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

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Abstract

This paper studies the transmission of distrust from investment advisory firms to their affiliated banks by exploiting the geographic dispersion of fraudulent investment advisory firms. Local communities exposed to fraudulent advisers withdraw deposits from the banks affiliated with such advisers, even though these banks play no part in the misconduct. These effects are significant when banks share names with fraudulent advisory firms or are located in areas with high social norms. I establish causality by exploring a quasi-natural experiment in which fraud is likely exogenously revealed. Overall, these findings show that distrust spillovers within the network of financial intermediaries.

Keywords: Bank, Deposits, Risk, ESG, Misconduct, Investment Advisors, Financial Affiliation, Market Discipline.

JEL Classification: G21, G23, G41.

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1. Introduction

How financial misconduct affects households' trust is of central importance for financial markets. A number of papers identify the negative economic consequences of financial misconduct (e.g., Graham et al. (2008); Karpoff et al. (2008a); Karpoff et al. (2008b); Guiso (2010); Giannetti and Wang (2016); Gurun et al. (2018); Egan et al. (2019)) and explain why and how financial fraud occurs (e.g., Dimmock and Gerken (2012); Liu (2016); Dimmock et al. (2018b); Patel (2020); Clifford et al. (2021); Dimmock et al. (2021); Karpoff (2021)).

Somewhat surprisingly, however, there is little evidence on whether financial misconduct can generate a spillover of households' distrust within the network of financial intermediaries where non-fraudulent and fraudulent entities are interconnected. As Figure 1 shows, assets managed through affiliations between investment advisory firms and banks have more than doubled over the last decade (e.g., cross-selling, client referrals, etc.). This increasing trend suggests that financial misconduct in investment advisory firms may induce spillover of households' distrust on their affiliated banks and has important implications for banking (in)stability and financial regulations.

{Insert Figure 1 about here.}

In this paper, I investigate whether banks experience deposit withdrawals following the revelation of fraud committed by their affiliated investment advisory firms, and the channels through which households lose trust in such banks. To identify the firm-level business affiliations, I exploit unique administrative reports of business affiliations between U.S. Securities and Exchange Commission (SEC)-registered investment advisory firms (RIA) and commercial banks in the United States from 2012 to 2021. Drawing on evidence that households are more likely to be aware of their local firms through social interactions or geographic proximity (e.g., Coval and Moskowitz (1999); Grinblatt and Keloharju (2001); Ivković and Weisbenner (2007); Seasholes and Zhu (2010); Pool et al. (2015); Giannetti and Wang (2016)), I exploit cross-sectional and time series variation in households' exposure to fraud by espousing that their exposure is significant when a fraudulent RIA is located in the the same county.

I find unambiguous evidence that the amount of bank deposits at the branch level abnormally decreases following the revelation of financial misconduct committed by their affiliated RIAs located in the same county. As the deposits of average households in the United States, in general, are fully insured by the Federal Deposit Insurance Corporation (FDIC),[1] the results imply that the decrease in deposits is not likely driven by financial losses associated with bank risks via a negative shock from fraud-revealed affiliated RIAs, but by lowered trust in financial intermediaries (Corsetti et al. (2010)).

To understand the impact of RIA fraud revelations on banks, I examine a differential impact of the fraud committed by bank-affiliated RIAs compared to the fraud committed by general RIAs. I find that banks experience increase in deposits following the revelation of the general RIA fraud cases, but the impact of fraud committed by bank-affiliated RIAs induce negative impact on banks deposits. These findings provide evidence that depositors not only response to the reputational damage on banks transmitted from their affiliated RIAs, but also the increased preference for bank deposits as a safe asset. In their study of a Ponzi scheme committed by Bernard Madoff, Gurun et al. (2018) find that local communities, where the victims of the scandal reside, relocate their funds to bank deposits from RIAs. Therefore, the impact on bank deposits might have different signs based on how much distrust originating from advisory fraud spillovers to banks. Advisory fraud can decrease deposits for banks affiliated with those fraudulent RIAs as distrust spillover to the bank dominates the incentives for depositors to seek safe assets. Taken together, my results identify a new channel where significant trust shock spillovers to each other through affiliations or operational networks.

To understand the underlying mechanism, I exploit cross-sectional variation in the reputational risk that a bank can share through its name with affiliated RIAs. Carey et al. (1998) document large variation in the lending specialization by the name of finance companies – some bank-affiliated finance companies systematically lend to less risky borrowers if they share a name with their parent bank due to reputational caution for the bank. Consistent with this intuition, my results show that distrust spillover is only significant for banks with a

[1]The standard deposit insurance coverage limit is $250,000 per depositor, per FDIC-insured bank, per ownership category (FDIC: *Deposit Insurance At A Glance*).

similar name as fraudulent RIAs. Although the affiliation relationship is public information, households might have limited information or resources to identify such an affiliation and reputation shock might only spillover to banks that can be recognized as the same group as the fraudulent RIAs. This evidence suggests that the main driver of deposit withdrawals is from the collapse of RIA's reputation shared with affiliated banks through its brand name.

The results also show that deposit outflows are significant among local communities with high social capital. Martin-Flores (2018) documents a negative correlation between a regional level of social capital and the detection of bank misconduct. That is, people living in areas with high social norms have a lower tolerance for misconduct. Consistent with this intuition, I find that only banks located in the area with high social norms experience significant deposit outflows when the fraud committed by their affiliated RIAs is revealed. In other words, local communities with high tolerance for misconduct do not show such significant withdrawals of deposits, strengthening the support for the statement that local communities or social networks is the main channel of distrust spillover on banks.

Who benefits from deposit outflows? Credit unions, which are governed by local community members and provide credit to local households (McKillop and Wilson (2011)), experience significant deposit inflows. I find that credit unions located in the county where banks experience significant deposit outflows, experience surging deposits in the year a fraud is revealed. This impact is stronger than the case of fraud committed by an RIA not affiliated with a bank. To get a sense of the reallocation effect of the trust shock, I conduct a simple back-of-the-envelope estimation. My estimate indicates that approximately 12% of deposit withdrawals flow into credit unions. Even though I cannot be certain about remaining withdrawals, I conservatively estimate that deposit flow to other banks which are not affiliated with RIAs substantially increased as a result of the fraud.

A potential concern is that local economic conditions might affect both the revelation of investment advisory misconduct and their affiliated banks' deposits. For instance, Povel et al. (2007) document that the revelation of fraud is most likely occurs at the entry of economic busts and local deposits might be negatively affected by local economic activity. To address this concern, I exploit the fact that a county usually has several different banks. This variation allows me to include county $\times$ time fixed effects, which remove any local time-varying variation that systematically affects the local deposit market.

An additional concern is related to the banks' strategic decisions regarding deposits to compete with deposits (e.g., Matutes and Vives (1996); Egan et al. (2017)). For instance, banks might strategically change their policy regarding deposits due to their expectation of the financial market, not due to the distrust shock from RIAs. To alleviate this concern, I exploit the fact that banks usually have multiple branches in various regions. Thus, this variation allows me to include bank $\times$ time fixed effects and remove any time-varying unobservable variation resulting from bank policy or bank-specific shock. I find that banks affiliated with fraudulent RIAs experience abnormal withdrawals in deposits of about 8% following the revelation of fraud, compared to other banks within the same county and the same banks in different counties.

I further mitigate concerns related to the interest rates of bank deposit products in that they could affect both financial advisory misconduct and the total quantity of deposits. For example, the decreased interest rates of deposit products might induce a change in depositors' investment portfolio allocation, tilting it to risky assets through RIAs, which might increase the chance of the detection of their misconduct. I find no significant changes in interest rates of deposit products around the shock, implying interest rates are not the mechanism driving my results.

Are my findings being driven by some other unobservable variables that not only correlate with the timing of revelation of fraud, but also affect the local deposit market? Admittedly, a fraud revelation may not occur randomly. For instance, RIAs might have private information about their affiliated banks they are affiliated and update their expectations of the future (local) economy. This might affect their incentives to commit the misconduct due to the anticipated change in future earnings. Moreover, unobservable factors correlate with the movement of deposits might attract the attention of regulatory agencies and increase the chances of detecting misconduct on affiliated entities, such as their asset management arms.

To rule out endogeneity concerns and establish the causal effect of fraud revelation, I also employ a quasi-natural experiment: the late trading mutual fund scandal that occurred in

2003. This scandal provides a good setting to study the distrust spillover for a number of reasons. First, the scandal was a sudden detection of ongoing RIA fraud by a whistleblower, and it created exogenous variation in fraud revelation. Second, because the fraud was first revealed through a major national newspaper, I can identify the exact date of public recognition of the misconduct. Third, RIAs involved in the scandal had branches in geographically dispersed regions. Consistent with the baseline results, I find that banks located in the same county as their affiliated RIAs involved in the scandal saw abnormal decreases in deposits of approximately 19%. The larger economic magnitude of the estimate than the baseline results reflects the largest reputational damage ever seen in the mutual fund advisory industry (Lauricella (2014)). This result is also robust to the interest rate channel. I also conduct event study to explore the dynamic impacts of the trust shock. I find that deposit amount continues the downward trend and does not reverse around after the fraud revelation. Overall, these results suggest that the trust shock from RIA misconduct might transmitted to their affiliated banks.

This paper is related to the literature on how trust in financial institutions affects the investor behavior. Guiso et al. (2008) shows that general trust impacts investor participation in the stock market. Similarly, Giannetti and Wang (2016) find that households reduce stock market participation due to the revelation of corporate securities fraud committed by firms headquartered in their state. In the mutual fund industry, the 2003 late trading scandal induced substantial fund outflow from funds involved in the scandal (e.g., Choi and Kahan (2007); Houge and Wellman (2005)). Similarly, Kostovetsky (2016) argues that mutual fund investors lose trust in funds and withdraw their funds after the announcement of changes in the ownership of fund management companies. Georgarakos and Inderst (2014) and Gennaioli et al. (2015) show that trust in money managers may affect investors' propensity to invest in risky assets. The paper most directly related to my paper is Gurun et al. (2018), who use a Ponzi scheme committed by Bernard Madoff and show that people residing in the same community as Ponzi scheme victims increase their investments towards bank deposits as a venue for safe assets. They identify the distrust spillover of investors within the investment advisory industry as exploiting Madoff shock; by contrast, I focus on spillover across industries via operational (financial) networks and use universal cases of detected misconduct among RIAs.

