Distrust Spillovers from Financial Advisors to Bank Branches*

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Abstract

Exploiting detailed administrative data on financial advisors and the geographic dispersion of bank branches, I find that, after advisory misconduct is exposed in a county, their affiliated bank branches in that county show abnormal decreases in deposits and small business loan originations. These effects are stronger when banks are geographically closer to affiliated advisors, face serious misconduct, have more uninsured deposits, are affiliated with advisors serving fewer retail clients, or are in socially-networked counties. I establish causality through the quasi-natural experiment of the mutual fund late-trading scandal. The results indicate that there are unexplored inter-industry distrust spillovers across financial intermediaries.

Keywords: Trust, Bank, Financial Misconduct, Investment Advisors, Small Business Credit, Financial Affiliation

JEL Classification: G21, G23, G41

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1. Introduction

The majority of households rely on financial advisory firms when making financial decisions (Foerster et al. (2017); Egan et al. (2019)). Recent studies, however, show that misconduct by advisory firms is common and induces significant distrust in advisors (Dimmock et al. (2018a); Gurun et al. (2018); Egan et al. (2019); Liang et al. (2020)). Tirole (1996) formalizes the theory of collective reputation and argues that entities within a network or group may be exposed to the same reputational risk in markets with information frictions. Given that about half of the assets in the U.S. financial advisory industry are managed by advisors affiliated with banks, such reputational risk from advisory misconduct might be transmitted to banks through affiliation networks (see Figure 1). Hence, understanding the contagion of trust shock from advisory firms to banks, which I am the first to point out, is an important pursuit not only because of the economic importance of trust in banks, but also because regulators have the potential to mitigate some of the reputational risk of banks.[1]

Despite earlier theoretical studies on collective reputation, empirical studies on the subject remain scarce, particularly in the context of financial intermediaries built on investors' trust.[2] While previous papers focus on the direct consequences for specific trust-collapsed entities or sectors, there is little large-sample evidence on the spillovers of trust shocks across different industries of financial intermediaries. Figure 1 shows that assets managed through affiliations between the banking industry and the investment advisory industry have more than doubled over the last decade.[3] Given this growing affiliation network between advisory firms and banks, I test whether trust shocks resulting from advisory misconduct may induce significant reputation spillover on their affiliated banks, subsequently leading to a decrease in deposits and lending activities for those banks.

In this paper, I evaluate whether the revelation of investment advisory misconduct leads to an abnormal decrease in deposits in banks affiliated with misconduct-revealed advisors, and whether this channel generates a negative externality in the bank loan

[1] See Hill (2019) for a discussion of regulations regarding the reputational risk of banks.

[2] Tirole (1996), Winfree and McCluskey (2005), Levin (2009), Fishman et al. (2018), and Neeman et al. (2019) examine the theoretical model of collective reputation.

[3] For example, banks and financial advisors execute cross-selling of products, client referrals to each other, compensation sharing, etc.

market. To generate cross-sectional and time-series variation in households' exposure to advisory misconduct, I assume that households are more likely to be exposed to misconduct from advisors operating in their county of residence. This assumption is based on prior studies indicating that individuals tend to be more familiar with local firms due to the local media, social interactions, or geographic proximity.[4] Furthermore, I find empirical evidence that the impact of distrust spillover is more pronounced when bank branches are in closer proximity to their affiliated investment advisory firms following the disclosure of their advisory misconduct.

I examine whether investment advisors' misconduct in a county abnormally reduces the deposits of their affiliated bank branches in that county and explore the channels through which depositors lose trust in such banks. Leveraging unique administrative data on business affiliations between U.S. Securities and Exchange Commission (SEC)-registered investment advisory (RIA) firms and Federal Deposit Insurance Corporation (FDIC)-insured banks in the United States from 2012 to 2021, I identify the affiliation links between RIAs and banks. I merge the affiliation data with comprehensive records of advisory misconduct and bank-branch-level administrative data on deposits to examine the impact of RIA misconduct on their affiliated bank branches. In addition, I use bank-county-level small business lending data from the Community Reinvestment Act to examine the negative externality in the bank loan market.

Conceptually, the revelation of RIA misconduct could have a positive or negative relation with the deposits of their affiliated banks. On the one hand, RIA misconduct updates investors' beliefs about risky assets, so an increase in the relative attractiveness of safe assets should increase bank deposits. Gurun et al. (2018) document the money inflow to bank deposits in the local communities that were exposed to the Ponzi scheme committed by Bernard Madoff. On the other hand, as Tirole (1996) shows, a key aspect of affiliation is that it produces collective reputation, and such group reputation directly determines individual reputation and vice versa. Thus, if the magnitude of reputation spillover dominates

[4] Coval and Moskowitz (1999), Grinblatt and Keloharju (2001), Ivković and Weisbenner (2007), Seasholes and Zhu (2010), Pool et al. (2015), Giannetti and Wang (2016), and Gurun et al. (2018) examine the informational advantage of local investors.

the increased incentive to relocate more funds to bank deposits as a safe haven, then the deposits in the banks affiliated with misconduct-revealed RIAs might decrease.

Ultimately, whether the revelation of advisory misconduct causes deposit withdrawals from affiliated banks is an empirical question. In this paper, I exploit within-county-year and within-bank-year variation to identify the relative magnitude of the impact on bank branches located in the same county as their affiliated RIAs whose misconduct is revealed, compared to other banks in the same county and the branches of the same bank located in other counties. Therefore, it is important to note that the magnitude of my estimates reflects the relative abnormal impact on bank branches exposed to the trust shock. The bank-year fixed effects control for any time-varying banks' strategic decisions regarding deposits to compete with other banks (e.g., Matutes and Vives (1996); Egan et al. (2017)). For instance, banks might strategically change their policy regarding deposits due to their expectations of the financial market, not due to the distrust shock from RIAs. As financial misconduct might be correlated with economic activity (e.g., Povel et al. (2007)), I include county-year fixed effects, which remove any local time-varying variation that systematically affects both the incentive to commit misconduct and the local deposit market.

I start by showing that, relative to the same bank's branches in other counties and other banks' branches in the same county, the deposits of bank branches located in the same county as their affiliated RIAs abnormally decrease by 11.5%-13.1% following the revelation of advisory misconduct committed by the affiliated RIAs. My findings also provide insight on the localized effects of collective reputation. I find that the magnitude of the abnormal withdrawals from banks depends on the distance from their nearest affiliated RIAs whose misconduct is revealed, meaning that banks that have closer proximity to their affiliated RIAs share more reputational risks. The localized effect of distrust spillover dies out within 100 miles, suggesting that social connections and local media play a role.

To evaluate the negative externality of distrust spillovers on the bank loan market, I examine changes in small business lending activity, which mostly rely on local bank branches (e.g., Becker (2007); Agarwal and Hauswald (2010); Nguyen (2019)). I find that bank branches located in the same county as their affiliated RIAs experience a significant abnormal decrease of 1.1%-3.6% in the total volume of small business loan originations, relative to branches of the same bank in other counties and other banks in the same county. These results are consistent with prior studies on information asymmetry in the small business loan market, which rely more on soft information for lower-credit borrowers, suggesting that small business borrowers experience asymmetric shocks from a contraction in the bank loan market (e.g., Petersen and Rajan (1994); Berger et al. (2017); Levine et al. (2020)).

Are my findings being driven by other unobservable variables that not only correlate with the timing of misconduct revelation but also affect the local bank deposit market? Admittedly, misconduct revelations may not occur randomly. For instance, RIAs might possess private information about their affiliated banks and adjust their expectations of the local economy accordingly. Moreover, unobservable factors correlated with changes in deposits may attract the attention of regulators and increase the likelihood of detecting misconduct in affiliated entities, such as RIAs. To address endogeneity concerns and establish the causal effect of advisory misconduct revelation on affiliated bank branches, I also employ a quasi-natural experiment: the 2003 late-trading mutual fund scandal. This scandal provides an ideal setting to study the distrust spillovers for several reasons. First, it involved the sudden detection of ongoing RIA misconduct by a whistleblower, and it created exogenous variation in misconduct revelation. Second, the misconduct was first revealed through a major national newspaper, enabling the identification of 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 the bank branches located in the same county as their affiliated RIAs involved in the scandal experienced abnormal decreases in deposits of approximately 11.8%-23%, relative to the same bank's branches in other counties and other banks' branches in the same county. Similarly, the volume of small business loans originated from such bank branches abnormally decreased by about 7.6%-11.4%. The larger economic magnitude of the estimates compared to the baseline results reflects the significant reputational damage observed in the mutual fund advisory industry (Lauricella (2014)). Notably, the magnitude is comparable to the net fund outflows of the scandal-involved mutual funds (McCabe (2009)).[5] These results suggest that the trust shock from RIA misconduct might be transmitted to their affiliated banks.

In unpacking the results, I document stark heterogeneity effects over the severity of RIA misconduct. I measure the severity of advisory misconduct in two ways. The first approach to measuring the severity captures the amount of monetary fines imposed on RIAs regarding the misconduct. I find that the effects of advisory misconduct on bank branch deposits and the origination of small business loans are more pronounced when monetary fines are larger. These findings suggest that depositors' response to RIA misconduct may be a function not simply of misconduct revelation itself but also of the perceived "seriousness" of the misconduct, under the assumption that more serious misconduct incurs higher fines. The second approach classifies misconduct into categories such as "transaction", "disclosure", "compliance" , and "others", based on the detailed contents of the allegations obtained from the reports, building on the methodology of Liang et al. (2020). I find that the spillover effects are strongest in transaction-related misconduct and consistent in other-related misconduct. Overall, these results are consistent with previous studies showing that severe misconduct induces a strong collapse of trust (e.g., Egan et al. (2019); Liang et al. (2020)).

To further explore mechanisms, I examine the characteristics of RIAs, banks, and local communities. Consistent with Gurun et al. (2018), I find that the spillover effects of advisory misconduct on bank branch deposits and the origination of small business loans are weakest among RIAs with a high concentration of individual retail clients, implying that a pre-existing level of trust from the local community provides a buffer to mitigate a reputational shock. I also find a significant effect for banks with a high uninsured deposit ratio, which aligns with studies indicating that uninsured depositors actively exert a form of market discipline and are prone to runs (e.g., Diamond and Dybvig (1983); Goldstein and Pauzner (2005); Iyer and Puri (2012); Egan et al. (2017)). Furthermore, I find that banks branches located in counties with high social norms experience significantly greater deposit outflows and lower origination volumes of small business loans following the revelation of misconduct committed by their affiliated RIAs, compared to those in other counties and

[5] McCabe (2009) documents that the scandal-involved mutual funds experienced a net annualized outflow of 10.4-12.6 percentage points more than other mutual funds following the scandal revelation.

other banks in the same county. To the extent that counties with high social capital exhibit low tolerance for financial misconduct (Martin-Flores (2024)), local communities with low tolerance for misconduct have significant withdrawals of deposits. Additionally, I find that, while the revelation of general RIA misconduct increases bank deposits, misconduct by bank-affiliated RIAs induces an additional negative impact on bank deposits. These findings provide evidence that depositors not only respond to reputational damage on banks transmitted from their affiliated RIAs, but they also view bank deposits as a safe asset.

This paper is related to the literature on how trust in financial institutions affects investor behavior. Guiso et al. (2008) shows that general trust impacts investor participation in the stock market. Similarly, Giannetti and Wang (2016) find that some households reduce stock market participation following revelations of corporate securities misconduct 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., Houge and Wellman (2005); Choi and Kahan (2007); McCabe (2009)). Similarly, Kostovetsky (2016) argues that mutual fund investors lose trust in funds and withdraw their investments after announcements 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). They identify distrust spillover within the investment advisory sector by exploiting the Madoff shock. By contrast, I focus on spillover across different financial industries where financial intermediaries are connected through affiliation networks. I leverage unique administrative data on the affiliation links of RIAs and comprehensive records of detected RIA misconducts. To my knowledge, this paper is the first to provide systematic evidence of distrust spillovers on banks from the affiliation network of financial intermediaries and establish causality by exploiting a quasi-natural experiment.

