, λ_i, remove all time-invariant characteristics of the bank branches, including the overall level of deposit volume, and reduces the effect of bank branch characteristics that are largely fixed over the sample period, such as regional factors. There fixed effects also remove the time-invariant part of the branch's business activities, such as products sold and customer characteristics. Including λ_i effectively means that our key independent variable is the within-bank-branch change in deposit amount and not its level.

Second, the county $\times$ year fixed effects, $\delta_{c,t}$, remove variation across bank branches located in the same county at a given year. Removing geographic heterogeneity is important as Parsons et al. (2018) show the significance of unexplained factors attributable to local culture. The local economic situation may affect bank branch deposits. By including these fixed effects, I remove the average effect that local economic factors on deposits. In general, misconduct on the region is correlated with local economy, but this changes in its time-series average is removed by the inclusion of these fixed effects. These fixed effects also remove time-varying demographic characteristics of the county.

Third, the bank institution $\times$ year fixed effects, $\eta_{b,t}$, remove the time-invariant characteristics of the bank institution that controls the branches, as well as time-varying bank branch characteristics such as changes in the bank institution's deposit strategies. As a strand of papers has shown the banks competition for deposits (Matutes and Vives (1996), Egan et al. (2017)), it is important to purge strategically policy for each banks under the competitive deposits market. Moreover, Removing bank institution effects is important as deposit is one of main source for monetary channel in credit decision in banking industry. Moreover, including $\eta_{b,t}$ effectively remove time-varying variation from monetary shock in credit market specific to individual bank institutions (Kashyap et al. (2002),Gatev et al. (2009), Berlin and Mester (1999)).

To further investigate the consistent impacts of investment advisory fraud to the volume of bank branch deposit, I employ a following modified event study design:

$$y_{i,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \beta Post_{i,t} + \boldsymbol{X}'_{i,t}\gamma + \varepsilon_{i,t}\,, \tag{2}$$

where $Post_{i,t}$ is equals to 1 if fraud committed by RIA, who has affiliation with the bank institution of branch i, has been revealed to public before or at year t. The coefficient β represent the average impact of co-located affiliates' fraud on bank deposits.

The baseline empirical model include multiple sets of fixed effects. County fixed effects (η_c) controls for time invariant characteristics of the bank deposit market in the county and state-year interactive fixed effect ($\zeta_{s,t}$) controls for common shocks and time varying factors at the state level. It is important to note that the year fixed effects also capture country-wide fraud occurrence implying that I estimate only the differential effect that exposure to fraud in a county has on depositors in that county. I cluster standard errors at the county level because the movement of county-level deposits is likely to be correlated over time.

4.2 Difference-in-Difference

As discussed earlier, an endogeneity concern is that of omitted variables correlated with both county bank deposit market and fraud occurrences from bank-affiliated RIAs in the county. For example, local social norms can affect both local deposit market and fraudulent behavior of the firms in the local region. Another concern is that fraud company may withdraw their bank deposits in the county where they are located for liquidity purposes to pay penalties, or redemption that clients might request after experiencing fraud from the advisory company. In this section, I address potential endogeneity problems by using an unique identification strategy and attempt to strengthen the causal link between county deposit volume and fraud committed by bank-affiliated RIAs. The identification strategy is a Difference-in-Difference approach based on the quasi-natural experiment exploiting 2003 mutual fund scandal as a shock that provides plausibly exogenous variation in fraud revelation to public.

4.2.1 Institutional background

In a September 3, 2003, New York Attorney General Eliot Spitzer issued a complaint against some RIAs that revealed specific types of abusive trading, allowing selected clients to profit at the expense of the other majority of clients. Following the scandal revelation, substantial regulatory agencies launched investigation into the whole investment advisory industry.

Most importantly, it was a sudden detection of the ongoing fraud that was wide-spread in the industry. Those specific fraudulent trading behavior had been existed at least as early as 1995 (McCabe (2009)). Even though several literature documented the evidence of such fraudulent trading (Bhargava et al. (1998); Goetzmann et al. (2001); Greene and Hodges (2002)), the fraudulent trading behavior of mutual fund management companies was well-concealed before September 2003. Therefore, 2003 mutual fund scandal provides an exogenous variation in RIAs' fraud revelation irrelevant to local deposits market or the fraudulent firms' condition. I can identify the exact date of public recognition of the fraud. This alleviates the concern about fraud timing issue in my baseline analysis where I used actual year when fraud happened. Moreover, since the RIAs involved in the scandal were major players in the investment advisory industry, I can identify individual banks who are in the same financial group with the fraudulent RIAs and test how much the banks affiliated with RIAs involved in the scandal affected relative to other banks. Table 2 provides the list of mutual fund families involved in the scandal, initial news data of the fraud, abusive trading strategies they did, regulatory agencies who investigated, and the parent company of main advisor for each mutual fund families. If the parent company is bank-holding-company, then I put red boxes on the name of that company in Table 2 and used at the analysis looking at individual banks.

{Insert Table 2 about here.}

4.2.2 Identifying MFS-experienced counties

To identify causal impact of MFS scandal from MFS-involved advisory firms to affiliated bank branches located at the same county, I construct my sample using mutual fund scandal occurred in late 2003.

{Insert Figure 6 about here.}

I identify '*Have Affiliated-Banks*' counties as those that have offices of any bank-affiliated RIAs that involved in MFS and '*No Affiliated-Banks*' counties as those that have any RIAs involved in MFS but not any bank-affiliated RIAs involved in MFS. Importantly, I conduct additional analysis on those counties. The main reason for the exclusivity is to match unobservable factors as many as possible between treatment and control counties. Previous literature on financial misconduct suggests that geographical social-norm is one of the main determinant of the financial fraud and those environmental factor cannot be explained by regulatory monitoring or firm characteristics (Parsons et al. (2018)). Therefore, counties who does not have fraudulent firm involved in the scandal may have fundamentally different characteristics relative to counties who have fraudulent RIAs.

My final DiD sample consists of 15 counties in control group and 50 counties in treatment group between 2001 and 2008. Figure 6 shows the dispersion of counties in my sample. As can be seen, location of these counties are well dispersed in the United States.

4.2.3 Difference-in-difference design

I employ a DiD approach to compare the change in county deposit volume for treatment counties with that for control counties. Specifically, I run the following regression:

$$y_{c,t} = \lambda_c + \eta_{s,t} + \beta Post \times Treat_{c,t} + \boldsymbol{X'_{c,t}}\gamma + \varepsilon_{i,t}\,, \tag{3}$$

where i indexes bank branch, b indexes bank institution, c indexes county, and t indexes year. *Post* is a dummy that equals to one since the any RIA, located at county same as bank branch i, involved in MFS is revealed in newspaper. *Treat* is a dummy that equals to one if the RIA, affiliated with bank of i and located at the same county as i, involved in MFS ever revealed in newspaper. Figure 6 shows the geographic location of the counties exposed to MFS. $\boldsymbol{X_{i,t}}$ is a vector of the control variables used in Eq. (1).

Similar to Eq. (1), I include county fixed effects (λ_c) to control time invariant characteristics of the bank deposit market in the county and state-year fixed effect ($\eta_{s,t}$) controls common shocks and time varying factors at the state level.