Moreover, this paper contributes to the literature that finds evidence of market discipline in banking based on financial information of banks (e.g., Saunders and Wilson (1996); Kelly and Gráda (2000); Schumacher (2000); Martinez Peria and Schmukler (2001); Gráda and White (2003); Maechler and McDill (2006); Schnabel (2009)). In the same spirit, recent studies show market discipline based on the non-financial information of banks. Iyer and Puri (2012) show that the local social network mitigates bank runs and depositors with high uninsured deposits are more likely to run from banks. Hasan et al. (2013) examine market discipline based on bad rumors about banks. Homanen (2022) shows the deposit withdrawals from banks who financed a controversial Dakota Access Pipeline project. In these papers, banks incur negative consequences from depositors due to their decision making. By contrast, in my setting, I examine that banks can experience market discipline that is unrelated to their behavior or decisions.

Finally, this paper also contributes to the literature on the consequences of misconduct by the investment advisory industry. Egan et al. (2019) and Egan et al. (2022) show that misconduct induces critical penalties for advisers and that certain fraudulent advisors repeat misconduct. Similarly, Liang et al. (2020) find significant mutual fund outflows following the revelation of misconduct committed by the fund's management company. Moreover, several studies show significant fund outflows or advisory contract changes after the mutual fund scandal in 2003 (e.g., Houge and Wellman (2005); Choi and Kahan (2007); Zitzewitz (2006); Qian and Tanyeri (2017); Warner and Wu (2011)). Similarly, Gurun et al. (2018) identify money outflows from investment advisory firms after the Madoff investment scandal in 2008. Many previous studies focus on the direct consequences of fraudulent entities or exploit a single event. By contrast, I focus on the negative externalities of comprehensive investment advisory fraud revelation on operational networks, where fraud-revealed firms make business partnerships with other non-fraudulent firms.

2. Hypotheses Development

My analysis focuses on how a depositor's trust on her bank at time t is a function of the reputational capital of her bank's affiliated RIA and her beliefs about the risks of investment assets and the safe assets, such as deposits. A depositor's trust in her bank might collapse through the bank's reputational damage transmitted from its affiliated RIA, and a depositor might withdraw her deposits in the bank followed by the collapse of trust. In my empirical tests, I capture cross-sectional variation in a bank's reputational capital with the revelation of fraud committed by an RIA that (1) is affiliated with the bank and (2) its branches are located in the same area as the affiliated bank. There are at least three fundamental reasons why trust shock to RIAs may transmitted to thier affiliated banks through social networks.

Firstly, due to the limited time and information, investors or depositors might consider her bank as a fraudulent entity only because it is associated with a fraudulent RIA, which is consistent with the concept of 'guilty by association'. For instance, approximately 18% of retail mutual fund holders purchased mutual funds through bank or savings institutions in 2021[2]. In addition, certain banks and RIAs under affiliations share the same brand or office building. Becuase of this advertisement or experience, households' perception on the banks' identity might be overlapped with those of its associated RIAs. For example, Carey et al. (1998) document large variation in the lending specialization by the name of finance companies due to the concern of reputational risk transmitted through their associations. Therefore, reputational damage on RIAs might be transmitted to their affiliated banks.

Secondly, due to the importance of social interactions and geographical proximity for investor behavior (e.g., Coval and Moskowitz (1999); Grinblatt and Keloharju (2001); Hong et al. (2004); Ivković and Weisbenner (2007); Seasholes and Zhu (2010); Pool et al. (2015); Gurun et al. (2018)), local residents are more exposed to the revelation of fraud committed by nearby firms. For instance, Giannetti and Wang (2016) show that coporate frauds affect its state residents' investment decisions. In particular, given that the investment advisory industry is

[2] See ICI Investment Company Fact Book (2021)

built upon trust and bears fiduciary duty, the revelation of investment advisory fraud could induce significant collapse of local communities' trust in their local financial intermediaries.

Thirdly, while previous studies on depositor behavior document the fundamental information is the main determinant of their investment decisions (e.g., Martinez Peria and Schmukler (2001); Maechler and McDill (2006); Saunders and Wilson (1996); Schumacher (2000); Schnabel (2009)), recent studies show that non-fundamental information affects depositor decisions (e.g., Iyer and Puri (2012); Iyer et al. (2013); Oliveira et al. (2015); Hasan et al. (2013); Brown et al. (2020)). For example, Homanen (2022) documents a decline in deposit growth of banks that financed an environment-harming project, suggesting that the non-financial preference of depositors may affect their investment decisions. Thus, depositors may not only react to fundamental information but also non-financial information or ethical issues about the banks and the revelation of fraud committed by their affiliated RIAs can affect depositors' investment decision.

Depositors' trust on banks might increase with their updated beliefs about the risk of risky assets due to the RIA fraud. The relation between investors' preference for bank deposits over risky assets and investment advisory fraud follows because, when investment advisory fraud is revealed to the public, investors will relocate their funds from RIAs to safe bank deposits. Gurun et al. (2018) document the money outflow from the investment advisory industry and inflow to bank deposits in the local communities that were exposed to the Madoff scandal. Collectively, investment advisory fraud might increase investors' demand for safe assets and induce money inflow to the banks.

Taken together, RIA misconduct can increase or decrease deposit amount in banks. If the magnitude of distrust spillover from an RIA to a bank through affiliations dominates the increased incentive to relocate more funds to bank deposits as a safe asset, then the deposit amount in the banks might be decreased and I call this the 'distrust-spillover' hypothesis. By contrast, if depositors' demand for safe assets, due to the updated belief on risky assets followed by an RIA fraud, dominates the magnitude of transmission of trust shock from an RIA to their affiliated banks, then the deposit amount in the bank might be increased and I call this the 'deposits as safe-haven' hypothesis. The null hypothesis is that the fraud committed by RIAs does not influence the affiliated banks. This may arise because local communities have limited effectiveness in sharing the distrust on local depositors or because RIA fraud does not update depositors' beliefs about the risk across different investment assets. Therefore, it is an empirical question as to whether or not investment advisory fraud might impact their affiliated banks.

3. Data

Three types of data sources are mainly used for the analysis: mandatory disclosure filings from RIA, deposit amount in bank branch level, and interest rates of retail deposit products in bank branch level. In this section I describe these sources and outline my sample construction.

3.1 Investment Adviser Data

The information regarding investment advisory firms that I use comes from Form ADV, which is the mandatory annual report submitted from RIA to the SEC. Form ADV includes general information about the business operations, ownership, affiliations, and historical disciplinary actions. I hand-collect historical Form ADV filings made by comprehensive RIAs.

To exploit the geographic dispersion of RIAs, I collect information on branch office locations from Schedule D in Form ADV, which requires a list of at least the 25 largest offices in terms of numbers of employees. Although, admittedly, certain RIAs may not submit the full list of their branch locations, listed branches can be considered as sizable offices to be recognizable in the local community, which is the mechanism of main results.

The main purpose of Form ADV is to provide various information including conflict of interest to protect investors. In that sense, any RIA must disclose relevant information about their financial industry affiliation on Schedule D of Form ADV. It requires firms to report if the RIA has a related person that "share business dealings", "operations", or "referring clients" with specific financial institutions. The definition of a related person, in Form ADV, is any employee (except employees related to clerical or administrative functions), director, or partner. Table 1 reports a partial list of affiliations with banks reported by RIAs. To link affiliation data to deposist data, I further match with Summary of Deposits from FDIC by the name and address of banks. As the affiliation link, Schedule D of Form ADV, is available from 2012, my sample comprises RIAs from 2012 to 2021.

{Insert Table 1 about here.}

I collect the historical disciplinary action against RIAs from the regulatory action disclosure reporting page in Form ADV. This part includes the name of the regulatory agency, initiation date of sanctions, amount of the penalty, and a brief summary of alleged misconduct. It covers universal regulatory actions against RIAs and includes any malfeasant behaviors. Figure IA.1 shows the number of misconduct cases filed against RIAs for each year. The types of misconduct include but are not limited to fee overcharging, intentional misinformation, and sub-optimal investment advice. Table 2 shows a partial list of advisory misconduct cases reported by RIAs.

{Insert Table 2 about here.}

3.2 Branch-level Deposit Data

To measure the movement and geographic dispersion of bank deposits, I collect data from the FDIC Summary of Deposits (SOD) database from 1994 to 2021. The FDIC 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 its annual survey.

To provide insight on how deposits are deployed, I use two levels of deposits to measure the impact on the level of deposits at banks affiliated with fraudulent RIAs. First, I use individual branch deposits for the main analysis and exploit their geographic dispersion and affiliated RIAs. This provides an opportunity to focus on the hyperlocal effects among regional communities and make it easier to sort out any confounding effect attributable to local factors (Parsons et al. (2018)).

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

To provide insight on whether the deposit movement is from the demand side or the supply side, I use granular branch-level deposit rate quotes provided by RateWatch. Ratewatch conducts weekly surveys to collect branch-level deposit rates on different types of products. The data covers about 78% of branches in the SOD data during 2001-2021. As I examine the movement of deposits, I focus on general retail deposit products of 6-month maturity, 12-month maturity of $10K certificates of deposit (CD), and money markets (MM) of $10k and $25k since they the most widely used retail deposit rates in the literature (e.g., Drechsler et al. (2017); Ben-David et al. (2017); Cortés and Strahan (2017); Jacewitz and Pogach (2018)). Because my deposit sample is annual, I average weekly deposit rates to an annual frequency for each branch.

3.3 Additional Data Sources

I collect county-level demographic information from the U.S. Census to construct the control variables from 2012 to 2021, including median age, household median income, and population. The social capital measure for U.S. counties is from the Northeast Regional Center for Regional Development (NRCRD) at Pennsylvania State University. The measure is calculated from principal component analysis based on the number of organizations (religious, civic and social, business, political, professional, labor, sports center, and sports team), voter turnout, Census response rate, and number of non-profit organizations (Rupasingha and Goetz (2008)). As the social capital index for 2014 is only available during my sample period which is from 2012 to 2021, I assign a constant social capital index on each county over my sample period. Appendix Table A.1 lists the definitions of the main variables used in this paper.

3.4 Summary Statistics

{Insert Table 3 about here.}

My final sample includes 126,637 commercial bank branches operating in 3,215 U.S. counties over the sample period running from 2012 to 2021. A total of 904,627 bank branch-year observations is included. Table 3 provides that about 6% of the branch-year sample experience incidents of fraud committed by their co-located affiliated RIAs. Moreover, 92% of fraud-exposed banks share a scommon name with their affiliated RIAs. Moreover, it shows that the average branch-level deposit in my sample is $133 millions and shows considerable variation in the variable, as indicated by a standard deviation of $2,425 millions. Most of bank branches are 'Brick & Mortar office' offices. Panel B of Table 3 reports additional summary statistics related to county-level variables from 2012 to 2021. The average county population is 103,687. The average median income is $50,372 for a single household in a county and the average median age is 41.28 years. About 16% of the county-year observations experience fraud committed by RIAs that operate in the same county and about 20% of county-year fraud is committed by a bank-affiliated RIA. In addition, Table 3 provides additional information related to credit union deposits. The average aggregated county-year level deposits of credit unions in my sample is $864,023.