This paper also contributes to the growing literature on collective reputation. Despite earlier theoretical works on the framework of collective reputation (e.g., Tirole (1996); Levin (2009); Fishman et al. (2010)), empirical studies examining the financial intermediaries remain scarce. Much of these studies focus on spillovers among competitors in the same industry or utilizes small samples (e.g., Jonsson et al. (2009); Liu et al. (2015); Gurun et al. (2018); Bai et al. (2022); Galloway et al. (2023)). By contrast, I investigate whether the affiliation network, where financial intermediaries in different sectors are interconnected, encompasses the contagion risks of inter-sector reputation spillover among financial intermediaries by using the comprehensive records of regulatory actions in the financial advisory industry.

This paper further relates to the literature that finds evidence of market discipline in banking based on the 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); Egan et al. (2017)). In the same spirit, recent studies show market discipline relates to the non-financial information of banks. For instance, Iyer and Puri (2012) demonstrate that the local social network mitigates bank runs, and depositors with high uninsured deposits are more likely to withdraw them from banks. Hasan et al. (2013) examine market discipline based on bad rumors about banks, while Homanen (2022) show deposit withdrawals from banks that financed the 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 find large-sample evidence that banks might experience market discipline that is unrelated to their behavior or decisions.

This paper also contributes to the literature on the consequences of misconduct in the financial advisory industry. Egan et al. (2019) and Egan et al. (2022) demonstrate that misconduct results in critical penalties for advisers, and certain advisors repeatedly commit misconduct. Dimmock et al. (2018b) show that the occurrence of advisory misconduct increases co-workers' propensity to commit misconduct. Liang et al. (2020) find significant mutual fund outflows following the revelations of misconduct committed by the fund's management company. Moreover, several studies show significant fund outflows or changes in advisory contracts after the 2003 mutual fund scandal (e.g., Houge and Wellman (2005); Zitzewitz (2006); Choi and Kahan (2007); Warner and Wu (2011); Qian and Tanyeri

(2017)). Similarly, Gurun et al. (2018) identify money outflows from investment advisory firms after the Madoff investment scandal in 2008. Previous studies mainly focus on the direct consequences of misconduct on specific trust-collapsed entities or sectors and exploit a single event. By contrast, I focus on the inter-sector negative externalities of comprehensive investment advisory misconduct revelations on operational networks, where misconduct-revealed firms engage in business partnerships with other non-misconduct-revealed firms.

2. Institutional Setting

In the U.S., firms known as registered investment advisers (RIAs), often referred to as "financial advisers," are regulated by the SEC, and employ investment adviser representatives (IARs). The Investment Advisers Act of 1940 defines an "investment adviser" as "any person or firm that: (1) for compensation; (2) is engaged in the business of; (3) providing advice, making recommendations, issuing reports, or furnishing analyses on securities, either directly or through publications". (Securities (2013)). All investment advisers with more than $100 million in assets under management (AUM) are required to register with the SEC, or with state securities regulators if the AUM is less than $100 million, as mandated by the Investment Advisers Act of 1940.[6] About 87% of IARs are also registered as brokers, defined as "any person engaged in the business of effecting transactions in securities for the account of others," under the Securities Exchange Act of 1934.

Investment advisers in the U.S have a fiduciary duty, which mandates putting their clients' interests ahead of their own interests at all times. Ensuring that investment advisers operate under a fiduciary duty and investors' interests are protected is the first of the three missions that the SEC states as their role to protect the investing public and others who rely on U.S. financial markets.[7] As a crucial element of the fiduciary duty involves the identification and monitoring of conflicts of interest, the SEC requires de-

[6] Before 2012, when the Dodd-Frank Wall Street Reform and Consumer Protection Act was applied, the threshold to file with the SEC was $25 million.

[7] See https://www.sec.gov/about/mission for the description of the missions of the SEC.

tailed disclosure of any information of investment advisers regarding potential conflicts of interest, such as the industry affiliations.

In efforts to promote transparency and protect investors, investment advisers are mandated by the SEC to annually file a Form ADV, which includes detailed information about the firm, such as business practices, client base, compensation, financial industry affiliations, custodial practices, and regulatory actions. Additionally, whenever there are material changes to the information in Form ADV, advisers are mandated to promptly distribute updates to regulators and clients. For example, if a regulatory action is initiated against an adviser, the adviser should promptly distribute the details of the action, including the contents of the allegations, to regulators and clients.

To ensure that investors have access to the necessary details of potential conflicts of interest, the SEC requires detailed information about advisers' financial industry affiliations with "related persons" in the Form ADV. A "related person" is defined as "any firm or person that: (1) is under common control with the investment adviser" and "(2) has business dealings in connection with advisory services provided to clients, conducts shared operations, refers clients or business to each other, shares supervised persons or premises, or has relationships that might create a conflict of interest with clients." Item 7 of Form ADV requests that investment advisers provide information on their financial industry affiliations. It classifies financial industries into 16 categories, and investment advisers must report if they have any "related person" in any given industry.[8] Appendix Figure A.1 displays an excerpt of affiliation disclosure from EAGLE ASSET MANAGEMENT INC based on its Form ADV as of December 8, 2023.

Panel A of Table 1 displays the frequency of industry affiliations reported in annual Form ADV filings from 2012 to 2021. The industry affiliations are not mutually exclusive, as each investment adviser might have affiliations with multiple industries at a given time. Roughly one in fifteen firms are affiliated with a banking institution. Given that almost half

[8] The list includes broker-dealers, other investment advisers, municipal advisors, security-based swap dealers, swap participants, commodity trading advisors, futures commission merchants, banking or thrift institutions, trust companies, accounting firms, law firms, insurance companies, pension consultants, real estate brokers, limited partners excluding pooled investment vehicles, and limited partners of pooled investment vehicles.

of the assets in the advisory industry are managed by advisors affiliated with banking institutions (see Figure 1), the fact that 6% of RIAs historically report their industry affiliation with banks implies that RIAs affiliated with the banking industry are the major players in the advisory market and have influential market power in the intermediary market. Panel B reports a partial list of affiliations with banking institutions reported by RIAs.

3. Data

I employ four microlevel data sets for the analyses: mandatory disclosure filings from RIAs, deposit amount at the bank branch level, small business lending data at the bank-county level, and the interest rates of retail deposit products at the 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 is sourced from Form ADV. Form ADV includes general information about business operations, client base, ownership, affiliations, and historical disciplinary actions. I hand collect the historical filings of Form ADV from the SEC.

To leverage the geographic dispersion of RIAs, I gather information on branch office locations from Schedule D in Form ADV, which mandates a list of branch offices to be provided.[9] I collect the list of affiliates from Item 7.A of Schedule D, which includes firm-level identification information of advisors' affiliated entities. As this information is available from 2012, my sample comprises RIAs from 2012 to 2021. To link affiliation data to deposit data, I further match it with the Summary of Deposits from the FDIC using the name and address of banks.[10]

[9] SEC requires reporting 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 recognizable in the local community, which is the mechanism of the main results.

[10] Approximately 83% of banking institutions reported as having affiliations with RIAs are matched with institutions in the FDIC Summary of Deposits database.

I collect historical disciplinary actions against RIAs from the regulatory action disclosure reporting page in Form ADV.[11] This section includes the name of the regulatory agency, initiation date of sanctions, amount of the penalty, and a detailed contents of alleged misconduct. It covers comprehensive regulatory actions against RIAs. Figure 2 displays the time-series frequency of RIA misconduct cases detected by regulatory agencies. I date each misconduct disclosure with the initiation date of the allegation based on Form ADV filings, assuming that this date is when the public became aware of the violation, a method commonly used in the literature (e.g., Egan et al. (2019); Liang et al. (2020)). Panel A of Table 2 presents the distribution of types of principal products involved in RIA misconduct. Excluding the 'Other' and 'No product' categories, equity (10.21%) is the most common investment product involved in misconduct, followed by insurance (7.81%). This distribution aligns with the most common investment products held by households, including stocks, insurance, annuities, and mutual funds (Campbell et al. (2010)). Panels B and C display the distribution of initiated regulatory agencies and principal sanctions in RIA misconduct cases, respectively. Appendix Table A.2 presents a partial list of advisory misconduct cases reported by RIAs.

Furthermore, following Liang et al. (2020), I assign the following types of RIA misconduct into each RIA misconduct case: transaction, disclosure, compliance-related, and other misconduct by analyzing the detailed contents of the allegations obtained from the Form ADV filings.[12] Transaction-related misconduct reflects malfeasance in the investment trading activity of RIAs, such as excessive charges of investment fees, unauthorized investment transactions, or unreasonable investment recommendations to clients. Disclosure-related misconduct includes cases such as the omission of key facts, misrepresentation, or incorrect advertisement. Compliance-related misconduct refers to cases where RIAs fail to comply with regulatory requirements such as registration, licensing, or proper governance structure. Panel D of Table 2 presents the frequency of miscon-

[11] I exclude cases where no violation was found ('dismissed', 'vacated', or 'withdrawn') and ongoing cases ('on appeal' or 'pending').

[12] The detailed methodology of misconduct classification is described in Liang et al. (2020).

duct types and shows that compliance-related misconduct is most common, followed by disclosure, transaction, and other types.

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 2012 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 into the movement of deposits, I utilize two levels of deposits to measure the impact on the level of deposits at banks affiliated with misconduct-revealed RIAs. First, I utilize individual branch deposits for the main analysis and leverage their geographic dispersion and affiliated RIAs. This approach allows for a focus on hyperlocal effects among regional communities and facilitates the sorting out of any confounding effects 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 misconduct affects the local (county) deposit market and exploit the heterogeneous characteristics within such misconduct. My final sample contains 27,978 county-year observations.

To examine the movement of deposit rates, I utilize granular branch-level deposit rate quotes provided by RateWatch. RateWatch conducts weekly surveys to collect branch-level deposit rates on various types of products. The data covers approximately 78% of branches in the SOD data during the period from 2001 to 2021. Given the focus on deposit movement, I concentrate on general retail deposit products with 6-month and 12-month maturities for $10,000 certificates of deposit (CD), as well as money market (MM) accounts with balances of $10,000 and $25,000. These products are among the most commonly used retail deposit rates in the literature (Drechsler et al. (2017); Ben-David et al. (2017); Cortés and Strahan (2017); Jacewitz and Pogach (2018)). Since my deposit sample is annual, I aggregate weekly deposit rates to an annual frequency for each branch.

Table 3 reveals that approximately 5% of the branch-year sample experiences incidents of misconduct committed by their co-located affiliated RIAs. The average deposit rate for a 12-month CD account with a balance of $10,000, which represents the most widely available rates, is about 0.29%. The average branch-level deposit in my sample is $133 million with considerable variation with a standard deviation of $2.4 billion. Most bank branches are categorized as 'Brick & Mortar office' offices.

3.3 Small business lending data

My measure of small business lending comes from the Community Reinvestment Act (CRA) small business lending data provided by the Federal Financial Institutions Examination Council (FFIEC). Under the CRA, all banking institutions regulated by the Office of the Comptroller of the Currency, the Federal Reserve System, or the FDIC, and meeting asset size thresholds are required to report the origination information of small business loans each year at the county level, based on the physical locations of the borrowing firms. These data include all newly originated commercial or industrial loans (C&I) of $1 million or less from banks that meet the asset size threshold established annually by the FFIEC.

The CRA data includes information on the total volume of originated loans in each borrowers' income group (low, moderate, middle, and high) that a bank makes in a county at different loan size categories. Each income group is defined by its relative ratio to the median family income (MFI) of each Metropolitan Statistical Area (MSA). The low-income group includes individuals with incomes less than 50% of the area median income, the moderate group includes incomes between 50% and 80% of MFI, the middle group is between 80% and 120% of MFI, and the high-income group includes individuals with incomes 120% or more of MFI. To evaluate changes in the overall amounts of small business loan originations across borrower income groups within a given bank-county-year, I aggregate the amounts to the bank-county-income group-year level.

I merge the CRA loan data with the SOD data, which includes location information for all bank branches. Since bank loan markets are geographically segmented and small business are most likely to borrow from their local bank branches (e.g., Petersen and Rajan (2002), Berger et al. (2005), Becker (2007), Agarwal and Hauswald (2010), Berger et al. (2017), and Nguyen (2019)), I assume that small business loans from a bank in a given county are originated from the branches of the bank located in that county. Panel B of Table 3 presents additional information related to the origination amounts of small business loans. My final sample matches CRA loans to counties where FDIC bank branches are located.