5. Main Results

5.1 Event Study Analysis

5.1.1 Branch-level permanent shock

I first examine the permanent impact of distrust on their affiliated bank branches by estimating Eq. (2) on deposits. Table 3 shows that an incident of RIA fraud affect affiliated bank, who located in the same county with the RIA, is negatively associated with the volumne of bank branch deposits over the long period. The coefficient estimates of $Post_{i,t}$ in most of specifications are negative and significant at the 1% level, suggesting that fraud occurrence is associated with a lower deposit volume.

Column (1)-(2) of Table 3 includes every counties in the sample. The coefficient on *Post* is significant and negative, indicating that deposits decrease by approximately

9% ,following the revelation of fraud committed by affiliated RIA, relative to other bank branches within the same county and other branches in other counties under the same banking institution as treated branches.

One concern with using full sample including counties that never experienced RIA fraud ever is that the treated groups might have totally different characteristics from not treated groups in the sample period (Parsons et al. (2018)) and it may confound with treatment impact. To address this concern, I keep only the counties that ever exposed to any RIA fraud. Column (3)-(4) report the estimates of Eq. (5) on such subsample (*Only Fraudulent sample*). Similar to column (1)-(2), coefficients indicate that the volume of deposits decreases by approximately 10% following fraud occurrence. This result supports the *distrust spillover* hypothesis which implies that distrust spillover holds.

Yet despite these sub-sample analysis, it is still concern that the treated groups might have a decreasing trend of deposits level even before the treatment shock. Moreover, fraud detection might be confounded with deposit market or economic trend. To alleviate such concerns, I conduct event-study analysis in Section 5.1.2 to identify the dynamics of treatment impact around the treatment shock and explore a quasi-natural experience in Section 5.2.1 to exploit exogenous variation in treatment variable.

{Insert Table 3 about here.}

5.1.2 Branch-level dynamics of deposits

To study the treatment dynamics of deposit movements, I estimate Eq. (1) on branch level deposits. The omitted period is the previous quarter prior to the revelation of misconduct committed by RIAs. Estimates are displayed in Figure 4.

{Insert Figure 4 about here.}

Prior to fraud revelation, I find little evidence of differential trend between branches. For $\tau < 0$, all treatment coefficients never reach significance, even at the 10% level and also in sub-sample consisted of only treated counties. This alleviate a concern that deposits has decreasing trend regardless of treatment and show systemic change after the treatment.

Following fraud revelation, deposits of bank branches decrease significantly among banks who are affiliated and located at the same county with the fraudulent RIA. Deposit declines by about 5% in the year of the event and by about 3% in the following two years (even though the two years after event shows insignificant, it is quite close to 10% significance level). Effects then gradually dissipate, reaching insignificance four years after revelation.

However, this result is quite hard to square with Gurun et al. (2018), which is looking at a single investment advisory firm fraud (Madoff Ponzi scheme) and show positive relation between fraud occurrence and county deposit volume. Thus, I further conduct county level analysis to investigate the impact of fraud committed by not bank-affiliated RIAs to the volume of county-aggregated deposits at Section 5.1.5

5.1.3 Regional bank vs. National bank

In this subsection, I examine whether the misconduct by affiliated RIA have different impact on different types of banks. I employ a modified version of Eq. (2) by interacting treatment indicator whether the bank institutions of the branch operates regionally or nationally in terms of every branch locations of each banks. Specifically, I estimate:

$$y_{i,t} = \alpha_i + \lambda_{c,t} + \beta Post_{i,t} + \gamma Post \times Regional\ Bank_{i,t} + \delta Regional\ Bank_{i,t} + \boldsymbol{X}'_{i,t}\eta + \varepsilon_{i,t}\,, \quad (4)$$

where $Regional\ Bank_{i,t}$ is the dummy variables equal to one if the bank institution of branch i operates every branches only in single regional areas. To be more specific, *State-regional Bank* (*County-regional Bank*) is an indicator variable equal to one if the bank of the branch i have branches in the single state (county). As with a standard DiD model, moreover, the coefficients on $Post \times Regional\ Bank_{i,t}$ represent the average difference in deposits between branches of banks operating in single region and branches of banks operates in multiple regions (national-wide).

{Insert Table 4 about here.}

The positive coefficient of interaction term in Table 4 shows that regional banks experience less impact than national banks. This difference is economically significant but statistically insignificant given that there is a little observations of regional banks who are affiliated with RIAs in the sample. This result is consistent with *distrust-spillover* hypothesis since regional banks usually have strong relationship with the local communities (Petach et al. (2021), Nguyen and Barth (2020), FDIC (2012)). This results might happen because of relatively small size of misbehavior on community banks. However, this concern can be alleviated since the correlation between the amount of penalty fined to RIA and its affiliated *State-regional Bank* (*County-regional Bank*) variable shows about -0.015 (-0.001). Therefore, this implies the human capital (trust) between community bank and local community might role as buffer for this negative news.

5.1.4 Brand-name commonality

To identify the mechanism behind this movement, I explore differential responses by the commonality of name between RIA and affiliated banks. I employ a modified version of Eq. (2) by interacting treatment indicator whether the branch use the common name with the fraudulent RIA's when fraud committed by the RIA is revealed to the public. Specifically, I estimate:

$$y_{i,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \beta Post_{i,t} + \gamma Post \times Common\,Brand_{i,t} + \boldsymbol{X}'_{i,t}\boldsymbol{\eta} + \varepsilon_{i,t}\,, \tag{5}$$

where *Common Brand* is the dummy variables equal to one if bank name of branch i share the common name with the afffilaited fraudulent RIA. As with a standard DiD model, moreover, the coefficients on $Post \times Common\,Brand_{i,t}$ represent the average difference in deposits between branches sharing common brand name with fraudulent affiliated-RIAs and other branches.

{Insert Table 5 about here.}

Table 5 shows that only the branches that share common name with fraudulent RIA experience decreasing volume of deposits significantly by about 5%. In other words, there is no significant change in the specific direction of volume of deposits for the rest of branches. This result highlights the mechanism of this deposit movement. Given that the correlation between the amount of penalty fined to RIA and *Common Brand* variable is about 0.073 for both of model (1) and model (2) in Table 5, this result alleviates concern whether the fraudulent RIAs are just withdrawing cash from affiliated local banks to pay the huge penalty since the result shows significant deposit withdraw only in branches who share names with fraudulent RIAs, which is orthogonal to the amount of penalty. Moreover, this strengthen the *distrsut spillover* hypothesis because most of investors would easily capture the affiliation information by the names of each institutions.

5.1.5 County-level dynamics of deposit

To further investigate the impacts of investment advisory fraud to county level deposit market, I employ a modified event study design to compare the impacts of bank-affiliated RIA fraud to those of other not bank-affiliated RIAs. Specifically, I estimate:

$$y_{c,t} = \lambda_c + \delta_{s,t} + \sum_{\tau=-4}^{4} \beta_\tau Fraud_{c,t}^{\tau} + \sum_{\tau=-4}^{4} \gamma_\tau Fraud(Affil)_{c,t}^{\tau} + \boldsymbol{X_{c,t}}\eta + \varepsilon_{c,t}\,, \tag{6}$$

where $Fruad_{c,t}^{\tau}$ is the dummy variables equal to one if fraud committed by any RIA located at county c is revealed to public in year t-τ and $Fruad(Affil)_{c,t}^{\tau})$ is the dummy variables equals to one if fraud committed by any bank-affiliated RIA, located at the same county c as their affiliated bank branches, is revelaed to public in year t-τ. As with a standard DiD model, moreover, the coefficients on $Fruad(Affil)_{c,t}^{\tau}$ represent the average difference in deposits between counties exposed in RIA fraud and counties exposed in fraud committed by bank-affiliated RIAs.