4. Methods and Baseline Results

This section describes my baseline econometric methods to analyze the impact of trust shock and the baseline results of the paper.

4.1 Difference-in-Differences

Identifying whether local residents lose their trust in banks that are affiliated with fraudulent RIA is complicated as various unobservable factors might affect both bank deposits and misconduct. To alleviate such potentially confounding variation, I use a novel empirical strategy that exploits granular multiple fixed effects in the baseline analysis. To assess how an RIA fraud detection impact their affiliated banks, I estimate various forms of the following model using the Poisson regression:

$$y_{i,b,c,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \beta Post_{i,b,c,t} + \boldsymbol{X'_{i,t}}\gamma + \varepsilon_{i,t} \,, \tag{1}$$

where $Post_{i,b,c,t}$ is equals to 1 if bank branch i of bank b is in the same county c with the RIA affiliated with bank b and the fraud committed by the RIA has been revealed to the public before or at year t. The coefficients of interest, β, then represents the average change between their revelation of RIA fraud and the previous years before bank branches are exposed to affiliated-RIA fraud relative to that same change over time among unexposed bank branches in the same county and the same bank's branches in other counties. The control variable, $\boldsymbol{X_{i,t}}$, includes the types of service a branch provides.

Recent econometric studies raise concerns about the using constant-adding log-linear estimation and shows that a fixed-effects Poisson model produces unbiased estimates (Cohn et al. (2022)). As deposits are viewed as a positive integer including zeros, I use Poisson regression to analyze deposit movements. To remove various potentially confounding variations, the specification also includes bank branch, county $\times$ year, and bank $\times$ year fixed effects.

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 the branch's relationship with depositors. These fixed effects also remove the time-invariant part of the branch's business activities, such as products sold and customer characteristics. Including λ_i means that the key independent variable is the within-bank-branch change in deposit amount, not its level.

Second, the county $\times$ year fixed effects, $\delta_{c,t}$, remove variation across bank branches located in the same county in a given year. Removing geographic heterogeneity is important as Parsons et al. (2018) show the significance of unexplained factors that are attributable to local culture. The local economic situation may also affect bank deposits. By including these fixed effects, I remove the average effect of local economic factors on deposits. In general, misconduct in the region is correlated with the local economy, but the changes in its time-series average is removed by the inclusion of these fixed effects. Moreover, these fixed effects also remove the 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 that controls the branches, as well as time-varying bank branch characteristics, such as changes in the bank's deposit strategies or any bank shock. Previous papers show that banks strategically compete for deposits (e.g., Matutes and Vives (1996), Egan et al. (2017)), thus it is important to strategically purge policy for each bank in the deposits market. Moreover, removing bank effects is important as deposits play a major role in credit decisions in the banking industry. For instance, including $\eta_{b,t}$ effectively removes time-varying variation from monetary shocks in credit markets specific to individual banks (e.g., Kashyap et al. (2002); Gatev et al. (2009); Berlin and Mester (1999)).

4.2 Event Study

To further investigate the dynamic impacts of investment advisory fraud on bank branch deposits, I estimate the following Poisson regression:

$$y_{i,b,c,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \sum_{\tau=-4}^{4} \phi_\tau D^{\tau}_{i,b,c,t} + \boldsymbol{X}'_{i,t}\gamma + \varepsilon_{i,t}\,, \tag{2}$$

where $D^{\tau}_{i,b,c,t}$ is a relative event-time dummy that equals to 1 if bank branch i of bank b is in the same county c with an RIA affiliated with bank b and fraud committed by the RIA has been revealed to the public exactly τ years ago if $\tau > 0$ or τ years after if $\tau < 0$. Following the recent event study analysis by McCrary (2007), Borusyak and Jaravel (2017), Atkin et al. (2018), and Higgins (2020), I do not drop observations that are further four years before or after the shock, but rather binning the endpoints by setting $D^{-4}_{i,t} = 1$ if $\tau \leq -4$ and $D^{4}_{i,t} = 1$ if $\tau \geq -4$; the omitted period is $\tau = -1$. The coefficients of interest, ϕ_τ, then represent the average change between time τ and the last year before bank branches are exposed to an affiliated RIA fraud relative to that same change over time among unexposed other banks' branches in the same county and the same bank's branches in other counties. The control variable, $\boldsymbol{X}_{i,t}$, includes the type of branch.

Similar to Eq. (1), Eq. (2) includes multiple sets of fixed effects. County *times* year fixed effects, $\delta_{c,t}$, control for the time-variant characteristics of the bank deposit market in the county, while the bank $\times$ year fixed effect, $\eta_{b,t}$, controls for time-varying bank polices on deposit market. Note that the branch fixed effects also remove the time-invariant characteristics of branches, including customized relationship with depositors.

Investigating the dynamics of the treatment effect from Eq. (2) allows me to verify the parallel trends assumption that there is no pre-treatment effect prior to the fraud revelation. If bank deposits shows a systematic decrease prior to fraud exposure, it may indicate that the economic situation correlates with the movement of bank deposits, which might increase incentives for specific RIA, that coordinate with bank, to commit advisory fraud. Thus, Eq. (2) allows me to alleviate concerns over the parallel trend assumption.

4.3 Baseline Results

To show that local residents, exposed to fraudulent RIAs, withdraw deposits from the banks that are affiliated with these RIAs, I estimate Eq. (1) at the amount of bank deposits at the branch level. Table 4 presents results from the difference-in-Differences (DiD) approach using Poisson regression.

{Insert Table 4 about here.}

Table 4 shows that bank branch deposits are negatively associated with the revelation of fraud committed by their affiliated RIAs. The coefficient estimates on the $Post_{i,t}$ indicator variable are all negative and significant at the 1% level, suggesting that misconduct by an RIA has a negative correlation with their affiliated banks' depositors deposit behavior. The results of the main specification in column (2) show that bank deposits decrease by approximately 9.3% ($e^{-0.098} - 1 \approx -0.0934$) following the revelation of fraud committed by their affiliated RIA located in the same county. This is economically large when compared with the median growth in deposits of approximately 0.5 % in my sample. As the specification includes $County \times Year$ fixed effect and $Bank \times Year$ fixed effect, the estimate is relative in magnitude compared to the average time-series change of other banks in the same county in that year and of the same banks in other counties.

One concern with using the full sample that includes counties that never experienced RIA fraud is that the treatment groups might have totally different characteristics than the untreated groups (Parsons et al. (2018)), which may confound the impact of the treatment. To address this concern, I use a subsample that only contains the counties exposed to bank-affiliated RIA fraud. Columns (3) and (4) report the estimates of Eq. (4) on this subsample. Similar to columns (1) and (2), the coefficients indicate that the volume of deposits decreases by approximately 9.7% ($e^{-0.102} - 1 \approx -0.097$) following the fraud occurrences. This result supports the distrust spillover hypothesis, which implies that distrust spillover holds.

To get a sense of the total economic effect of the trust shock, I estimate the impact on treatment bank branches as follows. First, for each branch I multiply the average yearly amount of deposits and then multiply the coefficient estimated from column (2). I then sum across all treatment branches at the county level, which gives an estimate of approximately $606 million given that average number of treatment branches per county is about 49, conditional on shock exposed counties.

Yet, there is still the concern that the treatment groups might have a decline in deposits level even before the treatment shock. Moreover, both bank deposits and fraud detection might be confounded by other unobservables.

To mitigate the concern that the treatment bank branches are following a different trend than those in other bank branches, I study the dynamics of deposit movements by estimating Eq. (2) at the branch deposits on the SOD sample from 1994 to 2021. The omitted period is the previous year prior to the revelation of RIA misconduct. Estimates are in Figure 2.

{Insert Figure 2 about here.}

Prior to misconduct revelation, I find no evidence of a differential trend between branches. For $\tau < 0$, all treatment coefficients never reach significance, even at the 10% level; there is also no such evidence in the subsample of only treated counties. These findings mitigate a concern that economic hardship in the bank deposit market might induce affiliated RIAs to commit fraud. Moreover, according to Dimmock et al. (2018a), RIA misconduct is often detected several years after it was took place. Thus, the possibility of reverse causality is extremely low since investment advisors cannot exactly predict the timing of both decreasing bank deposits and fraud detection by regulatory agencies.

As discussed above, following banks' exposure to the revelation of fraud committed by their affiliated RIA, the deposits of their bank branches decrease significantly, especially if thery are located in the same county as the fraudulent RIA. Deposits decline by about 5% in the year of the event and then it gradually dissipate, reaching insignificance thee years after the revelation. Collectively, results imply that local residents exposed to RIA fraud withdraw their deposits out from banks affiliated with such fraudulent RIAs, which provides support for the distrust spillover hypothesis.

5. Identification

In Section 4.3, I report a negative correlation between the revelation of investment advisory misconduct and their affiliated bank deposits. It remains challenging, however, to identify the causal impact of RIA misconduct on bank deposits. The key endogeneity concern is that of omitted variables correlated with both the bank deposits and fraud occurrences from bank-affiliated RIAs in the county. For instance, unobservable variables correlate with the movement of deposits might attract the attention of regulatory agencies and increase the chances of detecting misconduct on RIAs affiliated with banks. Additionally, there might be a concern regarding reverse-causality. RIAs can predict the timing of a local economic recession, which would likely also impact the local deposit market, and may increase their incentives to commit misconduct, even though it seems implausible. To establish the causal link, I need to generate an exogenous shock to misconduct revelation, while the shock should be unrelated to depositors' and RIAs' decisions.

In this section, I exploit a quasi-natural experiment to generate exogenous variation in fraud revelation to the public. I employ DiD approach for my identification strategy, and I also use an event study approach exploiting the 2003 mutual fund scandal (MFS). I study deposit movements in the bank affiliated with RIAs involved in the scandal in response to sudden detection of the misconduct to generate causal inferences regarding how the revelation of RIA misconduct affects depositors' decisions.

5.1 Institutional Background

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

Most importantly, it was a sudden detection of the ongoing fraud that was wide-spread in the industry. These fraudulent trading behavior began at least as early as 1995 (e.g., McCabe (2009)). Even though previous papers document 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, the 2003 MFS provides an exogenous variation in RIAs' fraud revelation that is irrelevant to the local deposits market or the fraudulent firms' condition.