3.4 Additional Data Sources

I collect county-level demographic information from the U.S. Census to construct control variables from 2012 to 2021, including median age, household median income, and population size. Additionally, I utilize a social capital measure for U.S. counties from the Social Capital Project by the Joint Economic Committee of the U.S. Congress. This measure is calculated from principal component analysis based on various variables, such as the share of births to women who were unmarried, share of own children living in a single-parent family, registered non-religious non-profits, religious congregations, election vote turnout, mail-back response rate, and violent crimes from data collected between 2006 and 2016.[13] Appendix Figure A.2 depicts the geographical distribution of the social capital index across the U.S. at the county level. Panel C 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 for a single household in a county is $50,372, and the average median age is 41 years-old.

[13]The county-level measures of social capital are limited, and this measure was constructed to overcome the shortcomings of previous sources of social capital indexes, such as the estimates from Pennsylvania State University's Northeast Regional Center for Rural Development. See U.S. Congress, Joint Economic Committee, Social Capital Project titled "The Geography of Social Capital in America." Report prepared by the Vice Chairman's staff, 115th Cong., 2nd Sess. (April 2018). See https://www.jec.senate.gov/public/index.cfm/republicans/sci/ for a detailed description of the methodology used to construct the social capital index at the county level and its several advantages over previous sources of social capital indices.

4. Methodology

Identifying whether local residents lose trust in banks affiliated with misconduct-revealed RIAs is challenging due to various unobservable factors that may affect both bank deposits and the revelation of RIA misconduct. To address this potentially confounding variation, I use a novel strategy that exploits granular multiple fixed effects in the baseline analysis. A bank branch in my sample is classified as a treatment bank branch if the branch operates in the same county as their affiliated RIA when its misconduct is revealed. To assess the impact of RIA misconduct revelation on their affiliated banks, I estimate various forms of the following model:

$$Deposits_{i,b,c,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \beta Post_{i,b,c,t} + \varphi \boldsymbol{X_{i,t}} + \varepsilon_{i,t}\,, \tag{1}$$

where $Deposits_{i,b,c,t}$ is the amount of deposits for branch i of bank b located in county c in year t. $Post_{i,b,c,t}$ equals one if the treatment bank branch i of bank b is located in the same county c as the RIA affiliated with bank b when misconduct is revealed, and the misconduct committed by the RIA has been revealed to the public before or at year t. The control variable, $X_{i,t}$, includes the types of services provided by branch i during year t. I cluster standard errors by bank branch, allowing for correlation of errors over time within each of the bank branches.

I aggregate RIA misconduct cases at the treatment bank branch-county-year level. In instances where a bank branch is subjected to repeated treatment through unrelated misconduct cases, I keep the earliest treatment year. Thus, I consider the treatment as occurring when the revelation of misconduct is formally disclosed by a regulatory agency.

Next, I employ Poisson regression for the main analysis. The main dependent variable is bank deposits, *Deposits*, at the branch level. Figure A.3 in the Appendix shows the skewed distributions with masses of values of zero for branch deposits. Recent econometric studies have raised concerns about using constant-adding log-linear estimation when the sample includes positive integers with a concentration of observations at zero. Cohn et al. (2022) demonstrate that a fixed-effects Poisson model produces unbiased estimates. Given that the deposits in my sample consist of positive integers with masses of values at zero, I use Poisson regression to obtain unbiased estimates of deposit movements. I also verify that the results are robust to different empirical specifications using the main outcome variables in constant-adding logs (Panel A of Appendix Table A.3).

To mitigate various potentially confounding variations, the Eq. (1) also includes bank branch, county-year, and bank-year fixed effects. First, the bank branch fixed effects, denoted as 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. The inclusion of λ_i ensures that the key independent variable is the within-bank-branch change in deposit amount, rather than its level.

Second, the county-year fixed effects, $\delta_{c,t}$, remove variation across bank branches located in the same county in a given year. Removing geographic heterogeneity is crucial, as demonstrated by Parsons et al. (2018), who highlight the significance of unexplained factors attributable to the local culture of financial misconduct. Additionally, the local economic situation may impact bank deposits. By including these fixed effects, I control for the average effect of local economic factors on deposits. In general, misconduct in the region may be correlated with the local economy, but the changes in its time-series average are removed by the inclusion of these fixed effects. Furthermore, these fixed effects also account for the time-varying demographic characteristics of the county.

Third, the bank institution-year fixed effects, $\eta_{b,t}$, remove the time-invariant characteristics of the banks that control the branches, as well as time-varying bank characteristics, such as changes in the bank's deposit strategies or any bank-specific shocks. Previous studies show that banks strategically compete for deposits (e.g., Matutes and Vives (1996); Egan et al. (2017)), highlighting the importance of strategic policies in the bank deposit market. Moreover, removing bank effects is crucial as deposits play a major role in credit decisions in the banking industry. For instance, including $\eta_{b,t}$ effectively eliminates time-varying variations from monetary shocks in credit markets specific to individual banks (e.g., Berlin and Mester (1999); Kashyap et al. (2002); Gatev et al. (2009)).

The coefficient of interest in Eq. (1) is β. This coefficient identifies the relative impact of RIA misconduct on their affiliated bank branches located in the same county. In this specification, the variation in the bank branches is limited to the time-series change for an individual bank branch relative to the average time-series change of other banks located in the same county in that year and the same bank located in other counties in that year. Therefore, it is important to note that the magnitude of β measures the relative impact on bank branches that are exposed to trust shock. If a reduction in trust in RIAs causes investors to move deposits relatively more out of those misconduct-revealed RIA-affiliated banks, compared to other banks in the same county and the branches of the same bank in other counties, then β should be negative, indicating that depositors who are more exposed to the RIA misconduct abnormally withdraw their deposits from banks affiliated with those RIAs following misconduct revelations.

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

$$Deposits_{i,b,c,t} = \lambda_i + \delta_{c,t} + \eta_{b,t} + \sum_{\tau=-4}^{4} \phi_\tau D^{\tau}_{i,b,c,t} + \varphi \boldsymbol{X_{i,t}} + \varepsilon_{i,t}\,, \tag{2}$$

where $D^{\tau}_{i,b,c,t}$ is equal to one if branch i of bank b is located in the same county c as their affiliated RIAs when their RIA misconduct is revealed and the year t is exactly τ years after (or before if τ is negative) the revelation of the RIA misconduct. Following the event study analyses by McCrary (2007), Borusyak and Jaravel (2017), Atkin et al. (2018), and Higgins (2022), 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 misconduct 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, $X_{i,t}$, includes the types of services provided by branch i during year t.

Similar to Eq. (1), Eq. (2) includes multiple sets of fixed effects. County-year fixed effects, $\delta_{c,t}$, control for the time-variant characteristics of the bank deposit market in the county, while the bank-year fixed effects, $\eta_{b,t}$, controls for time-varying bank polices that impact the deposit market. Note that the branch fixed effects also remove the time-invariant characteristics of branches, including the unique relationship with depositors. I cluster standard errors by bank branch, allowing for correlation of errors over time within each of the bank branches.

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 misconduct revelation. If bank deposits exhibit a systematic decrease prior to misconduct exposure, it may indicate that the economic situation correlates with the movement of bank deposits, which might increase incentives for specific RIAs, which coordinate with the bank, to commit advisory misconduct. Thus, Eq. (2) allows me to alleviate potential concerns over the parallel trend assumption.

5. Baseline results

In this section, I examine the impact of RIA misconduct revelations on the branches of banks affiliated with the misconduct-revealed RIAs. I leverage comprehensive records of enforcement actions against RIAs and affiliation links between banks and RIAs from 2012 to 2021.

5.1 Bank deposits

Panel A of Table 4 shows that bank branch deposits are negatively associated with the revelation of misconduct 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 the revelation of misconduct by an RIA has a negative correlation with the deposit inflow of their affiliated banks. The results of the main specification in column (2) show that the deposits of treatment bank branch decrease by approximately 11.5% ($e^{-0.122} - 1 \approx -0.1149$) following the revelation of misconduct committed by their affiliated RIA located in the same county.

Note that the specification includes county-year fixed effects and bank-year fixed effects. 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. Therefore, I interpret the magnitude of coefficients in Panel A of Table 4 as abnormal deposit movements, not the changes in raw level of deposits.

One concern with using the full sample that includes counties that never experienced RIA misconduct is that the treated bank branches might have totally different unobservable local factors affecting the culture of financial misconduct than the untreated bank branches (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 that are exposed to bank-affiliated RIA misconduct at least once during my sample period. Columns (3) and (4) report the estimates of Eq. (1) on this subsample. Similar to columns (1) and (2), the coefficients indicate that the volume of deposits decreases by approximately 11.9% ($e^{-0.127} - 1 \approx -0.119$) following the misconduct occurrences.

Yet, there is still the concern that the treatment groups might have a decline in deposits even before the treatment shock. Moreover, both bank deposits and misconduct 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 in the SOD sample from 2012 to 2021. The omitted period is the year prior to the revelation of RIA misconduct.

Figure 3 shows no evidence of a differential trend between branches prior to misconduct revelations. For $\tau < 0$, all treatment coefficients never reach significance; 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 misconduct. 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 misconduct detection by regulatory agencies.

As discussed above, following banks' exposure to the revelation of misconduct committed by their affiliated RIA, the deposits of their bank branches decrease significantly if they are located in the same county as their affiliated RIA. Figure 3 shows that Deposits decline by about 5% in the year of the event and then gradually dissipate, reaching insignificance three years after the revelation. Collectively, the results imply that local residents exposed to RIA misconduct withdraw their deposits from banks affiliated with such trust-collapsed RIAs, which provides support for the channel of distrust spillover.

To better understand the localized effect of a trust shock, I explore the heterogeneous effects on bank branches based on the distance between the branch and the misconduct-revealed RIA affiliated with the bank. Prior studies, such as Pool et al. (2015) and Gurun et al. (2018), show that investors' investment decisions exhibit collective patterns through local networks or communities, and these patterns depend on the degree of geographical proximity. Thus, a longer distance between a bank branch and its affiliated RIA will have a weaker impact on bank deposits, as social interactions or trust may be harder to establish among people over long distances. I use the specification from column (2) in Table 4 and define the *Post* indicator variable based on different distances between the ZIP Code of the bank branch and its nearest affiliated RIA whose misconduct is revealed. Specifically, I include a modified *Post* variable that indicates whether the affiliated RIA is within 1 mile, 1 to 10 miles, 10 to 30 miles, 30 to 60 miles, 60 to 100 miles, or 100 to 200 miles of the ZIP Code.

Figure 4 displays the coefficient estimates for these modified Post variables based on the distances. The figure demonstrates that deposits abnormally decrease as the distances between bank branches and their affiliated RIAs decrease. Banks with their nearest affiliated RIA within 1 mile experience an abnormal deposit outflow of -9.4% following the disclosure of misconduct committed by those RIAs, whereas those with their nearest affiliated RIAs located within 10 to 30 miles show a deposit outflow of -6.4%. Banks with a distance greater than 100 miles to their nearest affiliated RIA do not experience abnormal deposit outflows. Thus, these findings suggest that the spillover effect is transmitted through social interactions or local media, suggesting that local communities play an important role in mediating the strength of reputational spillovers.

However, these results are quite hard to compare to Gurun et al. (2018), who examine the Madoff scandal, which was a case of advisory misconduct 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 misconduct was detected. As the RIA in that case reported no affiliation with any banks, no banks likely experienced distrust spillover. Thus, to completely understand the heterogeneous impact of investment advisory misconduct on banks and compare my results to Gurun et al. (2018), in Section 7.5, I directly compare the impacts of bank-affiliated RIA misconduct to those of misconduct from RIAs not affililated with banking institutions.

5.2 Small business lending

In this section, I examine changes in small business lending activity at those bank branches following the RIA misconduct revelation. Since deposits are the main source of lending activity from banks to local firms and small businesses primarily rely on local bank branches and soft information to initiate new loans (e.g., Becker (2007); Agarwal and Hauswald (2010); Nguyen (2019)), I assume that the amounts of CRA loan originations filed by institutions at the county level are sourced from the local bank branches. Hence, a contraction in deposit supply is known to lead banks to contract lending (Drechsler et al. (2017)). To examine the effects of distrust spillover on the lending decisions of banks, I use CRA data from 2012 to 2021 to analyze the change in the total volume of CRA loans originated from treated bank branches around the trust shock.