Following existing literature (see, e.g. Gurun et al. (2018)), I include lagged values for population, median household income, and median age at the county level to take into account potential time varying factors that may related to banking activity.

To study the impacts on county level deposit market, I estimate Eq. (6) on county level deposits. The omitted period is $\tau = -1$. Estimates are displayed in Figure 5.

{Insert Figure 5 about here.}

Figure 5 displays estimated treatment effects and differential effects from estimation of Eq. (6). Prior to fraud revelation, I find little evidence of differential trend between counties. For $\tau < 0$, all treatment coefficients never reach significance and almost close to zero.

Following fraud revelation, the volume of deposits in county-year level increases significantly among counties where fraud committed by RIA in the county is revealed. On the other hand, the negative coefficients on $Fruad(Affil)_{c,t}$ indicates that the impact of fraud committed by bank-affiliated RIAs have additional negative impact to the impact of general case.

Moreover, the above results are in line with the literature (Gurun et al. (2018)), which shows increasing local deposit volume in the place where the victims of Madoff Ponzi scheme located. Since *Bernard L. Madoff Investment Securities LLC* is SEC-registered as non-bank-affiliated RIA, the Madoff Ponzi case can have positive impact on local deposit market based on the results from Figure 5. Moreover, as the Madoff Ponzi scheme is the world largest Ponzi scheme, it is also hard to say that the fraud is the general case. By using the universe of the U.S. investment advisory firm registered in SEC, the baseline results imply that the *distrust spillover* hypothesis is dominant in general relationship between the movement of bank deposit market and the fraud from RIA.

5.1.6 Branch deposit rates

As in most studies of bank deposits and market discipline (Park and Peristiani (1998), Cook and Spellman (1994), and Martinez Peria and Schmukler (2001)), the equilibrium quantity of deposits is determined by the interaction between the demand (banking institutions) and supply (depositors) of deposits. This raises the possibility of alternative mechanism that drives the decreasing level of deposits in my sample. In this section, I perform an additional analysis on the price (rate) of retail deposit products sold by each individual branches. The results on the impact on deposit rates addresses the concern that the change in depositors behavior is mechanical responses to the change of deposit rate. I estimate Eq. (2) on the rate of deposit products and the estimates are displayed in Table 6.

Table 6 finds insignificant coefficients in terms of both statistically and economically on every columns given that the average deposit rates are between 0.17% APY to 0.47% APY. In other words, the decreasing trends of deposit levels is not the outcome of increasing rates of deposit products and, thus, nullify the alternative channel that explains the main results.

{Insert Table 6 about here.}

5.2 Difference-in-Difference Analysis

5.2.1 Deposit volume analysis

Table 7 shows that coefficient for *Treat* × *Post* is negative and significant, suggesting that treated branches, that is, co-located with their affiliated RIAs involved in the scandal, exhibit a greater decrease in deposit volume relative to other banks within the same county and other same-bank branches in other counties, which is consistent with event study results.

Column (2) of Table 7 shows that the volume of deposits decreases by approximately 20% following MFS revelation relative to other non-treated branches within same county and other same-bank branches in other counties. Given that the scandal brought national-wide attention through major media (e.g., Wall Street Journal posted Fund Scandal Scorecard section in website for a long period), the economically strong magnitude of treatment effect is reasonable enough to consider such attention.

To address the concern that fraud-exposed counties might have fundamental unobservable difference than other counties (Parsons et al. (2018)) and it might cause confounding variation in my analysis. Therefore, column (4) of Table 7 is similar to baseline specification but only include local regions that ever experienced MFS in my sample. By comparing those regions, it may alleviate such concerns of heterogeneity in terms of fraudulent local culture. Column (4) shows that the treatment effect is about 26%, which is more severe than the results from whole sample.

{Insert Table 7 about here.}

To study the treatment dynamics of deposit movements, I estimate Eq. (1) on branch level deposits on DiD sample with only MFS experienced counties. The omitted period is the one quarter before the event quarter. Estimates are displayed in Figure 7.

Prior to fraud revelation, I find little evidence of differential trend between branches. For $\tau < 0$, all treatment coefficients never reach significance, even at the 10% level. Similar results to Section 5.1.2 strengthen the evidence to purge the existence of pre-trend before the fraud revelation and eliminate an alternative channel where bank risk may affect the fraud revelation because the variation of fraud detection was plausibly exogenous according to institutional background in Section 4.2.1.

Following fraud revelation, deposits of bank branches decreases significantly among banks who are affiliated and located at the same county with the fraudulent RIA. Deposit declines by about 20% in the year of the event and by about 30% in the following year relative to other banks in the same county and same banks in other counties. Interestingly, effects do not gradually dissipate and maintaining the decreasing trends. As the scandal had gained serious notoriety in a national wide, such permanent impact may be the reflection of trust bust of communities toward entities involved in the scandal.

{Insert Figure 7 about here.}

5.2.2 Deposit rates analysis

After establishing that fraud from bank-affiliated RIAs make depositors withdraw their bank deposits, I then explore how deposits rates changes after the event. As the scandal brought exogenous variation in fraud detection, the movements of deposit rates would shed light in identifying mechanism under this withdraw. If the deposit rates significantly decrease following the significant deposit withdraw, it would indicate the main result is just natural mechanic outcome from the change deposit demand. I estimate Eq. (3) on deposit rates of branches in my DiD sample matched with Ratewatch data.

{Insert Table 8 about here.}

Table 8 shows that the treated branches deposit rates do not show any significant change following MFS revelation event relative to other branches. Similar to Section 5.1.6, this implies that the deposit withdraw is at least not the result from the mechanical reaction to decreasing deposit rates, and shed lights on the mechanism of the movement of depositors. In other words, Table 8 identifies that motivation of such deposit movement is not from the price change of their deposit products.

6. Conclusion

Analyzing financial advisory companies that report affiliation with a banks in their SEC mandatory filings, I document a novel channel of depositor discipline. As bank-affiliated investment advisory companies attract the majority of AUM in the industry, their affiliation can be detrimental to bank institutions if the distrust from advisors can spillovers to affiliated sectors. I examine the impact of misconduct occurred in the financial advisory industry on the deposits of their affiliated banks. I find that both branch-level and county-level deposit volume is negatively associated with fraud in bank-affiliated advisory companies. Moreover, the impact is valid only banks who share the common name with fraud-revealed RIAs. Using event study design and difference-in-difference approach based on the quasi-natural experiment of mutual fund scandal in 2003, I establish a causal link between misconduct and bank deposits. Further, I show that the deposit rates is not deriving the main results alleviating concerns of the change of demand of deposits from banking institutions.

Overall, my evidence suggests that distrust on financial advisory industry spillover to banks through financial affiliation channel. By establishing a causal relationship between bank-affiliated advisors misconduct and bank deposits, my study suggests that policymakers should be aware of these financial-network-based operational risk for banking industry, which directly relates to financial stability of economy. Because of these spillover channel, which my work is the first to point out, I believe there is a need to more strict regulation for large financial conglomerates and their conflict of interests.