I can identify the exact date of public recognition of the fraud. This mitigates the concern about the possibility of early detection by the local community prior to that of the regulatory agencies. Moreover, since the RIAs involved in the scandal were major players in the investment advisory industry, I can identify the individual banks that are in the same financial group with the fraudulent RIAs and test how much the banks affiliated with the RIAs involved in the scandal were affected relative to other banks. I collect the detailed data regarding the revelation of 2003 MFS from Houge and Wellman (2005) and Qian (2011). Appendix Table A.2 provides the list of mutual fund families involved in the scandal, initial news data of the fraud, the abusive trading strategies they employed, the regulatory agencies involved, and the parent company of the main advisor for each mutual fund family.

5.2 Identifying Treated Banks

To identify the causal impact of the 2003 MFS from MFS-involved RIAs to their affiliated bank branches located in the same county, I construct the sample using SEC N-SAR filings and the CRSP Mutual Fund. I identify the names of MFS-involved mutual fund families from Appendix Table A.2 and link with CRSP Mutual Fund. Then, I identify the RIAs who were (sub)advisers of such mutual funds from N-SAR reports filed right before the revelations. As affiliation link is available from 2011 and the MFS scandal occurred in 2003, I re-define affiliation as the governance structure of an RIA. In other words, if an RIA and bank are in the same business group or under the same parent organization, the bank is defined to have an affiliation with the RIA. Thus, if the parent firm is a bank-holding company, then I define banks and RIAs under each bank-holding company as being affiliated.

I identify treated bank branches as those that are located in local communities significantly exposed to the scandal. Specifically, I require that (1) the bank is in the list of parent firms from Appendix Table A.2 and (2) the branch is located in the same county as the investment advisory firm involved in the scandal. I classify bank branches satisfying the above conditions as my treatment branches because local communities around these branches are likely to be more sensitive to the misconducts of their local firms. Similarly, I classify counties as treated counties if there is any treatment bank branches in the county.

Similar to the baseline analysis, I conduct additional analysis on those treated counties. Parsons et al. (2018) suggest that the geographical social norm is one of the main determinants of financial fraud and those environmental factors cannot be explained by regulatory monitoring or firm characteristics. Therefore, counties that do not have a fraudulent RIA involved in the scandal may have fundamentally different characteristics relative to counties that have fraudulent RIAs. Internet Appendix Figure IA.3 shows that the treatment banks do not appear to follow any discernible geographic pattern, which mitigates the concern that unobservable geographic factors that are correlated with misconduct drive the main results.

5.3 Main Results

To examine the casual effects of RIA misconduct revelation on their affiliated banks, I estimate Eq. (1) on bank deposits using the sample discussed in Section 5.2 from 2000 to 2007. The regressions below follow the same structure as those for the baseline results (Section 4.1), although I now use a different sample of branches affiliated with RIAs involved in 2003 MFS.

{Insert Table 5 about here.}

The results are reported in Table 5. Columns (1) and (2) show the results for the full sample of counties and columns (3) and (4) show the results for the sample counties that have any RIAs involved in the scandal. Column (2) shows that the volume of deposits decreases by approximately 19% ($e^{-0.214} - 1 \approx -0.193$) following the MFS revelation relative to other non-treatment branches within the same county and other same-bank branches in other counties. Given that the scandal brought national-wide attention, the economically strong magnitude of the treatment effect is reasonable enough to consider such attention.

Counties that have RIAs involved in huge scandals such as MFS, might have fundamental unobservable differences than other counties (Parsons et al. (2018)) and it might cause confounding variation in my results. Therefore, the regression for column (4) in Table 5 is similar to the baseline regression but only includes local regions that ever experienced the MFS. By comparing these regions, it may mitigate concerns of heterogeneity in terms of local social norms. Column (4) shows that the treatment effect is about 23% ($e^{-0.26} - 1 \approx -0.229$), which is more severe than the results from the whole sample.

I next address the concern that treated branches are following a different trend than those in other branches, which is a necessary condition for identification. I study the dynamics of deposit movements by estimating Eq. (2) on the SOD sample from 1994 to 2021 . The omitted period is the year prior to the revelation of misconduct committed by RIAs. Estimates are displayed in Figure 4.

{Insert Figure 4 about here.}

Figure 4 shows that there is a little evidence of a differential trend between branches prior to fraud revelation and verify the parallel trend assumption which is a key identifying assumption in the DiD approach. For $\tau < 0$, all treatment coefficients never reach significance, even at the 10% level. Similar results to the baseline results strengthen the evidence to purge the existence of a 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 5.1.

Following fraud revelation, the deposits of bank branches decreases significantly among banks who are affiliated and located in the same county as the fraudulent RIA. Deposits 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 the same banks in other counties. Interestingly, the effects do not gradually dissipate and maintaining the decreasing trends. The 2003 MFS exerted a significant and permanent impact and may be a reflection of the trust bust of communities toward entities involved in the scandal. Anecdotal evidence suggests that the larger economic magnitude of the estimate than the baseline results reflects the largest collapse of reputations the scandal had induced in the mutual fund advisory industry (Lauricella (2014)). In other words, this implies that the magnitude and persistent of bank deposit outflows depends on the severity of the trust shock from the misconduct.

Overall, the main results suggest that an exogenous increase in the detection of misconducts committed by fraudulent RIAs induces abnormal deposit withdrawals in banks affiliated with such fraud-revealed RIAs. This is consistent with a negative causal effect of RIA fraud revelations on the deposits amounts of their affiliated banks.

However, this result is quite hard to compare to Gurun et al. (2018), who examine the Madoff scandal, which was a case of advisory fraud committed by an RIA. They show that money outflows from RIAs and inflows to bank deposits in the local areas where the victims of the Ponzi scheme resided after the fraud was detected. As the RIA in that case reported no affiliation with any banks, no banks might experienced distrust spillover. Thus, to completely understand the impact of investment advisory fraud on banks and compare my results to Gurun et al. (2018), I conduct a county-level analysis and investigate the impact of advisory fraud committed by other types of RIAs to the volume of county-aggregated deposits in Section 6.1

6. Mechanisms

In Section 5, I illustrate the causal impact of advisory fraud on affiliated banks. Important questions remain unanswered regarding the mechanism behind these effects. Given the large differences in affiliations and local communities as well as significant variation in the fraud exposure, I explore institutional and regional heterogeneous effects in the setting of comprehensive RIA fraud cases spanning from 2012 to 2021. I also directly compare the effects of bank-affiliated RIA fraud to the rest of RIA fraud revelation events and explore the movement of the interest rates of deposit products around the trust shock.

6.1 Heterogeneity in Affiliation

To further investigate the impacts of investment advisory fraud to the deposit market at the county level and completely understand the general impact of RIA fraud on banks, I employ a modified event study design to calculate the differential impacts of bank-affiliated RIA fraud compared to every revelation of fraud committed by any RIA. Specifically, I estimate:

$$y_{c,t} = \lambda_c + \delta_{s,t} + \sum_{\tau=-4}^{4} \beta_\tau Fraud_{c,t}^{\tau} + \sum_{\tau=-4}^{4} \gamma_\tau Fraud(Affil)_{c,t}^{\tau} + \boldsymbol{X_{c,t}}\eta + \varepsilon_{c,t}\,, \tag{3}$$

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

Following previous studies (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 might be related to banking activity.

{Insert Figure 3 about here.}

To study the impacts on the deposit market at the county level, I estimate Eq. (3) on county-level deposits. The omitted period is $\tau = -1$. Figure 3 displays the estimated treatment effects and differential effects from estimation of Eq. (3). Prior to fraud revelation, I find little evidence of a differential trend between counties. For $\tau < 0$, all treatment coefficients never reach significance and are almost close to zero. Following fraud revelation, the volume of deposits at the county-year level increases significantly among counties where fraud committed by an 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 an additional negative impact to the impact in the general case.

Moreover, the results in Eq. (3) are in line with Gurun et al. (2018) who find that local deposit volume increase in the places where the victims of Madoff scandal are located. Given that Bernard L. Madoff Investment Securities LLC is an RIA reported as not bank-affiliated, the Madoff Ponzi case likely has a positive impact on the local deposit market consistent with the results in Figure 3. In other words, the result implies that the hypothesis of deposits as a safe haven holds in this type of advisory fraud.

Taken together, these findings provide further evidence that depositors not only response to reputational damage on banks transmitted from their affiliated RIA, but also the increased preference for bank deposits as a safe asset. Put differently, the impact on bank deposits might have different signs based on how much distrust originating from advisory fraud spillovers to banks. Advisory fraud can decrease deposits for banks affiliated with those fraudulent RIAs as distrust spillover to the bank dominates the incentives for depositors to seek safe assets. In other words, the distrust spillover hypothesis is dominant if banks are affiliated with fraudulent advisors, and the deposits as safe haven hypothesis significantly holds in other cases of advisory fraud, like the Madoff Ponzi scheme as in Gurun et al. (2018).

6.2 Commonality of Brand Name

I next explore the differential responses by the commonality of name between RIAs and their affiliated banks. Carey et al. (1998) document large variation in the lending specialization by the name of finance companies – some bank-affiliated finance companies systematically lend to less risky borrowers if they share a name with their parent bank due to reputational caution for the bank. Consistent with this intuition, distrust spillover might only be significant for banks with a similar name as the fraudulent RIAs.

I employ a modified version of Eq. (1) and interact the interacting treatment indicator of whether the exposed bank branches share a common name with the fraudulent RIA when fraud committed by the RIA is revealed to the public. Specifically, I estimate:

$$y_{i,b,c,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \beta Post_{i,b,c,t} + \gamma Post \times Common\ Brand_{i,t} + \boldsymbol{X'_{i,t}\eta} + \varepsilon_{i,t}\,, \tag{4}$$

where *Common Brand* is the dummy variable equal to one if the name of bank branch i shares a common name with their affiliated RIA whose fraudulent behavior is revealed. $Post_{i,b,c,t}$ is equals to one if bank branch i of bank b is in the same county c as the RIA affiliated with bank b and the fraud committed by the RIA has been revealed to the public before or at year t, and $\boldsymbol{X_{i,t}}$ are controls that includes the types of service a bank branch provides. The coefficients on $Post \times Common\ Brand_{i,t}$ represent the average difference in deposits between branches sharing a common brand name with fraudulent affiliated RIAs and other branches.

{Insert Table 6 about here.}

Table 6 shows that only the branches that share a common name with a fraudulent RIA experience an approximately 6% of a significant decline in deposit volume. By contrast, there is no significant change in the direction of the volume of deposits for the rest of the branches. This suggests that the recognition of households is driving the results and highlights the mechanism of this deposit movement.