The Eq. (3) in this section follows the same structure as those for the bank deposit data, although I now use bank-county-income group-year observations. Similar to Eq. (1), I estimate the following Poisson regression:

$$CRA\ Loan\ Amt_{b,c,g,t} = \lambda_{b,c} + \delta_{c,t} + \eta_{b,t} + \varphi_g + \beta Post_{b,c,t} + \varepsilon_{i,t}\,, \tag{3}$$

where $CRA\ Loan\ Amt_{b,c,g,t}$ is the origination amount of CRA loans for bank b in county c allocated to borrower income group g in year t. The main variable of interest is the *Post* indicator, which equals one if (1) bank branch(es) located in the same county as their affiliated RIA whose misconduct is revealed, and (2) the revelation year is before or during the given year t. I cluster standard errors by bank-income group and year level. Similar to the multiple granular fixed effects included in Eq. (1), my small business lending regression includes fixed effects for bank-county, bank-year, county-year, and income group. Additionally, similar to bank deposits, the origination amounts of CRA loans at the bank-county level show skewed distributions with masses of values of zero (see Figure A.4 in the Appendix), as not every bank originates CRA loans in every county. Due to recent concerns about using constant-adding log-linear estimation when the sample includes a concentration of observations at zero (Cohn et al. (2022)), I employ Poisson regression, which is known to provide unbiased estimates. I also verify that the results are robust to different empirical specifications using the constant-adding log-linear estimation (Panel B of Appendix Table A.3).

Panel B of Table 4 reports estimates of Eq. (3) on the origination amount of CRA loans, which follows the same general format as Panel A of Table 4. Columns (1) and (2) show the results for the full sample of counties, while columns (3) and (4) show the results for the counties where treated bank branches are located. I find that the origination amounts of small business loans at bank branches are negatively associated with the revelation of advisory misconduct committed by their affiliated RIAs located in the same county. The coefficient estimates on the $Post_{i,t}$ indicator variable are significantly negative, suggesting that misconduct by an RIA has a negative correlation with the origination of small business loans. The results of the main specification in column (2) show that the origination amounts from treated bank branches abnormally decrease by approximately 2.9% ($e^{-0.029} - 1 \approx -0.0286$) following the revelation of misconduct committed by their affiliated RIA located in the same county.

To address the concern of unobservable local determinants that might affect both local economy and the culture of financial misconduct (Parsons et al. (2018)), I also use a subsample that only contains the counties where treated bank branches are located during my sample period. Columns (3) and (4) report the estimates of Eq. (3) on this subsample. Similar to columns (1) and (2), the coefficients indicate that the volume of deposits decreases by approximately 3% ($e^{-0.030} - 1 \approx -0.03$) following the revelation of RIA misconduct.

These findings are consistent with the literature on asymmetric information costs for small firms in the credit market (e.g., Petersen and Rajan (1994); Berger et al. (2017)). Levine et al. (2020) argue that banks rely more on soft information to issue loans to small-sized firms, implying additional costs to process soft information compared to hard information (such as collateral or tangible assets).

To further investigate the dynamic impacts of investment advisory misconduct on small business loans, I estimate the following Poisson regression:

$$CRA\ Loan\ Amt_{b,c,g,t} = \lambda_{b,c} + \delta_{c,t} + \eta_{b,t} + \varphi_g + \sum_{\tau=-4}^{4} \phi_\tau D^\tau_{b,c,t} + \varepsilon_{i,t}\,, \tag{4}$$

where $D^\tau_{b,c,t}$ is equal to one if a branch of bank b is located in the same county c as their affiliated RIAs when their RIA misconduct is revealed and the year t is exactly τ years after (or before if τ is negative) the RIA misconduct revelation. I cluster standard errors by bank-income group and year level.

Figure 5 reports the coefficient estimates and confidence intervals of Eq. (4) on the total dollar volume of newly originated CRA loans. I find that loan origination volume shows a significant downward trend since the event year and does not reverse after the misconduct revelation. Taken together, these findings provide evidence that the revelation of RIA misconduct has a significantly negative externality on the small business loan market. These results are consistent with the effects of a contraction in deposit supply on banks' lending activity (Drechsler et al. (2017)).

6. Identification

As discussed earlier, it remains challenging to identify the causal impact of RIA misconduct on bank deposits. The key endogeneity concern is that of omitted variables that are correlated with both the bank deposits and the revelation of misconduct committed by 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 RIA-affiliated banks. To establish the causal link, I need to generate an exogenous shock to misconduct revelation, while the shock should be unrelated to the decisions of depositors and RIAs.

In this section, I exploit the quasi-natural experiment of the 2003 mutual fund scandal (MFS) to generate exogenous variation in misconduct revelation to the public. I employ a difference-in-differences (DiD) approach for my identification strategy. I also use an event study approach. I study deposit movements and small business loan originations in banks 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 and banks' loan activities.

6.1 Institutional background

On 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 others. 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 widespread in the industry. The 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 plausibly exogenous variation in RIAs' misconduct revelation that is irrelevant to the local deposits market or the misconduct-revealed firms' condition.

I can identify the exact date of public recognition of the misconduct. 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 misconduct-revealed 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.4 provides the list of mutual fund families involved in the scandal, initial news data of the misconduct, the abusive trading strategies they employed, the regulatory agencies involved, and the parent company of the main advisor for each mutual fund family.

6.2 Identifying treatment banks

To identify the causal impact of misconduct revelation 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.4 and link them with the 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 links are 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 treatment bank branches as those that are located in local communities significantly exposed to the scandal. Specifically, I require that (1) the bank is on the list of parent firms from Appendix Table A.4 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 the 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 treatment counties if there is any treatment bank branches in the county.

Similar to the columns (3) and (4) of Table 4, I conduct additional analysis on those treatment 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. Appendix Figure A.5 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.

6.3 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 6.2 from 2000 to 2007. The regressions follow the same structure as those for the baseline results (Table 4), although I now use a different sample of branches affiliated with RIAs involved in the 2003 MFS.

The results are reported in Panel A of 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 19.3% 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 columns (3) and (4) in Panel A of Table 5 is similar to the Eq. (1) 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 22.9%, which is more severe than the results from the whole sample. Anecdotal evidence suggests that the larger economic magnitude of the estimate than the baseline results reflects the largest declines to date in reputations that the scandal had induced in the mutual fund advisory industry (Lauricella (2014)). Notably, the size of the magnitude is comparable to the net fund outflows of MFS-involved mutual funds. McCabe (2009) documents that MFS-involved mutual funds experienced a net annualized outflow of 10.4%-12.6% relative to other mutual funds following the scandal revelation. This implies that the magnitude and persistent of bank deposit outflows depends on the severity of the trust shock occurred from the misconduct.

I next address the concern that treatment 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.[14] The omitted period is the year prior to the revelation of MFS by RIAs. Estimates are displayed in Figure 6.

Figure 6 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 $\tau < 0$, the treatment coefficients are not significant. Similar results to the baseline (panel B of Table 4) 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 discussed in Section 6.1.

To test whether the documented effects have negative externalities on the bank loan market, particularly on small business lending activity that mostly relies on local bank branches (Becker (2007); Agarwal and Hauswald (2010); Nguyen (2019)) and soft information for lower credit borrowers (Petersen and Rajan (1994); Berger et al. (2017); Levine et al. (2020)), I estimate Eq. (3) on the origination amounts of small business loans by the income group of borrowers from 2000 to 2007. I cluster standard errors by bank-income group and year level. The results are reported in Panel B of Table 5. I find that the total origination amounts of small business loans from the treatment banks show significant abnormal declines of 7.6%-11.4%, relative to other banks in the same county and the same banks in

[14]Since the sample period at $\tau = 3$ mainly includes observations from the 2008 financial crisis, I bin the years after $\tau = 3$ and before $\tau = -3$ to alleviate any concerns due to its impact on banks.

other counties. Similar to the results on deposits, the magnitudes are about 2-3 times larger than the baseline results due to the significant trust shock induced by the scandal.

Figure 7 shows the coefficients from estimation of Eq. (4) on the CRA sample using the same treatment sample as for Figure 6. The omitted period is the year prior to the revelation of MFS by RIAs and the estimates are displayed in Figure 7. I find little evidence of differential pretrends between treatment and control bank branches. Bank branches exposed to MFS show a significant decrease in the origination of small business loans after the revelation of the scandal involving their affiliated advisors.

Overall, the main results suggest that an exogenous increase in the revelation of misconduct committed by fraudulent RIAs induces abnormal deposit withdrawals in banks affiliated with these RIAs. This is consistent with a negative causal effect of RIA misconduct revelations on the deposits of their affiliated banks. Moreover, these effects induce negative externalities on banks' lending activities, especially on the origination of small business loans.

7. Mechanisms

Important questions remain regarding the mechanism behind these effects. In this section, I leverage comprehensive records of regulatory actions against RIAs from 2012 to 2021 and explore heterogeneous effects by the severity of misconduct, the clientele base of RIAs, the uninsured deposit ratio of banks, and the social capital of local communities. I also directly compare the impact of misconduct by bank-affiliated RIAs to the cases of general RIA misconduct revelation events.

7.1 Misconduct characteristics

I first explore differential responses by the severity of RIA misconduct. I measure the magnitude of the severity in two ways. The first approach to measuring the severity of misconduct captures the amount of monetary fine imposed on a RIA in a given year. This measure broadly captures the severity of misconduct, under the assumption that more serious misconduct incurs higher fines. I interact the *Post* indicator variable in Eq. (1) and (3) with the amount of monetary fines (in $100 millions) imposed on RIAs.[15]

Panel A of Table 6 shows that spillover effects are more pronounced when the fines imposed on an RIA are larger. Columns (1) and (2) show the results for bank branch deposits, while columns (3) and (4) show the results for the origination amounts of small business loans from the treatment bank branches. In the regressions for columns (2) and (4), I further restrict the sample to include counties where the treatment bank branches are located during the sample period. All specifications in Panel A consistently show statistically significant coefficients at the 1% level. Taking the standard deviation of *FineAmount* of 3.78, fines one standard deviation larger than average result in a 8% ($e^{-0.022\times3.78} - 1 \approx -0.08$) decrease in deposits for treatment bank branches from column (2). When examining its externalities on small business loan originations, I find that the origination volume of small business loans from treatment bank branches shows a more pronounced decrease when the advisory misconduct is more severe. In column (5) of Panel A, fines one standard deviation larger than average result in a 4.1% ($e^{-0.011\times3.78} - 1 \approx -0.041$) decrease in the origination amounts of small business loans from treatment bank branches.

The second approach I use measures the type of misconduct. Building on Liang et al. (2020), I assign the following categories into each RIA misconduct case: transaction, disclosure, compliance-related misconduct, and others based on the texts of the allegation contents obtained from the Form ADV filings. If misconduct cases relate to investment transaction activity, for instance "market timing" or "late trading" that were widely investigated during MFS, I assign the value of one for the indicator variable of *Transaction*. Similarly, I assign a value of one for misconduct cases if the detailed contents of allegations relate to information disclosure (fund operation) to the indicator variable of *Disclosure* (*Compliance*). The rest of the misconduct cases are classified as *Other*. As each case can involve multiple types of misconduct, the types of RIA misconduct are not mutually exclusive. The distribution of misconduct type is displayed in Panel D of Table 2.

[15] Appendix Figure A.6 displays the distribution of fines. The median fine for RIA misconduct is $75,000, and the mean fine is approximately $65,000,000. Therefore, the right-skewed distribution of monetary fines implies that the degree of misconduct is substantially severe, and the misconduct likely captures the wrongdoing of RIAs.

To better understand the heterogeneous effects by misconduct type, similar to Panel A of Table 6, I interact the *Post* indicator variable in Eq. (1) and (3) with *Transaction*, *Compliance*, *Disclosure*, and *Other* indicator variables.