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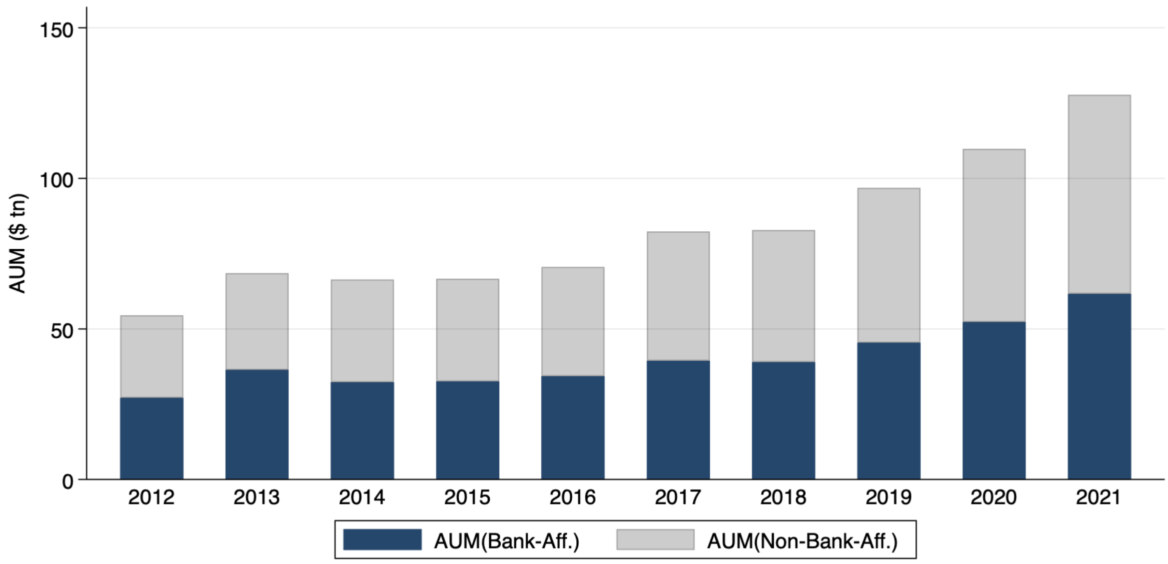
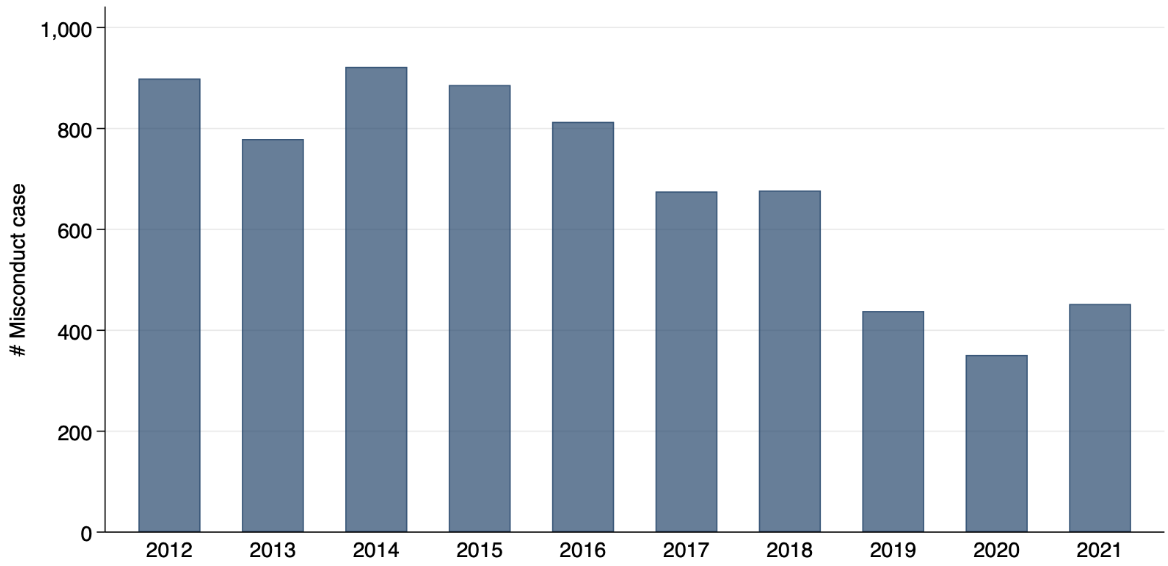
Figure 1



Annual AUM of Investment Management Companies

This figure shows the yearly aggregated asset-under-management (AUM) on SEC-registered financial advisory companies between 2012 and 2021. The below stack bar is AUM under RIAs who reports affiliation link with banking institutions. The above staked bar is AUM under RIA classified to *Bank-Affiliated RIA Misconduct*, who report of no affiliation link with banking institutions.

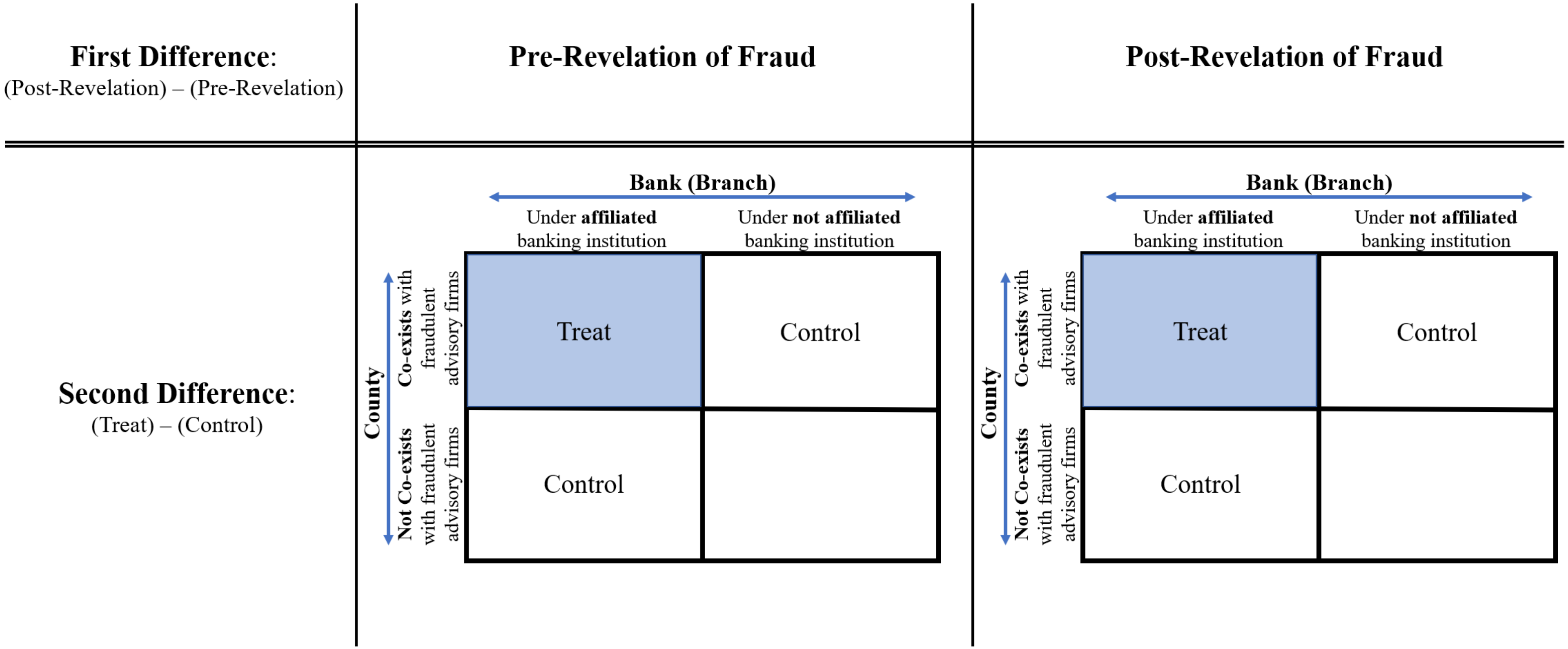
Figure 2



Disciplinary Action on RIA

This figure shows the total number of regulatory action on SEC-registered financial advisory companies between 2012 and 2021. The historical disciplinary action against RIA is collected from *Regulatory Action Disclosure Reporting Page* in Form ADV.