This is again consistent with the distrust spillover hypothesis and suggests that the changes in households preferences toward those fraud-exposed banks are the main underlying driver of the results. Households typically have limited resources to identify individual affiliation information, thus they might not distinguish between different financial entities if they share common names and their distrust might spillover to entities with the same brand name.

6.3 Local Social Capital

Next, I explore heterogeneity across U.S. counties in terms of social capital or civic norms that could induce a differential degree of distrust from fraud exposure. Martin-Flores (2018) documents that areas with higher social capital have less probability of experiencing bank misconduct behavior via a disciplining mechanism. Consistent with this intuition, fraud-exposed banks located in communities with high social capital may experience strong distrust from depositors and significant deposit withdraw following the revelation of fraud committed by their affiliated investment advisory firm.

The social capital measure is from the NRCRD and measured for 1997, 2005, 2009, and 2014. The measure employ principal components analysis to calculate using the number of establishments in social/recreational organizations (divided by the population per 1,000), voter turnout, Census response rate, and number of non-profit organizations (Rupasingha et al. (2006)). Because my sample period is from 2012 and 2021, I use the measure of 2014 to identify the heterogeneity of social capital across U.S. counties.

{Insert Table 7 about here.}

I partition the counties into two groups based on the measure of social capital, and re-estimate Eq. (1) on the branch deposits. I classify counties above the median of the social capital index as high social capital counties and rest of counties are classified as low social capital counties. Table 7 shows that RIA-fraud exposed banks in high social capital counties experience significant abnormal deposit outflows by approximately 10.3% following the revelation of fraud committed by their affiliated RIA located in the same county. The size of the magnitude is similar to my baseline results in Table 4.

By contrast, RIA-fraud exposed banks in low social capital counties experience no significant change in deposit volume following the shock. Furthermore, the economic magnitudes of the results are almost equal to zero, indicating that local communities or depositors with high tolerance for misconduct do not alter their deposit patterns to banks when the fraud committed by their affiliated RIA is revealed.

These findings provide further evidence that local community response to misconduct is the main underlying channel of depositors' movements against banks affiliated with fraudulent RIAs. Put differently, the sensitivity of local communities to social norms is associated with the degree of their response to banks affiliated with fraudulent RIAs. Taken together, households or local communities seems to be the driving forces behind this systematic pattern of market discipline.

6.4 Interest Rates of Deposit Products

As in most studies of market discipline in the banking literature (e.g., Park and Peristiani (1998); Cook and Spellman (1994); Martinez Peria and Schmukler (2001); Egan et al. (2017)), 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 an alternative mechanism that fraud exposure might escalate the price of bank deposits due to the increased cost of bank operations. It might drive the decreasing level of deposits in my sample, instead of the depositors distrust channel.

In this section, I examine the price (interest rates) of retail deposit products sold by each individual bank branches. The results on the impact on interest rates address the concern that the change in depositor behavior is a mechanical responses to the change in interest rates. If the systematic decreasing pattern of interest rates occurs after the RIA fraud, the main results of decreasing bank deposits may justify the mechanical outcome from the change in investment return.

{Insert Table 9 about here.}

I re-estimate Eq. (1) on the interest rate of deposit products. Table 9 shows statistically and economically insignificant coefficients on most of columns given that the average interest rates are between 0.11% APY and 0.29% APY depending on the type of deposit products. In column (2) of Panel A and B, 12-month $10k CD rates show positive correlation with fraud exposure, even though the economical significance is weak in that the magnitude is about 1.3% of average interest rates. This result shows that the decreasing deposit levels are not the outcome of increasing rates of deposit products and, thus, nullify the alternative channel that could explains the main results. In other words, depositors likely altered their investment decision based on non-financial information or non-monetary motivation, suggesting the existence of the distrust spillover hypothesis.

I next explore how interest rates change around the 2003 MFS. As the MFS brought exogenous variation in fraud detection, the movements of interest rates will provide insight on the underlying mechanism behind these withdrawals. If the interest rates significantly decrease after the withdrawals, it would indicate the main result is just a mechanical outcome from the increased demand for deposits, not due to the trust shock on treatment banks.

I use DiD sample constructed in Section 5.2 and I estimate Eq. (1) on interest rates. The coefficients in Internet Appendix Table IA.1 are insignificant both statistically and economically in most of columns. Similar to Table 9, this implies that the interest rates does not reflect deposit withdrawal and is not a mechanical reaction to decreasing interest rates, which provides insight on the mechanism of the deposit movements. Thus, the results in Internet Appendix Table IA.1 suggest that non-financial or non-monetary information can incentivize the depositor to alter their investment decision, which strengthens the existence of the distrust spillover hypothesis. This is also consistent with Brown et al. (2020) and Homanen (2022) that the information beyond financial fundamentals, such as rumors and environmental preferences, might also affect depositor decisions.

Taken together, these tests effectively rule out an alternative explanation for significant deposit outflows: that unobserved heterogeneity in deposit accounts causes people in fraud-exposed areas to respond differently to differing trust shock and that this response likely has nothing to do with advisory fraud.

6.5 Credit Unions

Commercial banks and credit unions have fundamentally different dimensions. In general, a credit union is governed by local community members and not allowed to affiliate with the general public (McKillop and Wilson (2011)). Therefore, depositors who lost their trust in banks affiliated with fraudulent advisory firms might relocate the withdrawn cash into the credit unions in their communities.

Data on credit union come from the National Credit Union Administration (NCUA). The data provide quarterly total deposits at the institutional level from 2012 to 2021 and I average quarterly total deposits to an annual frequency. While credit union data from the NCUA does not provide branch level deposit information, using an institution level of deposits seems not to be a major concern as most credit unions operates within a close local area (Homanen (2022)).

I aggregate the deposits of credit unions at county level based on the location of their headquarters. I estimate the following specification using the credit union samples:

$$y_{c,t} = \lambda_c + \delta_{s,t} + \beta Post_{c,t} + \boldsymbol{X_{c,t}}\eta + \varepsilon_{c,t}\,, \tag{5}$$

where $Post_{c,t}$ is the dummy variable equal to one if (1) fraud committed by an RIA affiliated with banks located in county c is revealed to the public before or at year t and (2) the RIA and its affiliated banks are located in the same county c. The coefficients of interest, β, represents the average difference in total credit union deposits between counties exposed to bank-affiliated RIA fraud and the county-year observations not exposed to bank-affiliated RIA fraud. The control variable, $\boldsymbol{X_{i,t}}$, includes 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. Eq. (5) includes *County* fixed effect, λ_c, and *State* $\times$ *Year* fixed effect, $\delta_{s,t}$, similar to Eq. (3).

{Insert Table 8 about here.}

Table 8 shows that credit union deposits are positively associated with the revelation of fraud committed by bank-affiliated RIAs located in the same county as the headquarters of credit union. The coefficients on $Post_{i,t}$ indicator over all columns are positive and significant, suggesting that depositors relocate withdrawn cash to their local credit unions. The results of the main specification (column (3)) shows that credit union deposits increase by approximately 8.5% ($e^{0.082} - 1 \approx 0.085$) following the revelation of fraud committed by bank-affiliated RIAs located in the same county. As the specification includes the $State \times Year$ fixed effect and $County$ fixed effect, the estimate is relative in magnitude compared to the average time series change of other counties in the state in that year.

To get a sense of the total economic effect, I calculate the estimate analogously to the calculation for the effect on treatment bank deposits. Using estimates in model 3, the total increase in credit union deposits due to the trust shock is approximately \$73 million ($0.085 \times$ \$864 million). When compared to my estimates of \$606 million for the total deposit withdrawals from bank branches, I can account for approximately 12% of deposit outflow as a result of the trust shock. Although I cannot be certain about where the remaining 88% is allocated, a conservative assumption would be that depositors allocate all of it to other banks who are unrelated to the fraudulent RIAs.

To address the concern that the treated counties (credit unions whose headquarters are located in the county same as the fraudulent bank-affiliated investment advisory firm) are following a different trend than those in the control (credit unions whose headquarter located in the county where no advisory fraud by advisory firms is detected), I study the dynamics of deposit movements by estimating modified version of Eq. (2) at county level using the credit union sample. Internet Appendix Figure IA.2 shows no evidence of a differential trend between credit unions before fraud revelation. For $\tau < 0$, all treatment coefficients never reach significance. The results show that the revelation of advisory fraud is not significantly associated with the movements of credit union deposits prior to the revelation, but show significant positive deposits to credit unions in the year of shock.

To further investigate a differential impact of the fraud committed by bank-affilited RIAs compared to the fraud committed by other types of RIAs, I estimate the following specification using the credit union samples:

$$y_{c,t} = \lambda_c + \delta_{s,t} + \sum_{\tau=-4}^{4} \beta_\tau Fraud(Not\,Affil)^{\tau}_{c,t} + \sum_{\tau=-4}^{4} \gamma_\tau Fraud(Affil)^{\tau}_{c,t} + \boldsymbol{X_{c,t}}\eta + \varepsilon_{c,t}\,, \tag{6}$$

where $Fruad(Not\,Affil)^{\tau}_{c,t}$ is a dummy variable equal to one if fraud committed by RIA, not affiliated with banks, located in county c is revealed to the public in year t+τ and $Fruad(Affil)^{\tau}_{c,t}$ is the dummy variable equal to one if fraud committed by any bank-affiliated RIA, located in the same county c as their affiliated bank branches, is revealed to the public in year t+τ. The coefficients on $Fruad(Affil)^{\tau}_{c,t}$ represent the average difference in deposits between counties exposed to bank-affiliated RIA fraud and counties exposed in fraud committed by not bank-affiliated RIAs at $t = \tau$. I aggregate the amount of bank deposits at county and year level. Eq. (6) includes *County* fixed effect, λ_c, and *State* $\times$ *Year* fixed effect, $\delta_{s,t}$, similar to Eq. (3).

Figure 5 displays the estimated differential effects from the estimation of Eq. (6) on the county level total deposits of credit unions. Prior to fraud revelation, I find little evidence of a differential trend between two groups of counties. For $\tau < 0$, all treatment coefficients never reach significance and are almost close to zero. Following fraud revelation, the volume of credit union deposits increases in every fraud cases. While credit unions located in the county where treatment bank branches are located experience an abnormal deposit growth of approximately 11% during the year of shock, other types of RIA fraud also generate 5% increase in abnormal deposits at the year of event. In other words, fraud committed by bank-affiliated RIA induce approximately 6% abnormal inflows to deposits in credit unions relative to frauds by other types of RIAs. The fact that the effect is stronger in case of fraud committed by bank-affiliated RIAs than the other types of RIA fraud suggests that distrust on RIA may significantly spillover to their affiliated banks, which is consistent with distrust spillover hypothesis. Moreover, these results are in line with the Homanen (2022), who implies that credit unions are one of the beneficiaries of deposit windfall from commercial banks when depositors lost trust in their banks based on non-fundamental information.