In Panel B of Table 6, columns (1) to (3) show the results for the full sample of counties and columns (2) to (4) show the results for the counties that ever experienced bank-affiliated RIA misconduct. Most of the specifications consistently show that the negative effects of RIA fraud revelations on their affiliated banks stem from transaction-related misconduct, resulting in decreases in deposits (columns (1) and (2)). In column (2) of Panel B, the estimate on $Post \times Transaction$ indicates that misconduct classified as transaction-related decrease deposits by 20.9%. Furthermore, other-related misconduct consistently show a negative impact on bank deposits and the origination amounts of small business loans. The coefficient on $Post \times Other$, non-classified misconduct, shows an 18.9% decrease in deposits (column (2))and 7.2% decrease in the origination of small business loans (column (4)).[16] These results are consistent with the view that investors or households react more to misconduct that is likely to directly harm the clients, rather than simply clerical errors or mistakes. Egan et al. (2019) examine the impact of RIA misconduct disclosure and find that severe misconduct is associated with higher penalties to individual investment advisors. Taken together, the results suggest that depositors' responses and their externalities on bank lending activities may be a function of not only the revelation of misconduct per se, but also the perceived severity of the misconduct.

7.2 Advisor characteristics

Nearly all financial advisers advertise their services based on trust, experience, and dependability, rather than on past performance (Mullainathan et al. (2008)). Gennaioli et al. (2015) demonstrate that investors' trust in their asset managers plays an important role

[16] One example of other-related misconduct is the FINRA enforcement action against Citigroup Global Markets Inc. in 2014. The RIA steered its research analysts to offer favorable research coverage to certain firms. The monetary fine imposed on the RIA was $55 million. This also implies substantial unfair practices that harm investors' trust.

in the operations of the managers, and suggest that high trust capital from their clients might provide a buffer to mitigate negative shocks on managers.

In this section, I examine how trust capital from clients affects the magnitude of RIA distrust shock on its affiliated banks. Gurun et al. (2018) observe that a greater concentration of individual clients is much less likely to experience the effects of trust shock, and implies the concentration of individual clients as the proxy of the amount of trust capital in RIAs.[17] I use the ratio of retail clients—individuals other than high net worth individuals—among the total clientele base for the treatment RIAs in the earliest treatment year from Form ADV filings and create indicator variables for each quartile based on this ratio at the given year. Then, I use the specification for column (2) of Table 4 and interact the *Post* variable with indicator variables for whether the misconduct-revealed RIA is in each quartile of the ratio of retail clients during the year of the earliest treatment year. The coefficient estimates on these indicators, interacted with the *Post* indicator, are plotted in Figure 8.

The plot (A) of Figure 8 shows that the abnormal withdrawals of bank deposits abnormally decreases as their affiliated RIA has a high ratio of retail clients. Banks affiliated with RIAs in the lowest quartile of the individual client ratio experience average abnormal outflows in deposits of approximately 22%, while those in the highest quartile do not experience significant abnormal deposit outflows. The fact that the magnitude of outflows is monotonically decreasing as RIAs have a higher ratio of retail investors suggests that the pre-existing level of trust that has been accumulated between RIAs and its clients plays an important role in reducing the spillover of the trust shock when the RIA misconduct is revealed to the public.

I also explore the documented effects on the origination of small business loans. I interact the *Post* indicator in Eq. (3) with indicator variables for each quartile based on the ratio of retail clients. The estimates of the interacted coefficients are displayed in plot (B) of Figure 8. The figure shows that the negative relationship between the ratio of retail clients and the origination amounts of small business loans is largest among the lowest

[17] Gurun et al. (2018) show that RIAs with a high concentration of individual clients are more likely to provide financial planning services, and less likely to charge performance-based fees or hold custody of client assets.

quartile of the retail client ratio. Notably, the magnitude of this negative correlation monotonically decreases as the ratio of retail clients increases, even though the largest quartile shows a slightly higher negative magnitude than the third quartile and has higher standard errors. This is also consistent with Levine et al. (2020), who find that small business loan borrowers heavily rely on soft information and are likely to be highly elastic to credit supply contractions. This suggests that the high trust capital of RIAs prior to their revelation of misconduct plays a significant role in buffering the negative externalities of trust shocks from advisory misconduct on their affiliated banks.

7.3 Bank characteristics

Uninsured depositors actively monitor the bank risks and exert a form of market discipline on the banks (e.g., Diamond and Dybvig (1983); Diamond and Rajan (2001); Goldstein and Pauzner (2005); and Iyer and Puri (2012)). Egan et al. (2017) document that uninsured depositors are significantly sensitive to bank risks and prone to withdraw deposits, creating instability in the banking sector. Thus, bank branches with a higher ratio of insured deposits might experience stronger deposit withdrawals following the revelation of misconduct by affiliated RIAs. Unfortunately, any information regarding uninsured deposits is not available at the bank branch level. Instead, I obtain bank-level quarterly estimates of uninsured deposit levels from bank call reports, and use second quarter estimates as yearly observations to match with SOD, which measured deposit amounts as of June 30 of each year. I then calculate the ratio of uninsured deposits to total deposits and refer it as the *Uninsured Deposit Ratio*.

I interact the *Post* indicator variable in Eq. (1) with *Uninsured Deposit Ratio* of the treatment banks and the results are reported in columns (1) and (2) of Panel A of Table 7. Columns (1) to (3) show the results for the full sample of counties, while columns (2) to (4) show the results for the counties where the treatment bank branches are located. All specifications consistently show that the deposit withdrawals are more pronounced when banks have more uninsured deposits. In column (2), the estimate on *Post* $\times$ *Uninsured Deposit Ratio* indicates that a 100 bps increase in *Uninsured Deposit Ratio* is associated with a 16 bps decrease in the deposits of bank branches co-located with affiliated RIAs following the revelation of those RIAs' misconduct.

To further investigate whether the reputational spillover effects occur only in top banking institutions that are part of large financial conglomerates, I define an indicator variable for banks that belong to the top ten in the U.S. in terms of total assets in a given year and refer to them as the *Top 10 Banks*. I then add an indicator variable $Post \times Top\,10\,Banks$ in Eq. (1). Panel B of Table 7 shows that all specifications have statistically insignificant coefficients in the interacted terms, but significant coefficients in the *Post* indicator variable. In other words, the spillover effects are not more pronounced in the top ten largest banks. These findings indicate that the negative spillovers of RIA misconduct to their affiliated banks also consistently exist in small banks.

To examine the effects on small business loan origination, I interact the *Post* indicator variable in Eq. (3) with the $Uninsured\ Deposit\ Ratio$ of treatment bank and the $Top\,10\,Banks$ indicator. The results are reported in columns (3) and (4) of Panels A and B in Table 7. I find significant heterogeneous effects by uninsured deposits on the origination of small business loans, which is the same as the results on columns (1) and (2). Furthermore, the heterogeneous effects by bank asset size show a similar pattern as the results for bank deposits in that large banks do not experience additional spillover effects.

7.4 Social capital of local communities

In this section, I explore how the spillover effects may depend on how high the intensity of the civic norm or the networks of relationships among local communities. Prior papers define social capital as a civic norm or shared social network that determines the level of trust (e.g., Putnam (1993); Fukuyama (1995); Guiso et al. (2011)) and affects the behavior of individuals (e.g., Guiso et al. (2004); Rupasingha et al. (2006); Guiso et al. (2008)).

Social capital plays an important role for the collective investment decisions within communities(e.g., Giannetti and Wang (2016); Duflo and Saez (2002); Duflo and Saez (2003)). Martin-Flores (2024) documents that areas with higher social capital have less probability of experiencing bank misconduct behavior via a disciplining mechanism exerted by local depositors. Consistent with this intuition, RIA misconduct-exposed banks located in communities with high social capital may experience strong distrust from depositors and significant deposit withdrawals following the revelation of misconduct committed by their affiliated investment advisory firm. Therefore, I use the context of the level of social capital in each county to estimate the heterogeneous effects.[18]

I obtain the measure of county-level social capital from the Social Capital Project by the Joint Economic Committee of the U.S. Congress. The measure calculate the social capital index based on social, economic, demographic, health, insurance, and crime rates. Section 3 provides additional information about the measurement used in this section. I split the U.S. counties in my sample into two groups based on the level of social capital. I classify counties above the median of the social capital index as high social capital counties and the rest as low social capital counties.

I interact the *Post* indicator variable in Eq. (1) and (3) with an indicator variable, *High Social Capital*, for whether the county belongs to high social capital counties. The results are reported in Table 8. Columns (1) and (3) present results for the full sample of counties, and columns (2) and (4) present results for the counties where the treatment bank branches are located. The coefficients in columns (1) and (2) of Table 8 show that RIA-misconduct exposed bank branches in high social capital counties experience additional significant abnormal deposit outflows of 16.1%-16.8% more than the banks in low social capital counties, following the revelation of misconduct committed by their affiliated RIAs located in the same county. The coefficients in columns (3) and (4) show that the origination of small business loans from bank branches co-located with their affiliated advisors in counties with high social capital abnormally decreases by an additional 0.7%-2.9% following the revelation of misconduct committed by their affiliated RIAs located in the same county, although the coefficient in column (4) shows no statistical significance. Taken together, the collective degree of networks within local communities seems to be the driving force behind this systematic pattern of distrust spillover.

[18] Paldam (2000) discusses trust, ease of cooperation, and network as the main foundations of social capital.

7.5 Heterogeneity in affiliation type

To further investigate the general impacts of financial advisory misconduct on banking institutions and on the local deposit market, I compare the impacts of bank-affiliated RIA misconduct to those of not bank-affiliated RIA misconduct. I employ a modified event study design to compare the effects of bank-affiliated RIA and other RIA-committed misconduct. Specifically, I estimate:

$$Deposits_{c,t} = \lambda_c + \delta_{s,t} + \sum_{\tau=-4}^{4} \beta_\tau Misconduct_{c,t}^{\tau} + \sum_{\tau=-4}^{4} \gamma_\tau Misconduct(Affil)_{c,t}^{\tau} + \varphi \boldsymbol{X_{c,t}} + \varepsilon_{c,t}\,, \tag{5}$$

where $Misconduct_{c,t}^{\tau}$ is a dummy variable equal to one if misconduct committed by any RIA located in county c is revealed to the public in year t+τ and $Misconduct(Affil)_{c,t}^{\tau}$) is the dummy variable equal to one if misconduct 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 $Misconduct(Affil)_{c,t}^{\tau}$ represent the average difference in deposits between counties exposed to RIA misconduct and counties exposed in misconduct committed by bank-affiliated RIAs at $t = \tau$. I aggregate the amount of bank deposits at the county-year-level to study the impacts on the local deposit market. The omitted period is $\tau = -1$. Following previous studies (e.g., Gurun et al. (2018); Parsons et al. (2018)), I include 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 RIA misconduct and banking activity. I cluster standard errors by county, allowing for correlation of errors over time within each county.

Figure 9 displays the estimated treatment effects and differential effects from estimation of Eq. (5). Prior to misconduct 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 misconduct revelation, the bank deposits at the county-year level abnormally increase significantly among counties where misconduct committed by an RIA in the county is revealed. On the other hand, the negative coefficients on

$Misconduct(Affil)_{c,t}$ indicate that the impact of misconduct committed by bank-affiliated RIAs has an additional negative impact to the impact in the general case.

Moreover, the results from Eq. (5) are in line with Gurun et al. (2018), who find that local deposit volume increases in the places where the victims of the 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 9. In other words, my results imply that the hypothesis of deposits as a safe haven holds in this type of advisory misconduct.

Taken together, these findings provide further evidence that depositors not only respond to reputational shock on banks 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 spillover to the bank dominates the incentives for depositors to seek safe assets. The distrust spillover channel might dominant if banks are affiliated with misconduct-revealed advisors, and the channel of deposits as safe haven might significantly hold in other cases of advisory misconduct, like the Madoff Ponzi scheme as in Gurun et al. (2018).

7.6 Deposit rates

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: the exposure to RIA misconduct might mechanically escalate the price of bank deposits due to the increased cost of bank operations, not through the distrust spillover channel.

In this section, I examine the deposit rates of retail deposit products sold by each individual bank branch. Bank branches decide their deposit rate based on the local deposit market or competition, separately from other branches of the same bank in other local areas (Drechsler et al. (2017)). If the systematic decreasing pattern of interest rates occurs after the RIA misconduct, the main results of decreasing bank deposits may justify the mechanical outcome from the change in investment return.