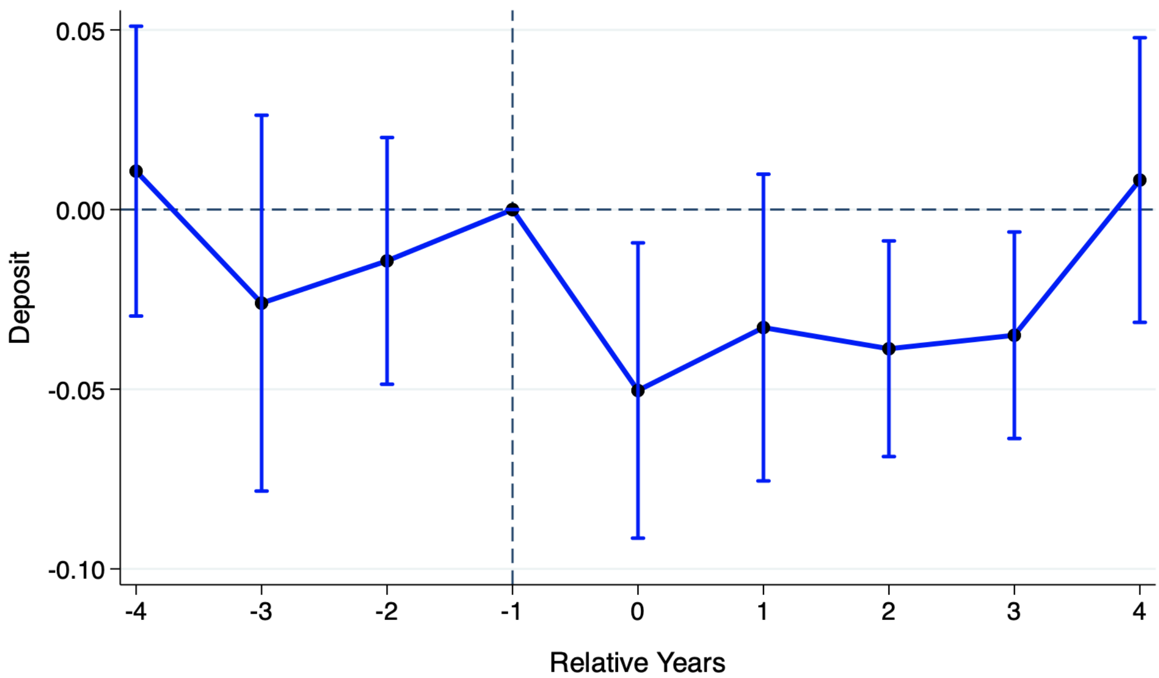
Figure 3



Empirical Methodology

This figure describes the variation used in the main specification where the treated bank branches are those whose affiliated investment advisory firm, located at the same county, has exposed to fraud revelation. The empirical methodology is based on comparison of bank branches to: (i) other branches under different banks at the same county and (ii) other branches under the same banks at different counties.

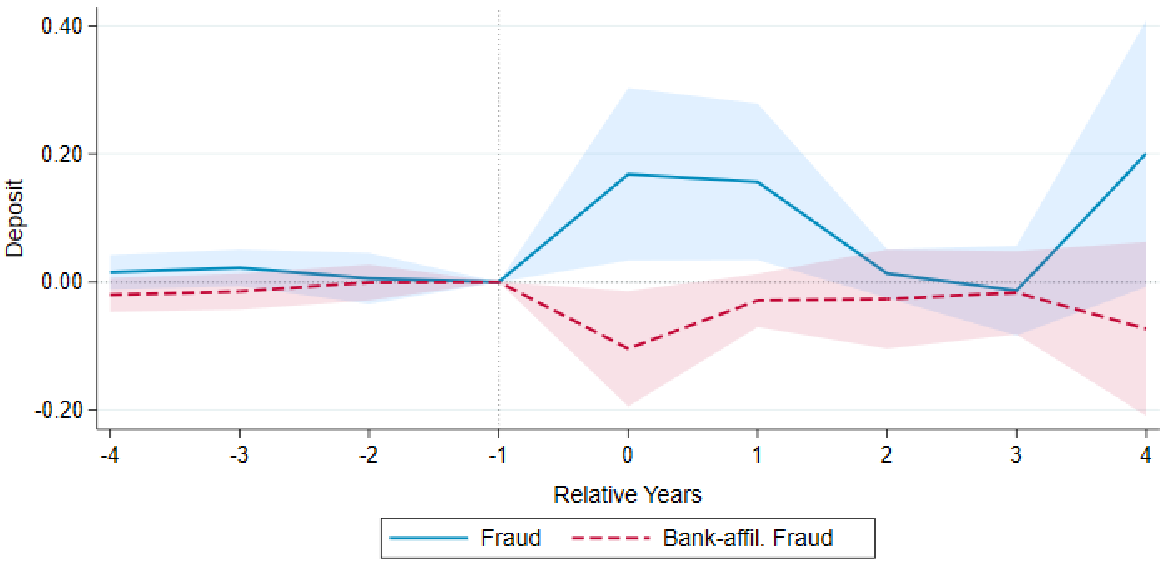
Figure 4



Effects on Bank Branch Deposits

This figure shows event study time-dummies coefficients and 95% confidence intervals from estimating Eq. (1) on the volume of bank branch level deposits. Controls include those used in model 2 of Table 3. Standard errors are clustered by bank branch-level. Sample includes branch level deposit panel data from 2012 to 2021. The dotted vertical line represents the omitted period.