7. Conclusion

In this paper, I examine the impact of misconduct that occurs in the investment advisory industry on the deposits of their affiliated banks and document a novel channel of depositor discipline. I identify affiliations and misconduct cases using mandatory regulatory reports filed by investment advisory firms. I find that both branch-level and county-level deposit volume is negatively associated with the fraud committed by bank-affiliated advisory companies. Moreover, the impact is only valid for banks who share a common name with fraud-revealed advisors and are located in counties with high social norms. Using a difference-in-difference approach and event study design based on the quasi-natural experiment of the 2003 mutual fund scandal, I establish a causal link between investment advisory misconduct and bank deposits. I also show that the deposit rates are not driving the main results, alleviating concerns of the change in deposit demands from banks.

More broadly, my findings that trust shock from investment advisors spillovers to affiliated sectors implies the existence of a negative externality of fraud revelation within the network of relationships between financial intermediaries where non-fraudulent and fraudulent entities are interconnected. While researchers find that financial misconduct may impact households' trust in a fraudulent entity or industry (e.g., Karpoff et al. (2008a); Guiso (2010); Giannetti and Wang (2016); Gurun et al. (2018); Egan et al. (2019); Liang et al. (2020)), far less attention has been paid to the contagion of distrust on other connected entities or even industries through an operational network. The causal relation I find between investment advisory misconduct and bank deposits suggests that policymakers should be aware of these financial network-based operational risks in the banking industry, which directly relates to financial stability of the economy. Due to this spillover channel, which I am the first to point out, there is a need for stricter regulations on large financial conglomerates and their conflict of interests.

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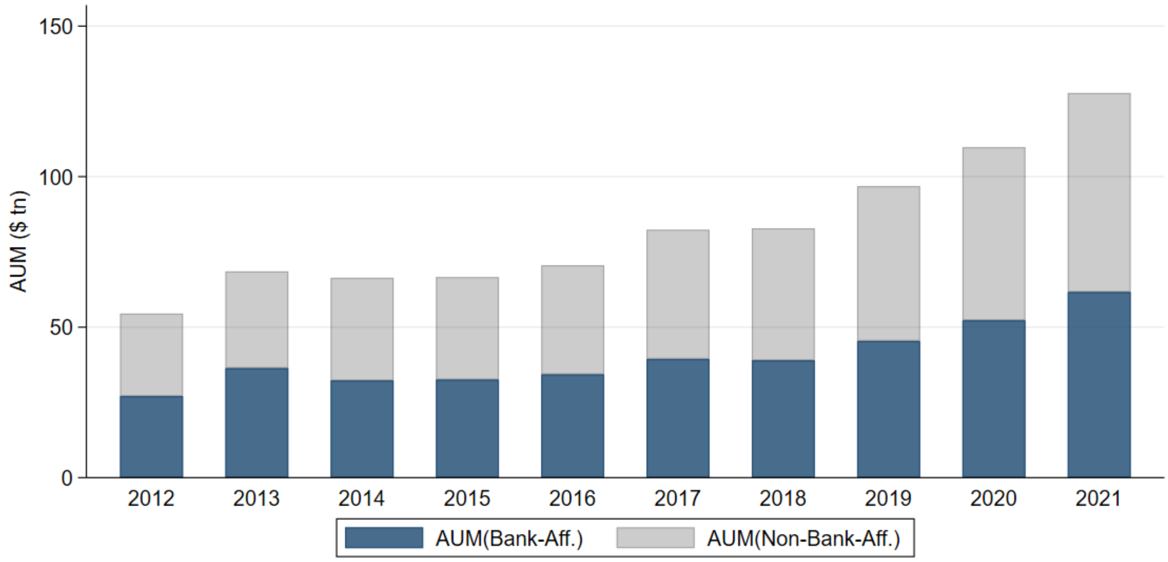
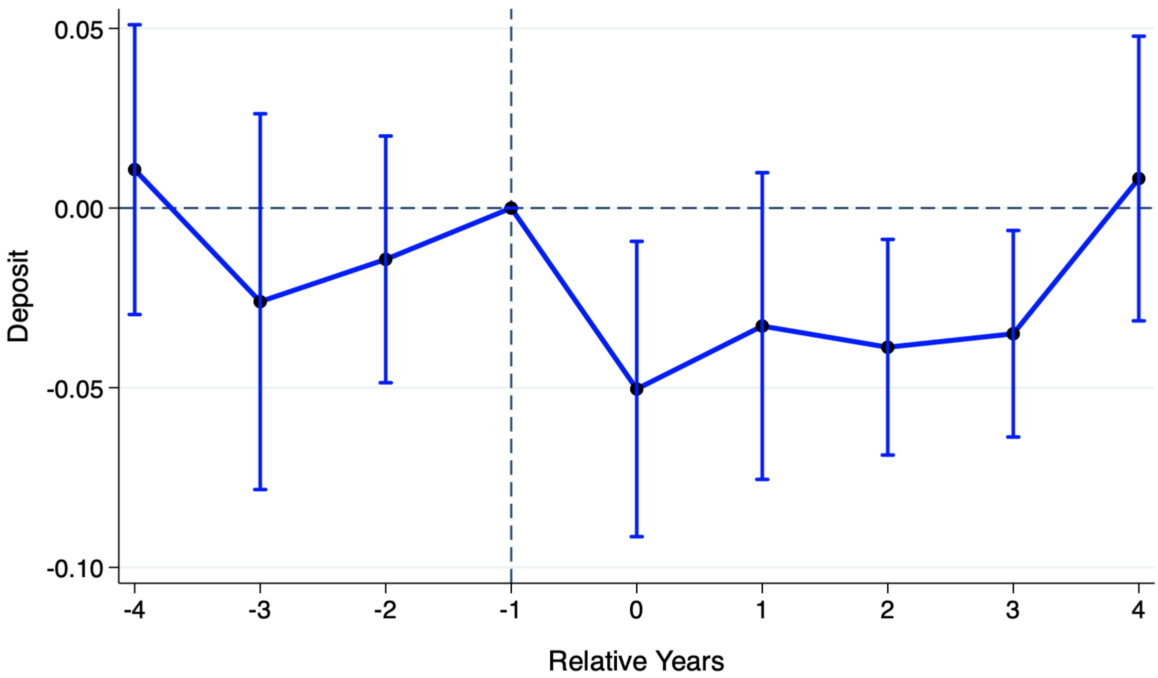
Figure 1. AUM of Investment Management Companies



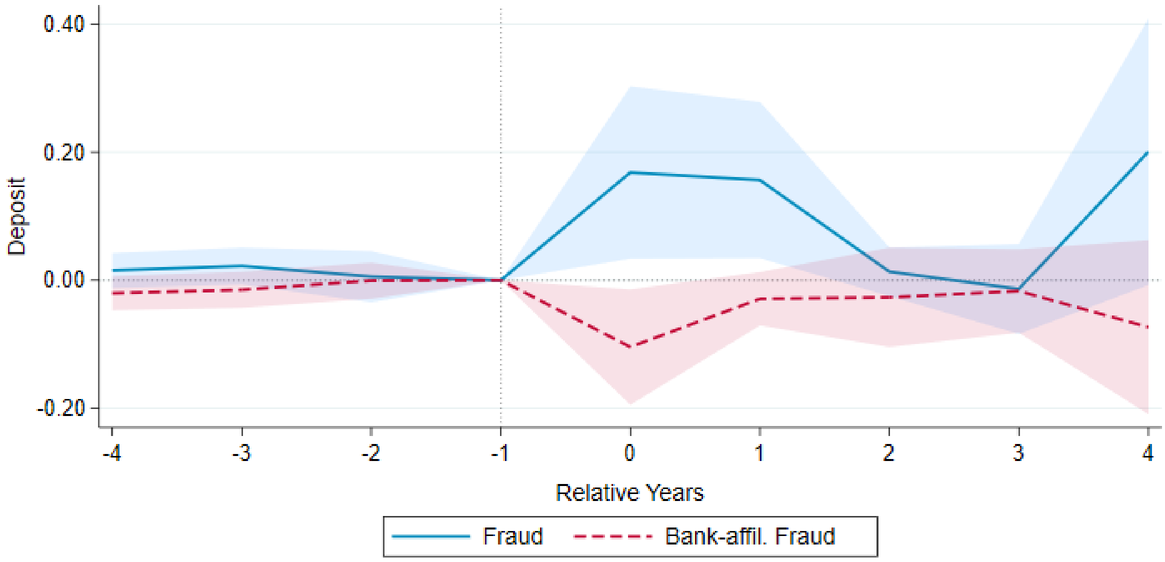
This figure shows the yearly aggregated asset under management (AUM) on SEC-registered investment advisers (RIA) between 2012 and 2021. The below stack bar is AUM under RIAs that report an affiliation with banking institutions. The above stacked bar is AUM under RIA classified to bank-affiliated RIA misconduct, who report no affiliation with banking institutions.