I re-estimate Eq. (1) on the interest rate of deposit products using OLS regression.[19] Panels A and B of Table 9 show the results from the full sample of counties and the subsample of counties where the treatment bank branches are located, respectively. Most specifications in Table 9 show statistically significant, but economically insignificant coefficients on most of account types given that the average interest rates are between 0.1% and 0.3% APY depending on the type of deposit product. In column (2) of Panel A, 12-month $10k CD rates show a significantly marginal increase with an affiliated RIA's misconduct exposure, even though the economical significance is weak in that the magnitude is about 0.8% of the average APY. This result suggests that the decreasing deposit levels are not the outcome of an increase in the interest rates of the deposit products and, thus, nullify the alternative channel that could explain the main results.

8. Conclusion

In this paper, I examine the impact of financial advisory misconduct on the deposits and loan activities of their affiliated banks and document a novel channel of reputational spillovers. Using unique administrative data on financial advisory firms, I find that bank branches experience abnormal deposit outflows and a decrease in the origination volume of small business loans following the revelation of misconduct committed by their affiliated financial advisors that are co-located in the same county. Cross-sectional tests suggest that the effects are more pronounced when bank branches locate closer to their affiliated advisors, face severe misconduct cases, or affiliated with advisors with a low level of pre-existing trust from local communities. In addition, I find that the results are pronounced for banks that have a high ratio of uninsured deposits or are located in counties with high social norms. Exploiting the quasi-natural experi-

[19]Since the deposit rate data do not have zero values or a mass of values at zero, I use OLS regression instead of Poisson regression.

ment of the 2003 mutual fund late-trading scandal, I also establish a causal link between investment advisory misconduct and bank deposits.

More broadly, my findings that the trust shock from investment advisors, spillovers to affiliated banking institutions implies the existence of collective reputation and a negative externality of misconduct revelation within the network of relationships between financial intermediaries where non-misconduct-revealed and misconduct-revealed entities are interconnected. While researchers find that financial misconduct may impact households' trust in a trust-collapsed entity or industry (e.g., Karpoff et al. (2008); 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 across different financial sectors through an operational network. This paper provides evidence of the spillover effects of investment advisory misconduct on bank deposits and banks' originations of small business loans, suggesting that policymakers should be aware of these financial network-based operational risks in the banking industry, which directly relates to the financial stability of the economy.

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Figure 1: AUM of Investment Management Companies

This figure shows the yearly aggregated assets under management (AUM) of SEC-registered investment advisers (RIA) between 2012 and 2021. The black area represents AUM managed by RIAs that report an affiliation with banking institutions. The upper stacked gray area represents AUM managed by RIAs classified to non-bank-affiliated RIAs, who report no affiliation with banking institutions.

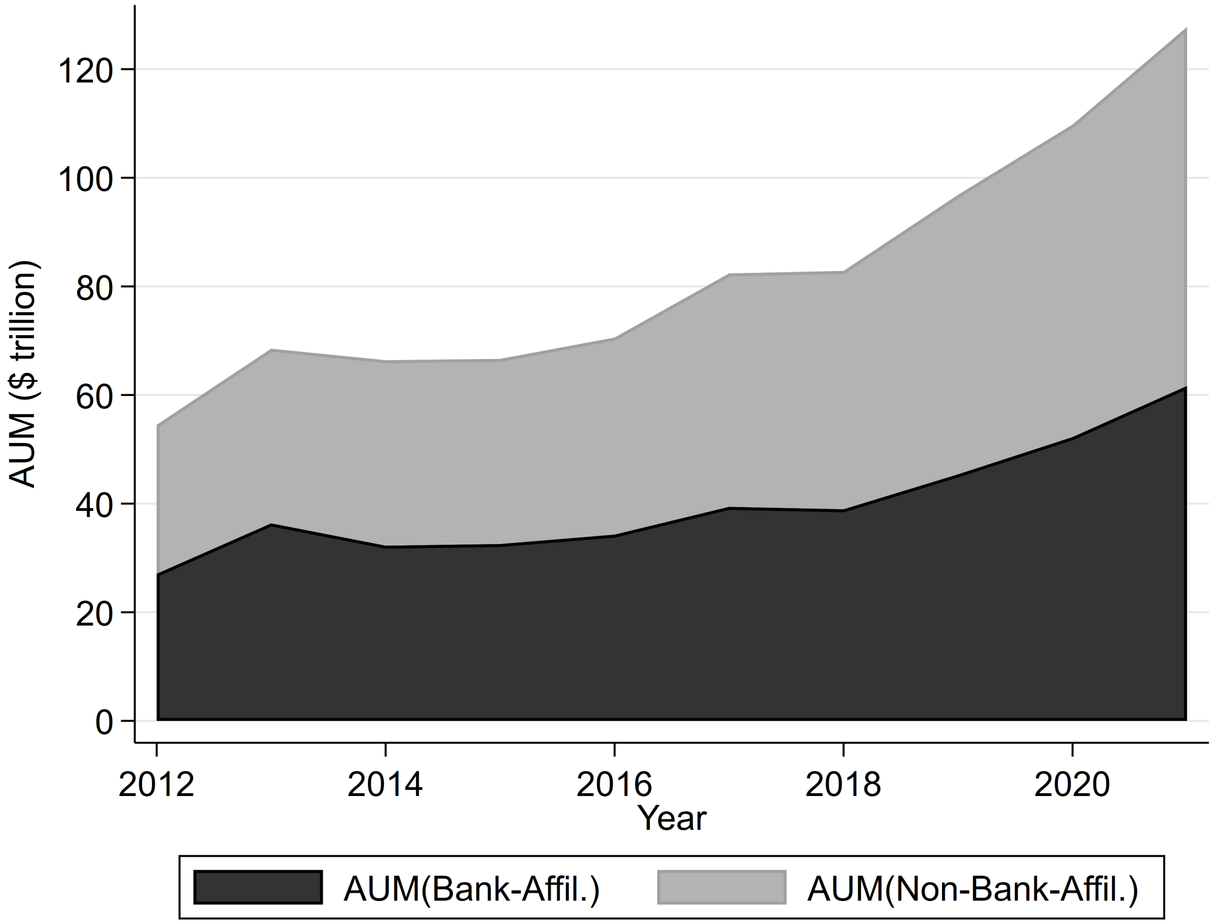


Figure 2: Distribution of RIA Misconduct Type

This figure displays the number of disciplinary actions taken by regulatory agencies against RIAs from 2012 to 2021. The black bars represent the cases disclosed by RIAs that report an affiliation with banking institutions. The stacked gray bars above represents the cases disclosed by RIAs that report no affiliation with banking institutions.

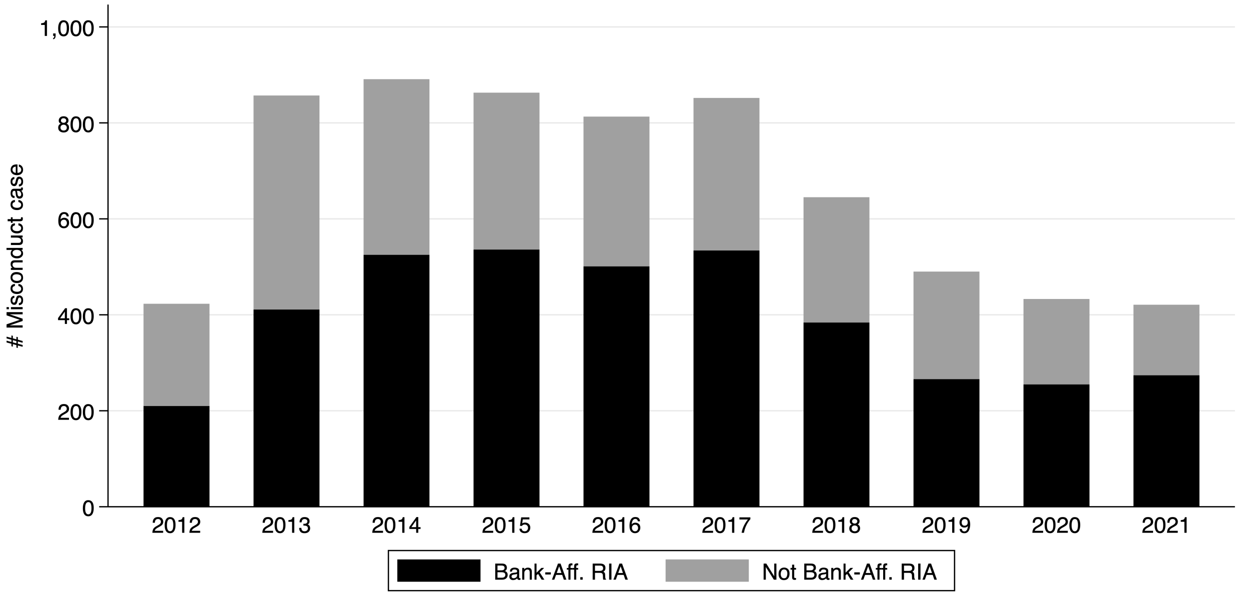


Figure 3: Effects on Bank Branch Deposits

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 variables 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.

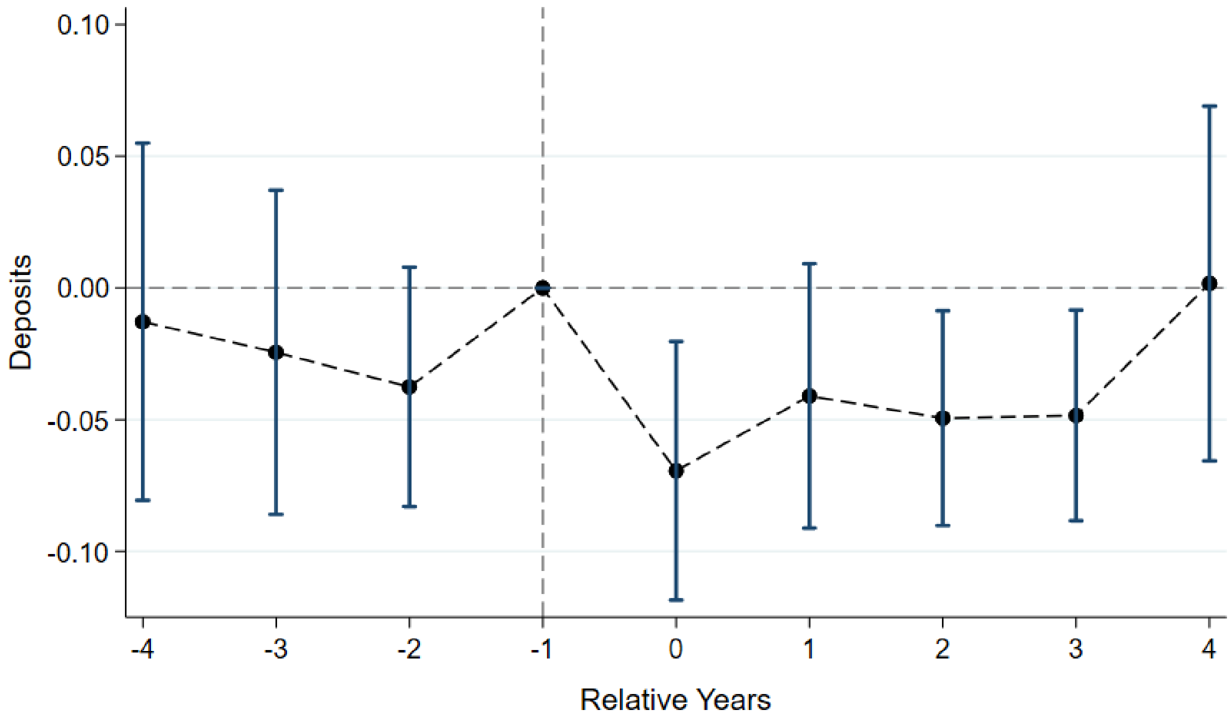


Figure 4: Effects on Bank Branch Deposits: Heterogeneity in Distance from RIAs

This figure displays estimates of the distance from misconduct-revealed RIAs to their affiliated banks located in the same county on the changes in the bank deposits around the revelation of RIA misconduct. Estimates and standard errors are estimated using the model estimated for column (2) of Table 4, which includes branch, county-year, and bank-year fixed effects and is estimated using data from 2012 to 2021. The model also includes indicator variables that indicate the proximity of the closest affiliated RIAs to the bank branch ZIP Code. These variables indicate whether the closest affiliated RIAs, whose misconduct is revealed, is within 1 mile of the ZIP Code, from 1 to 10 miles, from 10 to 30 miles, from 30 to 60 miles, from 60 to 100 miles, or from 100 to 200 miles of the ZIP Code. The coefficient estimates on these indicators interacted with the *Post* indicator are plotted, along with their 90% confidence intervals and standard errors are clustered by bank branch.