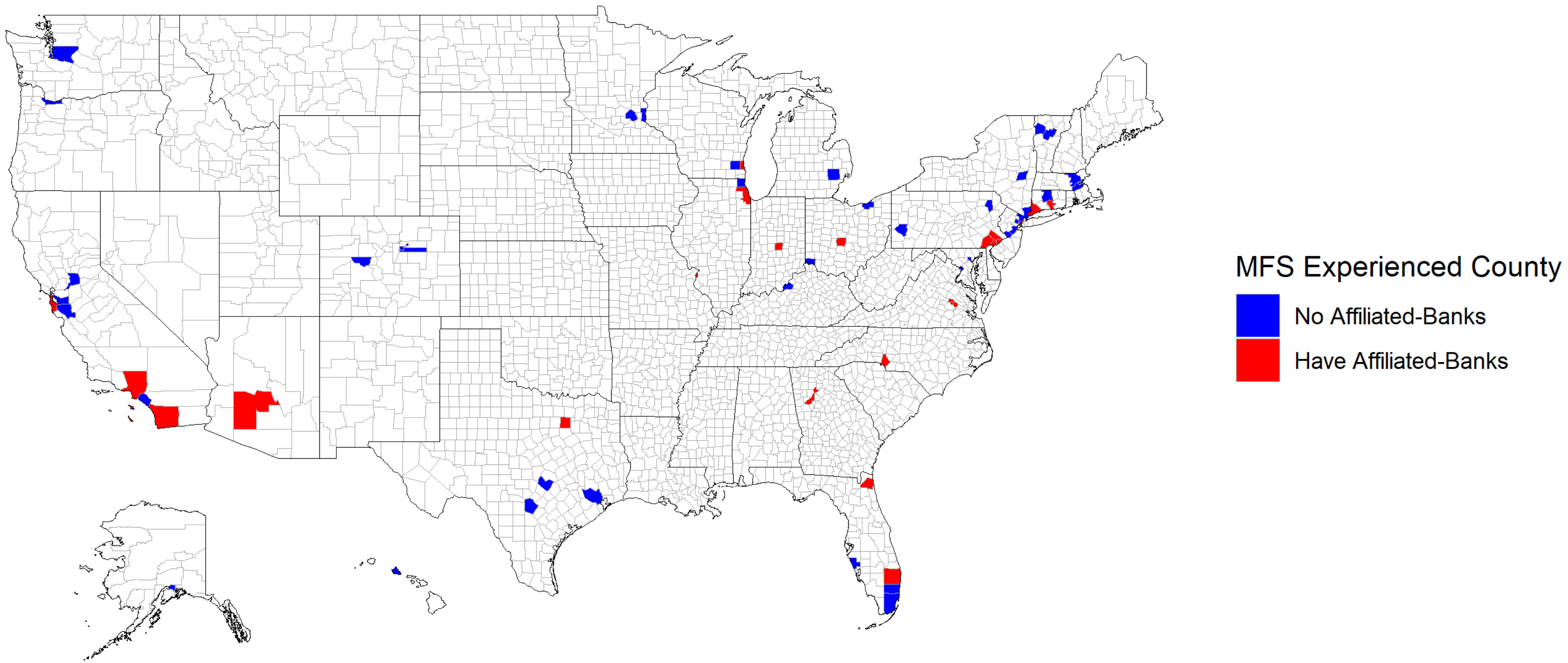
Figure 5



Effects on Deposit Market in county level

This figure shows event study time-dummies coefficients and 90% confidence intervals from estimating Eq. (6) on the volume of aggregated county-year level deposits. Includes time-varying controls (population, median age and median income of households) at the county level. Standard errors are clustered by county. Sample includes branch level deposit panel data from 2012 to 2021. The dotted vertical line represents the omitted period.

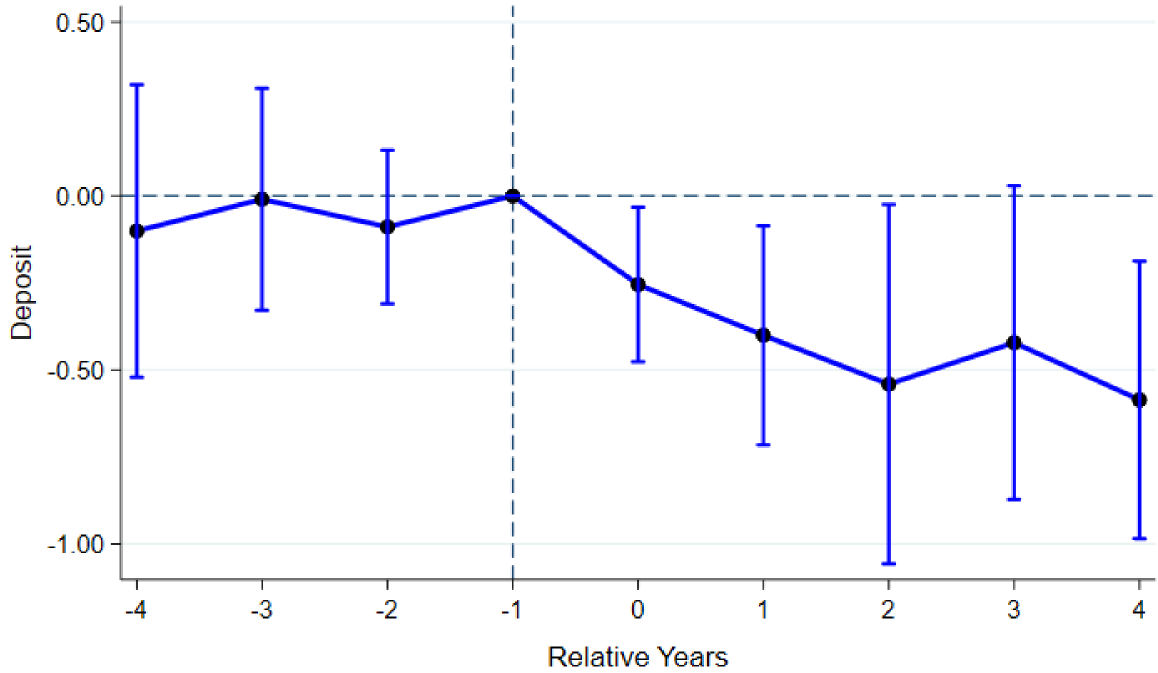
Figure 6



Geographic Distribution of RIAs involved in MFS

The map shows the location of RIAs involved in the mutual fund scandal initially revealed in late 2003. Section 4.2.2 outlines the sample construction. Data on the location of major branches for each RIAs are obtained from SEC Form ADV *Schedule D*. Counties where bank-affiliated fraudulent RIAs involved in MFS located are classified as *Treated* and otherwise as *Control* group.

Figure 7



Quasi-natural Experiment: Effects on Bank Branch Deposits

This figure shows event study time-dummies coefficients and 95% confidence intervals from estimating Eq. (3) on the volume of bank branch deposits. Controls include those used in model 2 of Table 7. Standard errors are clustered by bank branch. Sample includes branch level deposit panel data from 2000 to 2007 on counties displayed in Figure 6. The dotted vertical line represents the omitted period.

Table 1. Summary Statistics

	Mean	SD	Median	N
A. Bank branch level				
Deposits (in thousand $)	132,915	2,425,070	45,815	904,627
Deposit rates (APY %)				76,111
CD 6m (10k)	0.30	0.26	0.25	75,362
CD 12m (10k)	0.47	0.36	0.39	75,843
MM (10k)	0.17	0.16	0.13	71,651
MM (25k)	0.21	0.18	0.15	71,847
Branch service				904,627
Brick & Mortar office	90.86%			821,960
Retail office	5.33%			48,173
Drive-through facility	2.48%			22,465
Mobile/Seasonal office	0.58%			5,202
Administrative office	0.33%			2,950
Trust office	0.21%			1,911
Cyber office	0.20%			1,842
Military facility	0.01%			124
Fraud event	0.06	0.24	0.00	904,627
Common brand $\mid$ Fraud event	0.92	0.27	1.00	54,851
B. County level				
Population	103,687	329,959	26,241	27,978
Median income	50,372	13,646	48,245	27,978
Median age	41.28	5.29	41.20	27,978
Fraud county	0.16	0.37	0.00	27,978
Bank-affil. fraud county	0.04	0.18	0.00	27,978

This table displays the summary statistics for the bank branch-year level and county-aggregated-year level deposit data and fraud related variables used in the study. Sample period is from the year 2012 to 2021. Branch level *deposits* is the amount of deposits from FDIC. *CD 6m (or 12m) (10k)* is the rate of *Certificate of Deposits (CD)* 6-months (or 12-months) maturity for 10k deposits. *MM (10k) (25k)* is rate of *Money Market (MM)* deposits for 10k (20K). *Branch service* is categorical variable that defines the type of service the branch office provides. *Fraud event* is equal to one if the bank of each branch is affiliated to RIA whose fraud is revealed at given year. *Common brand — Fraud event* is conditional indicator variable equals to one if the name of bank share common brand name with fraudulent RIA under the case of *Fraud event* is equal to one. *Population* is the number of population for each county-year. *Median income (age)* is the median income (age) of household for each county-year. *Fraud (Bank-affil. fraud) county* is equal to one if fraud committed by RIA (bank-affiliated RIA) located in the same county at each year.