Figure 2. Effects on Bank Branch Deposits



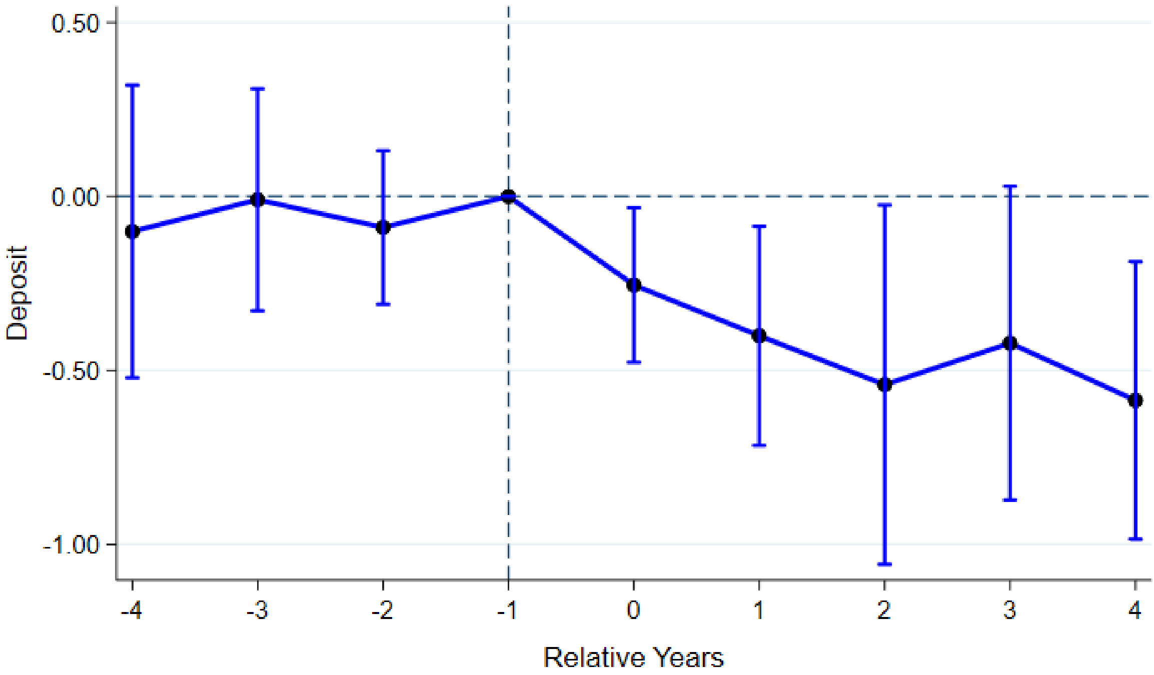
This figure shows event study time dummy coefficients and 95% confidence intervals from estimating Eq. (2) on the volume of bank branch-level deposits. Controls include categorical variable of bank branch services. Standard errors are clustered at the bank branch-level. The sample includes branch level deposit panel data from 2012 to 2021. The dotted vertical line denotes the omitted period.

Figure 3. Effects on Deposit Market at the County Level



This figure shows event study time dummy coefficients and 90% confidence intervals from estimating Eq. (3) on the volume of aggregated county-year level deposits. Controls include time-varying controls (population, median age and median income of households) at the county level. Standard errors are clustered at the county level. Sample includes branch level deposit panel data from 2012 to 2021. The dotted vertical line denotes the omitted period.

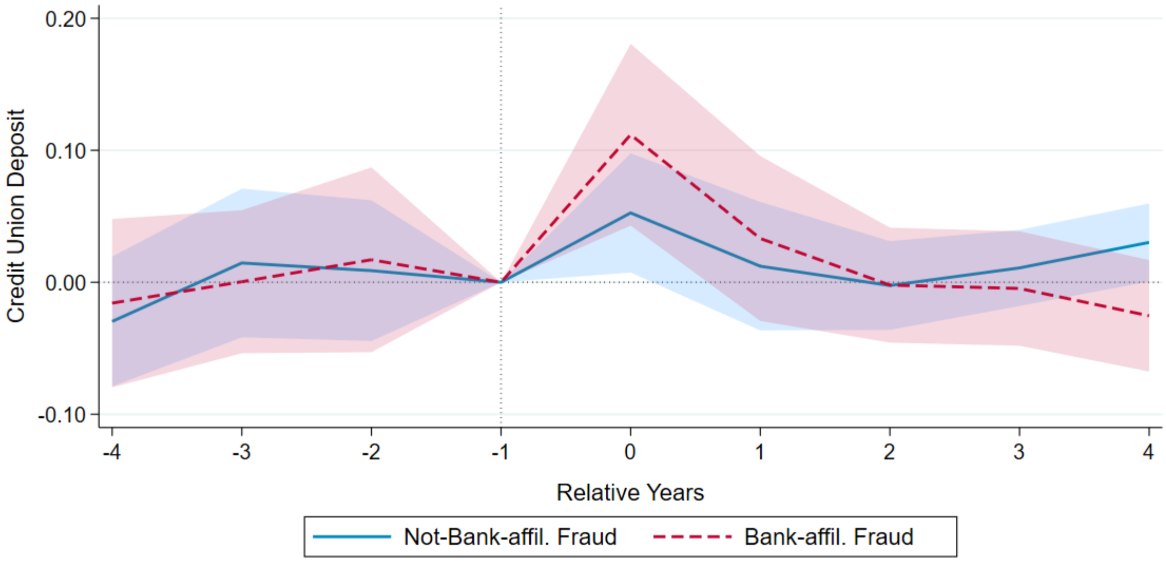
Figure 4. Quasi-natural Experiment: Effects on Bank Branch Deposits



Quasi-natural Experiment: Effects on Bank Branch Deposits

This figure shows event study time-dummies coefficients and 95% confidence intervals from estimating Eq. (2) on the volume of bank branch deposits using DiD sample (see Section 5.2). Controls include categorical variable of bank branch services. Standard errors are clustered by bank branch. The dotted vertical line represents the omitted period.

Figure 5. Effects on Credit Union Deposits at the County Level



Effects on Credit Union Deposits at the County Level

This figure shows event study time dummy coefficients and 90% confidence intervals from estimating Eq. (6) on the volume of county-level credit union deposits. Controls include those used in model 2 of Table 8. Standard errors are clustered at the state $\times$ year level. Sample includes panel data of county level credit union deposits from 2012 to 2021. The dotted vertical line denotes the omitted period.

Table 1. Financial Industry Affiliation: Example

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
NIKKO ASSET MANAGEMENT CO LTD	08/16/2012	SUMITOMO MITSUI TRUST BANK
NAPIER PARK CAPITAL MANAGEMENT LLC	12/06/2012	CITIBANK, N.A.
TCW INVESTMENT MANAGEMENT CO	12/20/2012	SOCIÉTÉ GÉNÉRALE BANK AND TRUST
WELLS FARGO ADVISORS, LLC	07/24/2014	WELLS FARGO BANK
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

This table provides an example of financial industry affiliation between banks and investment advisory firms. ADV filings report financial industry affiliation of SEC-registered investment advisory firms. 'Name of Advisory Firm' is the full legal name of adviser. 'Filing Date' is the date of ADV filing when it reports the affiliation. *Reported Affiliated Bank* is the legal name of the affiliated entity.

Table 2. Regulatory Action: Example

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.

This table provides an example of disciplinary actions on SEC-registered investment advisory firm. ADV filings report the historical records of regulatory actions applied to advisory firms. *Name of Advisory Firm* is the full legal name of adviser. *Initiation Date* is the date of initiation of each regulatory action. *Regulatory* is the name of regulatory authority and *Allegation* is brief description of misconduct

Table 3. 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 %)				
CD 6m (10k)	0.18	0.22	0.1	805,548
CD 12m (10k)	0.29	0.32	0.19	807,173
MM (10k)	0.11	0.14	0.07	761,494
MM (25k)	0.13	0.15	0.1	763,460
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 | 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
Credit Uinon Deposits (in thousand $)	864,023	3,452,256	98,610	13,658

This table reports the summary statistics for deposit, misconduct, and demographic data used in the study. Sample period is from 2012 to 2021. Panel A shows branch-level observations. Branch services is a categorical variable that shows the types of service the branch provides. Panel B shows county-level observations. Variable definitions are in Appendix Table A.1.

Table 4. 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
Pseudo R^2	0.984	0.986	0.985	0.986
Observations	855,725	853,595	461,173	461,173

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 RIAs located at the same county as 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. *Post* is an indicator variable set to one since the detection of fraud committed by co-located affiliated RIA. Controls include categorical variable of bank branch services. Parentheses enclose standard errors. Standard errors are in parentheses and are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5. Quasi-natural experiment of Mutual Fund Scandal for Bank Branch Deposit

	Full Sample		Fraudulent Sample	
	Deposits	Deposits	Deposits	Deposits
	(1)	(2)	(3)	(4)
Post	-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

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 5.2 outlines the sample construction and *Treat* is dummy that equals to one if the affiliated branch located in *Treated* sample in Section 5.2. 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 services. Standard errors are in parentheses and are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 6. 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
Pseudo R^2	0.984	0.986	0.985	0.986
Observations	855,725	853,595	461,173	461,173

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 RIAs located at the same county as 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. *Post* is an indicator variable set to one since the detection of fraud committed by a co-located affiliated RIA. Controls include categorical variable of bank branch services. Standard errors are in parentheses and are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 7. The Effect on Affiliated Bank Branch Deposits: Social Capital by Counties

	Full Sample		Fraudulent Sample	
	(1) Low Social Capital	(2) High Social Capital	(3) Low Social Capital	(4) High Social Capital
Post	-0.000	-0.109***	0.002	-0.115***
	(0.016)	(0.041)	(0.017)	(0.042)
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
Pseudo R^2	0.981	0.991	0.980	0.991
Observations	556,602	284,525	334,120	122,935

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 as 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. Controls include categorical variable of bank branch services. 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. The Effect on Credit Union Institutions

	(1)	(2)	(3)
Post	0.078**	0.064**	0.082**
	(0.031)	(0.030)	(0.037)
Controls	No	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
State × Year FE	No	No	Yes
Pseudo R^2	0.959	0.960	0.960
Observations	13,529	12,167	12,164

Standard errors in parentheses

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

This table presents the results of the Poisson regression on the aggregate volume of credit union deposits at county level following the revelation of fraud committed by affiliated RIAs located at the same county as the headquarter of each credit unions. The sample period is 2012-2021 and the unit of analysis is the county-year level. The dependent variable is the aggregate volume of credit union deposits at county level. *Post* is an indicator variable set to one since the detection of fraud committed by a co-located affiliated RIA. Controls include population, median age, and median income at county × year level. Standard errors are in parentheses and are clustered at the state × year level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 9. 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	0.003	0.012^{***}	0.002	0.003
	(0.005)	(0.004)	(0.004)	(0.004)
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
Pseudo R^2	0.207	0.220	0.164	0.166
Observations	784,639	786,233	740,953	743,060
B. Only fraud-experienced counties				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post	0.001	0.014^{***}	0.001	0.003
	(0.005)	(0.005)	(0.004)	(0.004)
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
Pseudo R^2	0.224	0.244	0.183	0.186
Observations	422,420	423,003	394,269	395,249

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 as 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. *Post* is an indicator variable set to one since the detection of fraud committed by a co-located affiliated RIA. *CD 6m (10k)* is deposit rates of 6-month maturity $10k certificate of deposits (CD). *CD 12m (10k)* is deposit rates of 12-month 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 services. Parentheses enclose standard errors. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Appendix