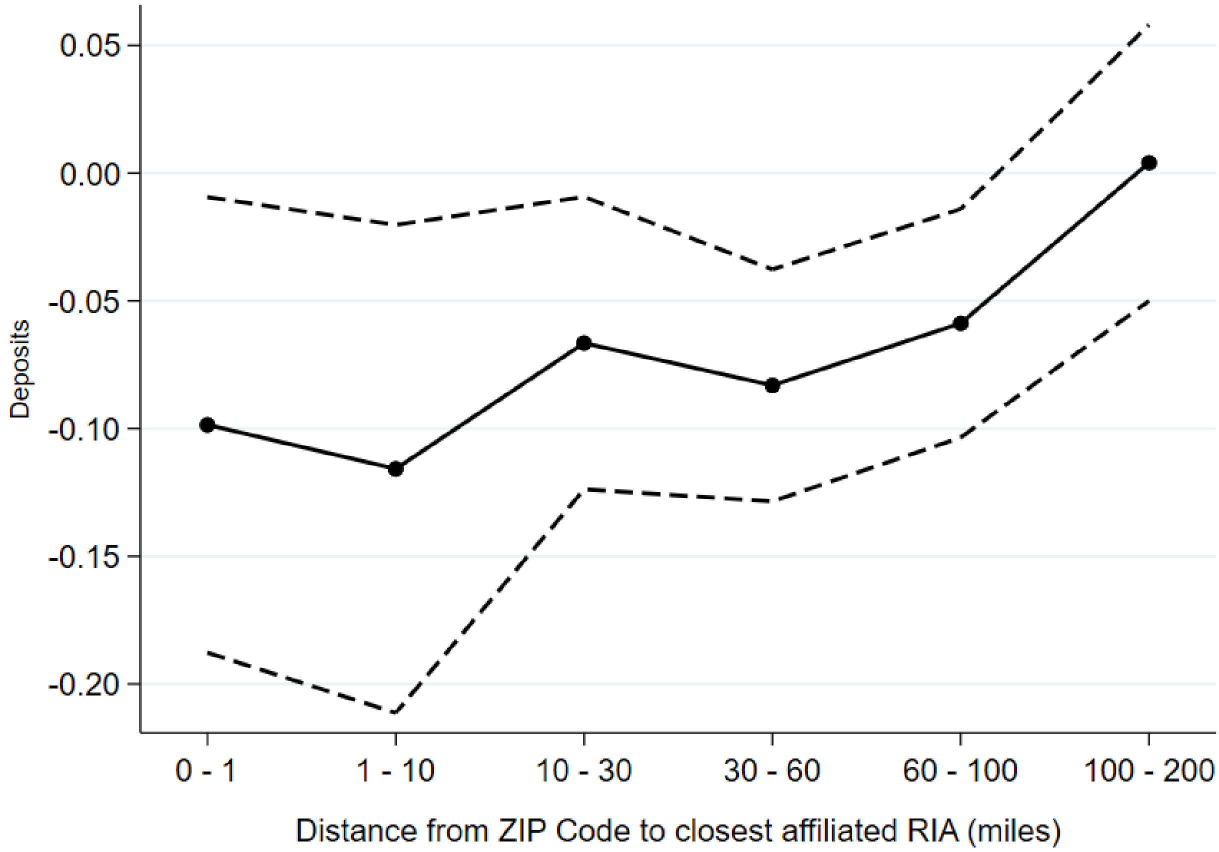


Figure 5: Effects on Small Business Lending

This figure shows event study time dummy coefficients and 95% confidence intervals from estimating Eq. (4) on the origination amount of CRA loans. Observation is at the bank-county-income type-year level and standard errors are clustered at the bank-income group and year level. Bank-county, bank-year, county-year, and borrower income group fixed effects are included. The dotted vertical line represents the omitted period.

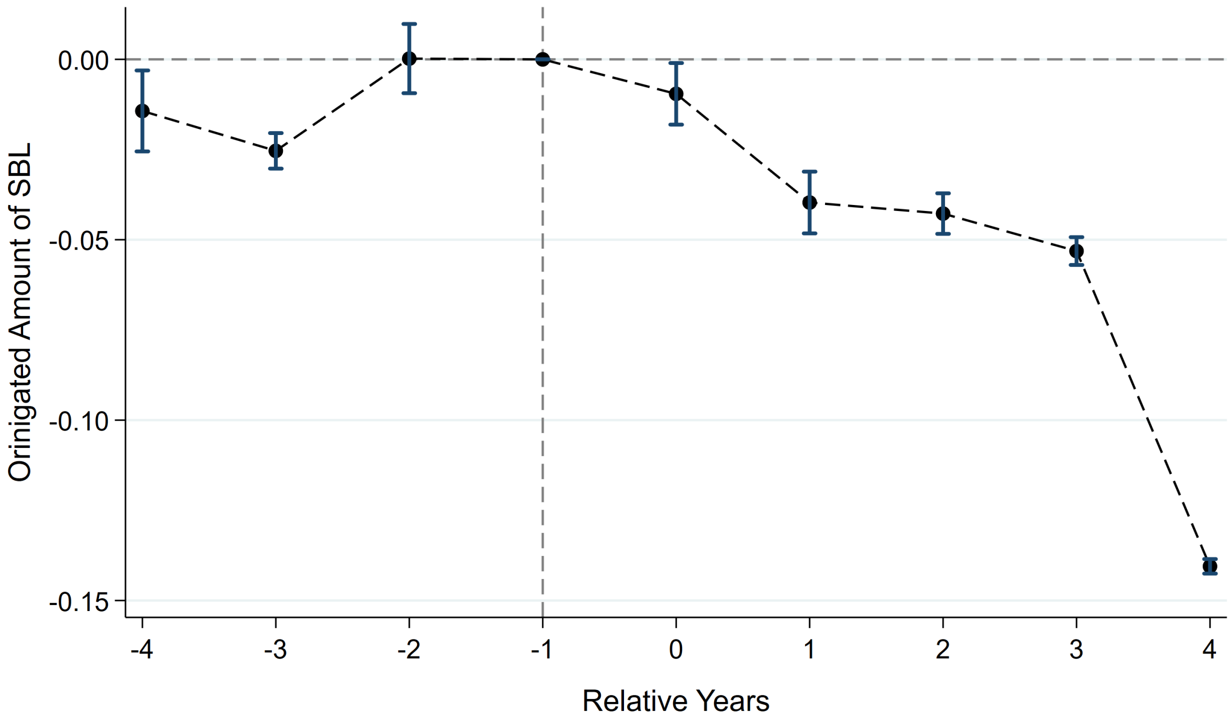


Figure 6: Quasi-natural Experiment: Effects on Bank Branch Deposits

This figure shows event study time dummy coefficients and 95% confidence intervals from estimating Eq. (2) on the volumes of bank branch deposits using the DiD sample (see Section 6.2). Controls include categorical variable of bank branch services. Standard errors are clustered by bank branch level. The dotted vertical line represents the omitted period.

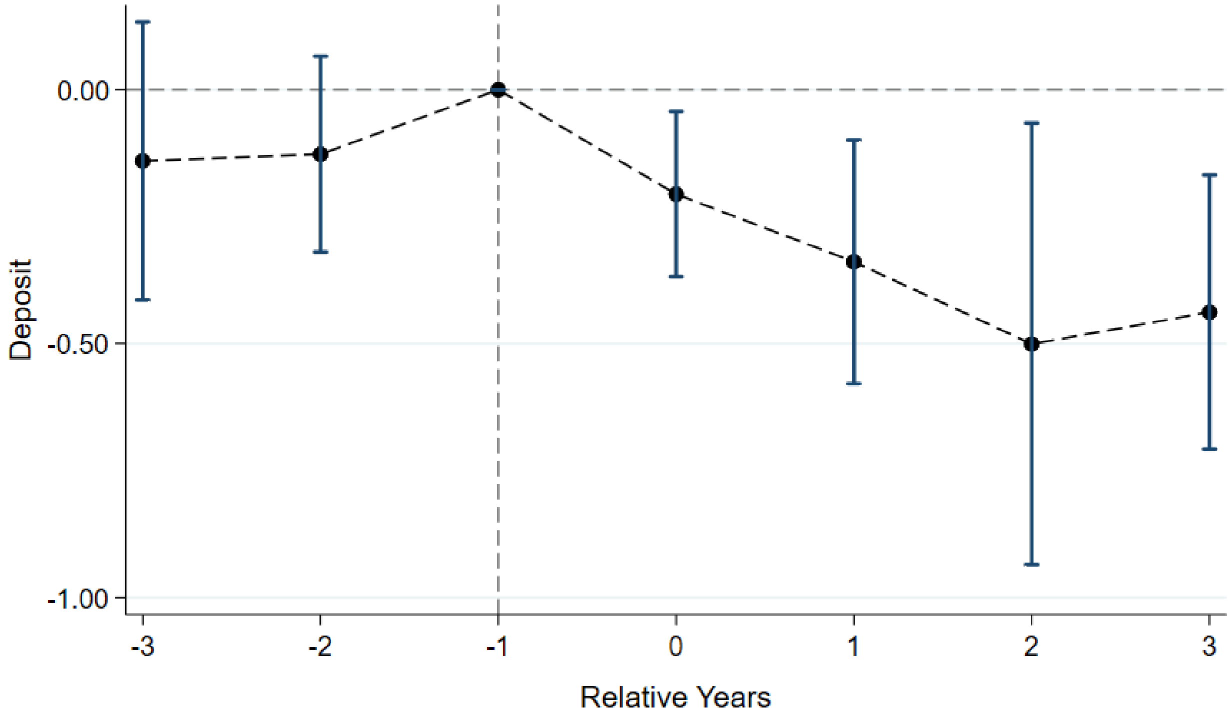


Figure 7: Quasi-natural Experiment: Effects on Small Business Loans

This figure shows event study time-dummies coefficients and 965% confidence intervals from estimating Eq. (4) on the origination amount of CRA loans using DiD sample (see Section 6.2). Observation is at the bank-county-income type-year level and standard errors are clustered at the bank-income group and year level. Bank-county, bank-year, county-year and borrower income group fixed effects are included. The variables are defined in Appendix Table A.1. The dotted vertical line represents the omitted period.