Table 2. Mutual Fund Families involved in Mutual Fund Scandal

Fund family	Initial news date	Practice under investigation	Regulator involved	Parent Firm
Janus Funds	9/3/03	Market timing	SEC/NY State AG	Janus Capital Group
Nations Funds	9/3/03	Market timing + Late trading	SEC/NY State AG	$\boxed{\text{Bank of America}}$
One Group Funds	9/3/03	Market timing	SEC/NY State AG	$\boxed{\text{Bank One}}$
Strong Capital	9/3/03	Market timing	SEC/NY State AG	Private
Franklin Templeton	9/3/03	Market timing	California AG	$\boxed{\text{Franklin Resources}}$
Gabelli Funds	9/3/03	Market timing	SEC	Gabelli Asset Mgmt.
Putnam Investment	9/19/03	Market timing	SEC/MA State AG	Marsh & McLennan
Alliance Berstein	9/30/03	Market timing	SEC/NY State AG	Alliance Capital
Fed Alger	10/3/03	Late trading	SEC/NY State AG/NY Supreme Court	Private
Federated	10/22/03	Market timing + Late trading	SEC/NASD/NY State AG	Federated Investors
PBHG Funds	11/13/03	Market timing	SEC/NY State AG	Old Mutual PLC
Loomis Sayles	11/13/03	Market timing	Internal Probe	CDC Asset Mgmt.
Excelsior/US Trust	11/14/03	Market timing + Late trading	SEC/Maryland AG	$\boxed{\text{Charles Schwab}}$
Fremont	11/24/03	Market timing	SEC/NY State AG	Private
AIM/Invesco	12/2/03	Market timing	SEC/NY State AG/Colorado AG	Amvescap PLC
MFS	12/9/03	Market timing	SEC/NY State AG	Sun Life Financial
Heartland	12/11/03	Trading practices + Pricing violation	SEC	Private
Seligman	1/7/04	Market timing	NY State AG	Private
Columbia Funds	1/15/04	Trading practice	SEC/NY State AG	$\boxed{\text{FleetBoston Financial}}$
Scudder Investment	1/23/04	Market timing	SEC/NY State AG	$\boxed{\text{Deutsch Bank AG}}$
PIMCO	2/13/04	Market timing	California AG/New Jersey AG	Allianz Group
RS Investment	3/3/04	Market timing	SEC/NY State AG	Private
ING Investment	3/11/04	Market timing + Late trading	NY State AG/NASD	ING Groep NV
Evergreen	8/4/04	Market timing	Mass. AG/NASD	$\boxed{\text{Wachovia}}$
Sentinel	10/7/04	Market timing	SEC	Private

List of fraudulent funds: This table displays the list of mutual fund families involved in mutual fund scandal in late 2003. This includes the name of fund family, the initial news date when fraud reported for each fund family, the illegal trading behavior investigated, the regulatory agencies investigated, and the parent company of main advisor for each fund family. If the parent company is bank-holding-company, then I put red boxes on the name of that company in Table 2 and used at the analysis looking at individual banks. The sources are from Houge and Wellman (2005) and Qian (2011).

Table 3. The Effect of RIA Fraud Revelation on Affiliated Bank Branch Deposits

	Full sample		Only Fraudulent sample	
	(1)	(2)	(3)	(4)
Post	-0.082***	-0.098***	-0.099***	-0.102***
	(0.031)	(0.029)	(0.033)	(0.030)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	No	Yes	No
County × Year FE	No	Yes	No	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Clutser	Branch	Branch	Branch	Branch
Pseudo R^2	0.984	0.986	0.985	0.986
Observations	855,725	853,595	461,173	461,173

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the Poisson regression on the volume of deposits in bank branches following the revelation of fraud committed by affiliated RIA located at the same county with the bank branch. The sample period is 2012-2021 and the unit of analysis is the branch-year level. The dependent variable is the volume of deposits. The *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA occurred. Controls include categorical variable of bank branch service. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 4. The Effect on Affiliated Bank Branch Deposits: Regional Bank vs National Bank

	Full sample		Fraudulent sample	
	Deposits (1)	Deposits (2)	Deposits (3)	Deposits (4)
Post	-0.083**	-0.082**	-0.082**	-0.082**
	(0.037)	(0.036)	(0.037)	(0.036)
Post × State-regional Bank	0.079		0.083	
	(0.070)		(0.069)	
State-regional Bank	-0.043		-0.061	
	(0.033)		(0.042)	
Post × County-regional Bank		0.082		0.083
		(0.100)		(0.100)
County-regional Bank		0.011		-0.001
		(0.049)		(0.058)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.984	0.984	0.984	0.984
Observations	868,021	868,021	469,734	469,734
Cluster	Branch	Branch	Branch	Branch

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the Poisson regression on the volume of deposits in bank branches following the revelation of fraud committed by affiliated RIA located at the same county with the bank branch. The sample period is 2012-2021 and the unit of analysis is the branch-year level. The dependent variable is the volume of branch deposits. The *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA occurred. *State-regional Bank* (*County-regional Bank*) is an indicator variable set to one if the bank institutions have branches in a single state (county). Controls include categorical variable of bank branch service. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5. The Effect on Affiliated Bank Branch Deposits: By Name Commonality

	Full sample		Fraudulent sample	
	(1)	(2)	(3)	(4)
Post	0.073	-0.036	0.051	-0.046
	(0.062)	(0.035)	(0.057)	(0.037)
Post × Common Brand	-0.172**	-0.067*	-0.164***	-0.061
	(0.067)	(0.041)	(0.062)	(0.043)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	No	Yes	No
County × Year FE	No	Yes	No	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Clutser	Branch	Branch	Branch	Branch
Corr(fine,common brand)	.073	.073	.073	.073
Pseudo R^2	0.984	0.986	0.985	0.986
Observations	855,725	853,595	461,173	461,173

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the Poisson regression on the volume of deposits in bank branches following the revelation of fraud committed by affiliated RIA located at the same county with the bank branch. The independent variable is interacted with indicator variable *CommonBrand*, which equals one if the name of bank institutions and fraudulent RIA share the common part. The sample period is 2012-2021 and the unit of analysis is the branch-year level. The dependent variable is branch deposits. The *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA occurred. Controls include categorical variable of bank branch service. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 6. The Effect on Bank Branch Deposit Rates