Table A.1. Variable Definitions

Variable	Definition	Source
Panel A. Branch level		
Deposits	Deposits of Bank branch office as of June 30th (in thousand $).	FDIC Summary of Deposits
Deposit rates	APY of bank deposit products (in percentage).	RateWatch
CD 6m (10k)	APY of $10k Certificate of Deposits (CD) of 6 months maturity.	RateWatch
CD 12m (10k)	APY of $10k CD of 12 months maturity.	RateWatch
MM (10k)	APY of $10k Money market account (MM).	RateWatch
MM (25k)	APY of $25k MM.	RateWatch
Branch service	Type of service the bank branch office provides.	FDIC Summary of Deposits
Common brand	Indicator variable that equals to one if bank share common name with their affiliated RIA conditional on their advisory misconduct is revealed by regulators.	SEC Form ADV, FDIC Summary of Deposits
Panel B. County level		
Population	The yearly total population of county.	Census
Median income	The yearly median income for a single household in a given county.	Census
Median age	The yearly median age of population in a given county.	Census
$Fraud$	Indicator variable that equals to one if fraud committed by any RIA located at given county is revealed to public in a given year.	SEC Form ADV
$Fraud(Affil)$	Indicator variable that equals to one if fraud committed by any bank-affiliated RIA located at given county is revealed to public in a given year.	SEC Form ADV
Credit union deposits	The yearly aggregated deposits of credit unions whose headquarter is located at given county.	National Credit Union Administration (NCUA)
Social capital	The county-level first principal components based on the number of establishments in social/recreational organizations (divided by population per 1,000), voter turnout, Census response rate, and number of non-profit organizations at year 2014 (Rupasingha et al. (2006)).	Northeast Regional Center for Rural Development (NRCRD)

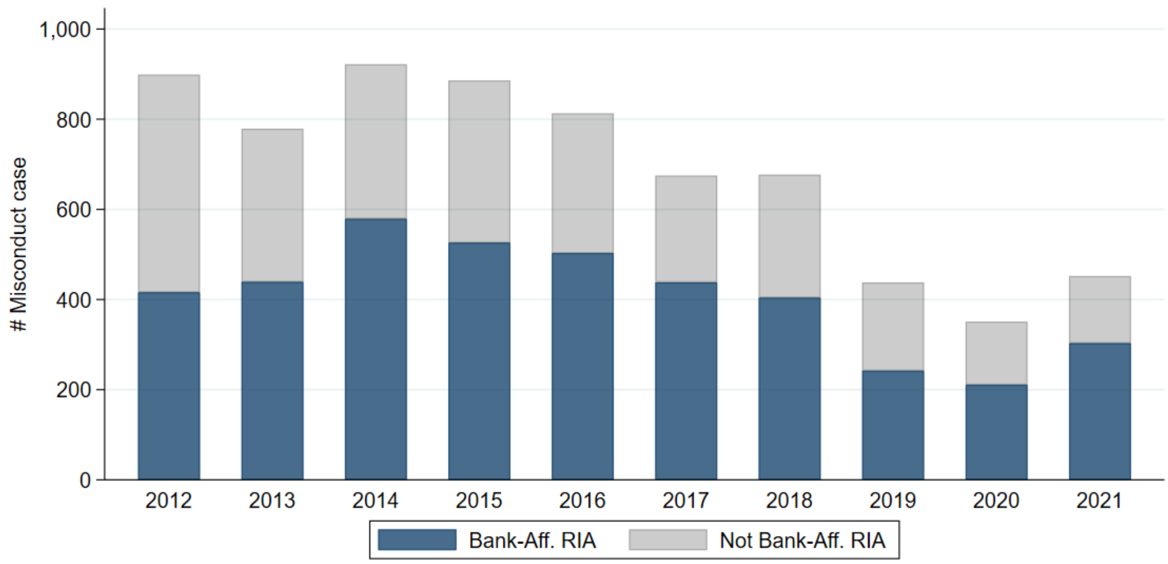
Table A.2. Mutual Fund Families involved in Mutual Fund Scandal

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, initial news date when fraud reported for each fund family, illegal trading behavior investigated, 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 A.2 and used at the analysis looking at individual banks. The sources are from Houge and Wellman (2005) and Qian (2011).

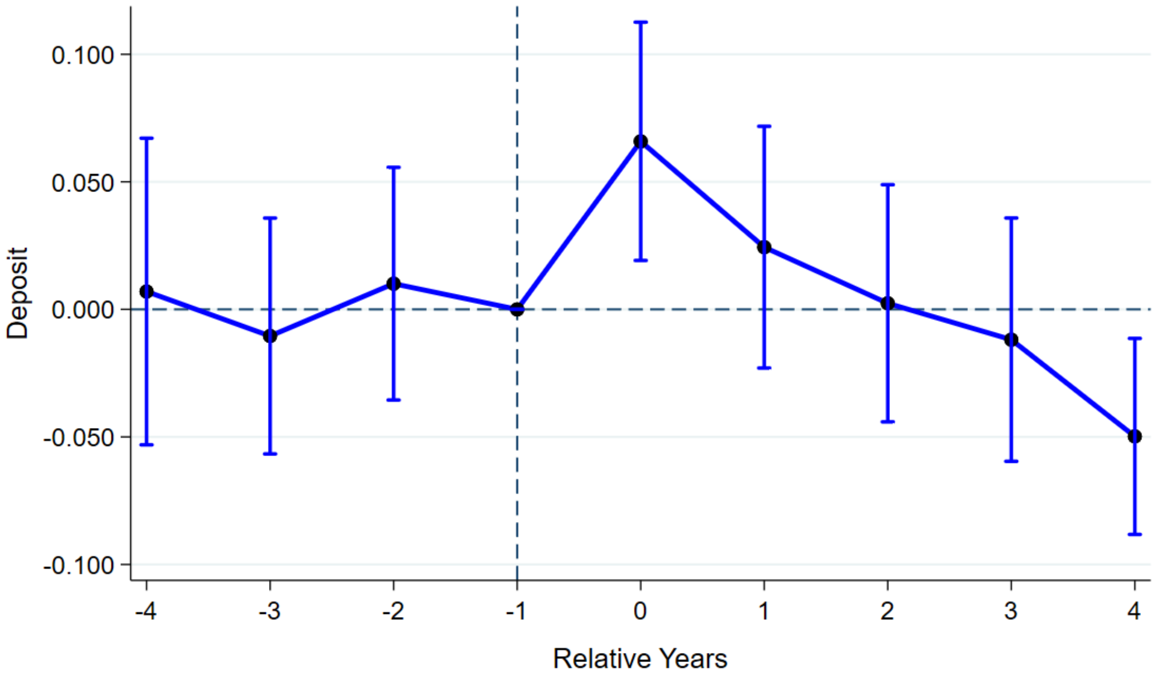
Internet Appendix to
"Distrust Spillover on Banks:
The Impact of Investment Advisory Misconduct"

Figure IA.1. Disciplinary Action on RIA



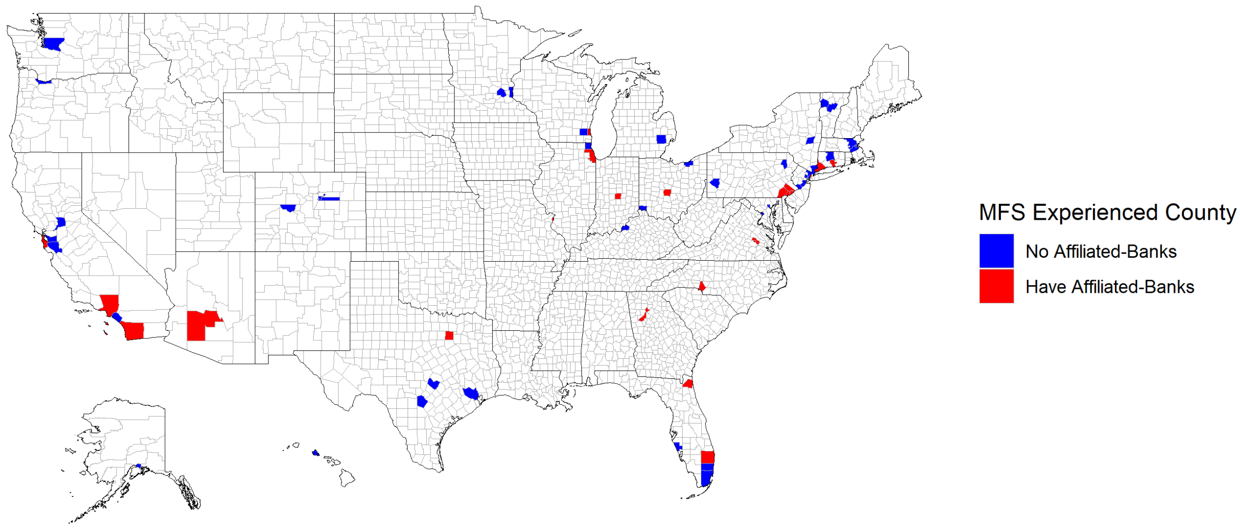
This figure shows the total number of regulatory action on SEC-registered financial advisory companies (RIA) between 2012 and 2021. The below stack bar is total number of detected misconduct against RIAs who reports affiliation link with banking institutions. The above stacked bar is total number of detected misconduct against RIA classified to bank-affiliated RIA misconduct, who report of no affiliation link with banking institutions. The historical disciplinary action against RIA is collected from 'Regulatory Action Disclosure Reporting Page' in Form ADV.

Figure IA.2. Effects on Credit Union Deposits



This figure shows event study time dummy coefficients and 95% confidence intervals from estimating Eq. (5) on the volume of county-level deposits of credit unions. Controls include time-varying controls (population, median age and median income of households) at the county level. Standard errors are clustered at the state × year level. Sample includes panel data of county level credit union deposits from 2012 to 2021. The dotted line denotes the omitted period.

Figure IA.3



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. I outline the sample construction in Section 5.2. 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 are classified as Treatment and otherwise as Control group.

Table IA.1. 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	-0.001	-0.022***	-0.011	0.026
	(0.011)	(0.009)	(0.017)	(0.018)
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
Pseudo R^2	0.170	0.159	0.196	0.207
Observations	98,142	98,213	97,067	97,154
B. Only fraud-experienced counties				
	CD 6m (10k) (1)	CD 12m (10k) (2)	MM (10k) (3)	MM (25k) (4)
Post × Treat	0.010	-0.020*	0.011	0.030
	(0.013)	(0.012)	(0.026)	(0.025)
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
Pseudo R^2	0.176	0.168	0.179	0.195
Observations	14,520	14,529	14,476	14,468

This table reports the difference-in-difference (DiD) test results on sample constructed as Section 5.2 which outlines the sample construction and *Treat* is dummy that equals to one if the affiliated branch is in *Treated* sample. 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 following the detection of fraud committed by RIAs affiliated with treated bank branch. *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 services. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.