A. Full sample				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post	-0.010	-0.009	-0.002	-0.002
	(0.008)	(0.011)	(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Adj R^2	0.891	0.864	0.880	0.891
Observations	17,945	18,145	16,404	16,554
Cluster	Branch	Branch	Branch	Branch
B. Only fraud-experienced counties				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post	-0.011	-0.011	-0.001	-0.002
	(0.008)	(0.011)	(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Adj R^2	0.873	0.883	0.896	0.913
Observations	9,857	9,903	8,970	9,050
Cluster	Branch	Branch	Branch	Branch

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the regression on the rate of deposit products in bank branches following the revelation of fraud committed by affiliated RIA located at the same county with the bank branch. The sample period is 2012-2021 and the unit of analysis is the branch-year level. The dependent variable is branch deposits. The *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA occurred. *CD 6m (10k)* is deposit rates of 6-months maturity $10k certificate of deposits (CD). *CD 12m (10k)* is deposit rates of 12-months maturity $10k CD. *MM (10k)* is deposit rates of $10k money market (MM). *MM (25k)* is deposit rates of $25k MM. Panel B only includes observations of counties that ever experienced treated shocks. Controls include categorical variable of bank branch service. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 7. Quasi-natural experiment of Mutual Fund Scandal for Bank Branch Deposit

	Full sample		Fraudulent sample	
	Deposits	Deposits	Deposits	Deposits
	(1)	(2)	(3)	(4)
Post × Treat	-0.126	-0.214**	-0.262**	-0.260**
	(0.125)	(0.106)	(0.126)	(0.119)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	No	Yes	No
County × Year FE	No	Yes	No	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.99	0.99	0.99	0.99
Observations	651,149	649,288	148,785	148,785
Cluster	Branch	Branch	Branch	Branch

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the Poission regression of difference-in-difference (DiD) test results on the effect of financial misconduct committed by bank-affiliated RIAs on affiliated the volume of bank branch. Section 4.2.2 outlines the sample construction and *Treat* is dummy that equals to one if the affiliated branch located in *Treated* sample in Section 4.2.2. The dependent variable is the volume of bank branch deposits at a given year. *Post* is a dummy that equals to one for years since revelation of fraud committed by affiliated RIAs involved in MFS. The sample period is 2000-2007 and the unit of analysis is the bank branch-year level. Controls include categorical variable of bank branch service. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 8. Quasi-natural experiment of Mutual Fund Scandal for Bank Branch Deposit Rates

A. Full sample				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post × Treat	-0.038	-0.079	0.113	0.177
	(0.074)	(0.070)	(0.155)	(0.178)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Adj R^2	0.938	0.941	0.860	0.860
Observations	11,327	11,347	10,747	10,763
Cluster	Branch	Branch	Branch	Branch

B. Only fraud-experienced counties				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post × Treat	-0.050	-0.126	-0.047	0.036
	(0.105)	(0.108)	(0.135)	(0.157)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Adj R^2	0.930	0.930	0.840	0.833
Observations	1,559	1,574	1,451	1,442
Cluster	Branch	Branch	Branch	Branch

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the difference-in-difference (DiD) test results on the effect of financial misconduct committed by bank-affiliated RIAs on affiliated the deposit rates of bank branch. Section 4.2.2 outlines the sample construction and *Treat* is dummy that equals to one if the affiliated branch located in *Treated* sample in Section 4.2.2. The sample period is 2000-2007 and the unit of analysis is the branch-year level. The dependent variable is branch deposits. The *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA occurred. *CD 6m (10k)* is deposit rates of 6-months maturity $10k certificate of deposits (CD). *CD 12m (10k)* is deposit rates of 12-months maturity $10k CD. *MM (10k)* is deposit rates of $10k money market (MM). *MM (25k)* is deposit rates of $25k MM. Parentheses enclose standard errors. Panel B only includes observations of counties that have RIAs involved in Mutual Fund Scandal occurred in late 2003. Controls include categorical variable of bank branch service. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

A. Appendix

Table A.1. Example of Financial Industry Affiliation for Advisory Firms

Name of Advisory Firm	Filing Date	Reported Affiliated Bank
CITIGROUP GLOBAL MARKETS INC.	03/30/2012	CITIBANK, N.A.
CHASE INVESTMENT SERVICES CORP.	07/27/2012	J.P. MORGAN CHASE BANK NATIONAL ASSOCIATION
NIKKO ASSET MANAGEMENT CO LTD	08/16/2012	SUMITOMO MITSUI TRUST BANK, LIMITED
NAPIER PARK CAPITAL MANAGEMENT LLC	12/06/2012	CITIBANK, N.A.
TCW INVESTMENT MANAGEMENT CO	12/20/2012	SOCIÉTÉ GÉNÉRALE BANK AND TRUST
BNY CONVERGEX EXECUTION SOLUTIONS LLC	03/30/2012	THE BANK OF NEW YORK MELLON TRUST COMPANY, N.A.
MERRILL LYNCH, PIERCE, FENNER & SMITH INCORPORATED	11/20/2013	BANK OF AMERICA CALIFORNIA, NATIONAL ASSOCIATION
WELLS FARGO ADVISORS, LLC	07/24/2014	WELLS FARGO BANK, NATIONAL ASSOCIATION
HIGHBRIDGE CAPITAL MANAGEMENT, LLC	07/21/2014	J.P. MORGAN CHASE BANK N.A.
RBC CAPITAL MARKETS, LLC	10/20/2014	ROYAL BANK OF CANADA
EAGLE ASSET MANAGEMENT INC	06/17/2016	RAYMOND JAMES BANK, N.A.
THE DREYFUS CORPORATION	01/22/2018	THE BANK OF NEW YORK MELLON SA/NV
PNC CAPITAL ADVISORS LLC.	03/29/2019	PNC BANK, NATIONAL ASSOCIATION

Examples of individual affiliation link between banks and investment advisory firms: This table provides a sample list of affiliated banks reported by SEC-registered investment advisory companies from Form ADV Item 7.

Table A.2. Examples of Fraud Cases committed by Investment Advisory Firms

Name of Advisory Firm	Initiation Date	Regulatory	Allegation
CITIGROUP GLOBAL MARKETS INC.	01/18/2012	FINRA	Failed to comply with various disclosure requirements including research reports.
CHASE INVESTMENT SERVICES CORP.	04/04/2012	CFTC	Unauthorized usage of client funds ($250 million - $1 trillion).
NIKKO ASSET MANAGEMENT CO LTD	01/28/2012	FSA (JAPAN)	Insider trading.
NAPIER PARK CAPITAL MANAGEMENT LLC	09/21/2012	CFTC	Violation of speculative position limits
TCW INVESTMENT MANAGEMENT CO	07/17/2012	SFC (Hong King)	Provided false information of certain fees and charges to customers.
BNY CONVERGEX EXECUTION SOLUTIONS LLC	01/24/2012	FINRA	Misreport of short position over 300,000 shares.
WELLS FARGO ADVISORS, LLC	07/15/2014	FINRA	Sold products to clients at unfair price.
HIGHBRIDGE CAPITAL MANAGEMENT, LLC	01/17/2014	State of North Carolina	Provided wrong information of auction rate securities.
RBC CAPITAL MARKETS, LLC	09/16/2014	FINRA	Executed at unfair price for client orders.
EAGLE ASSET MANAGEMENT INC	05/18/2016	FINRA	Failed to report suspicious transaction (AML).
THE DREYFUS CORPORATION	11/29/2017	FCA (UK)	Insider trading.

Examples of Advisory Misconduct Cases: This table provides examples of disciplinary action filed against advisory firms reported in Form ADV.