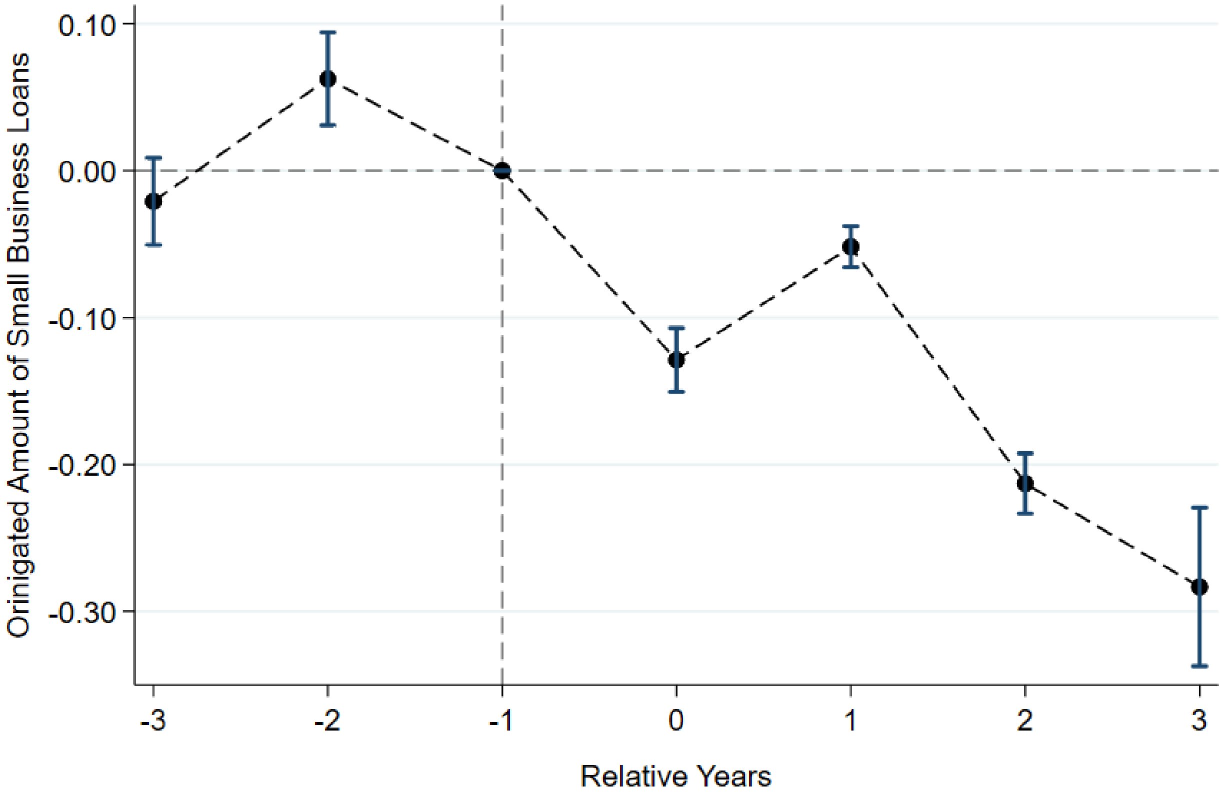
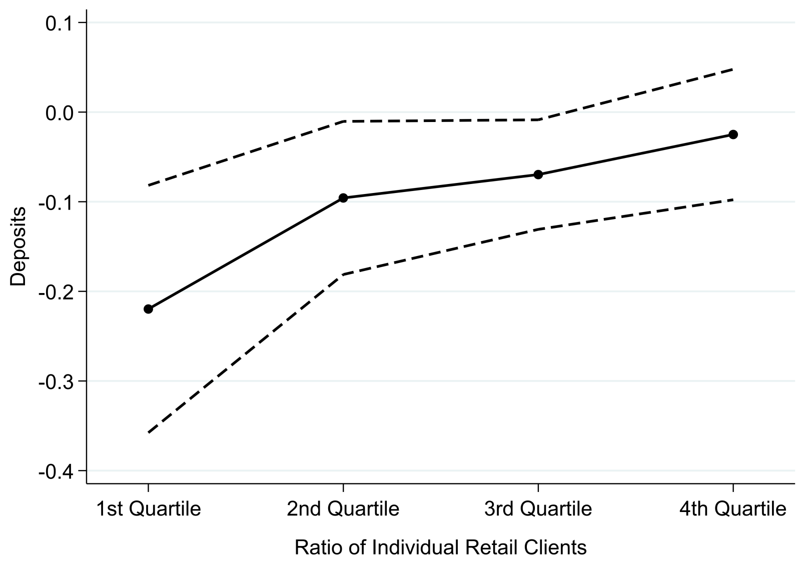


Figure 8: Ratio of Retail Clients: Bank Branch Deposits

This figure displays estimates of the ratio of individual retail clients (individuals other than high net worth individuals) of RIAs on the changes in the deposits (plot (A)) and CRA loan origination amounts (plot (B)) of bank branches affiliated with misconduct-revealed RIAs and located in the same county as those RIAs. Specifically, in plots (A) and (B), estimates and standard errors are estimated using the model estimated in column (2) of panel (A) and panel (B) of Table 4, respectively. The model also includes an indicator variable indicating the quartiles of the ratio. These indicate whether misconduct-revealed RIAs are in the 1th quartile, 2nd quartile, 3rd quartile, or 4th quartile of the ratio. The coefficient estimates on these indicators interacted with the *Post* indicator are plotted, along with their 95% confidence intervals.

(A) Bank Branch Deposits



(B) CRA Loan Originations

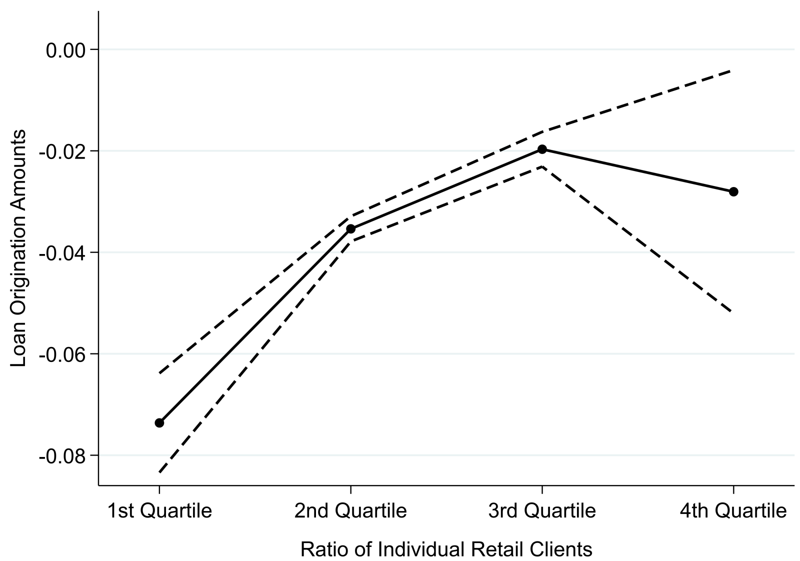


Figure 9: Effects on Deposit Market at the County Level

This figure shows event study time dummy coefficients and 90% confidence intervals from estimating Eq. (5) 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. The sample includes branch level deposit panel data from 2012 to 2021. The dotted vertical line denotes the omitted period.

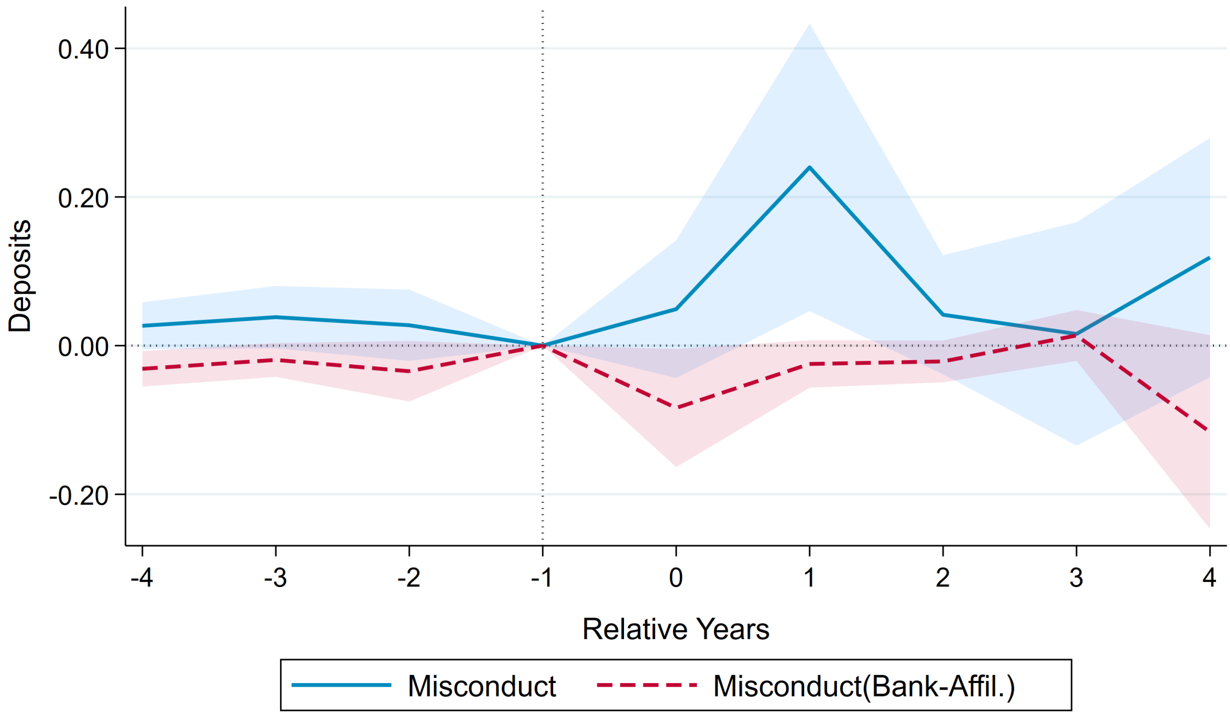


Table 1: Financial Industry Affiliation

Panel A provides the the number and percentage of annual ADV filings that report affiliation with a specific industry. The sample covers ADV filings from 2012 to 2021. Panel B 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. The *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.

Panel A: Affiliated Industry

Industry	Frequency	Ratio
Pooled investment vehicles	44,139	0.36
Other Adviser	41,933	0.34
Broker-dealer	23,335	0.19
Commodity adviser	21,210	0.17
Insurance company	19,715	0.16
Accounting firm	8,503	0.07
Banking or thrift institutions	7,751	0.06
Trust company	7,512	0.06
Limited partnerships	6,325	0.05
Pension consultant	5,989	0.05
Real estate broker	5,094	0.04
Law firm	4,463	0.04
Municipal advisor	3,187	0.03
Futures commision merchant	2,086	0.02
Swap dealer	736	0.01
Swap participant	82	0.00

Panel B: Examples of Affiliation with Banking Institutions

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 Tust
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, N.A.

Table 2: Overview of Advisory Misconduct Cases

This table provides the frequency and percentage of advisory misconduct, the comprehensive regulatory actions on RIAs from 2012 to 2021, regarding the principal products, regulatory agencies, principal sanctions, and types of misconduct. Panels A, B, and C present the principal products, regulatory agencies, and principal sanctions involved in advisory misconduct, respectively. SRO stands for ”self-regulatory organization”. Panel D presents the types of misconduct cases, indicating whether the case involved transaction, disclosure, or compliance-related misconducts following the methodology of Liang et al. (2020). The *Other* type includes all allegations whose contents do not include compliance, disclosure, or transaction-related misconduct. The misconduct types are not mutually exclusive.

	N	Percent
Panel A: Principal Products		
Equity	697	10.21
Insurance	533	7.81
Futures	371	5.44
Options	338	4.95
Debt	315	4.62
Mutual Fund	305	4.47
Annuity	116	1.70
Derivative	88	1.29
No Product	1,914	28.05
Others	2,147	31.46
Panel B: Regulatory Agencies		
Foreign	981	14.87
SEC	1,022	15.49
SRO	2,074	31.43
Other Federal	817	12.38
State	1,704	25.83
Panel C: Principal Sanctions		
Cease and Desist	1,102	18.26
Civil and Administrative Penalties	3,553	58.88
Censures	108	1.79
Restitution	100	1.66
Suspension	777	12.88
Others	394	6.53
Panel D: Misconduct Types		
Transaction	2,752	0.41
Disclosure	4,845	0.72
Compliance	739	0.11
Others	1,970	0.29

Table 3: Summary Statistics

This table reports the summary statistics for the deposit, misconduct, and demographic data. The 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.

	Mean	SD	Median	N
Panel A: Bank Branch Level				
Deposits (in thousand $)	132,915	2,425,070	45,815	904,627
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
Deposit rates (APY% $\times$100)				
CD 6m (10k)	18.27	21.51	10	805,548
CD 12m (10k)	29.36	31.88	19	807,173
MM (10k)	10.83	13.78	7	761,494
MM (25k)	13.28	15.49	10	763,460
Misconduct event	0.05	0.21	0	904,627
Panel B: Bank - County Level				
Total Originiation Amount of Small Business Loans (in thousand $):				
Low Income	75.11	694.05	0	889,618
Moderate Income	312.59	1,637.36	0	889,618
Middle Income	861.66	3,301.61	75	889,618
High Income	572.13	3,099.58	0	889,618
Panel C: County Level				
Population	103,687	329,959	26,241	27,978
Median income	50,372	13,646	48,245	27,978
Median age	41	5	41	27,978
Fraud county	0.14	0.35	0	27,978
Bank-affil. fraud county	0.03	0.16	0	27,978

Table 4: Effects on Affiliated Bank Branch Deposits

This table presents the estimates of Eq. (1) on the volume of deposits (Panel A) and CRA loan origination (Panel B) in bank branches following the revelation of misconduct committed by their affiliated RIAs located in the same county as the bank branch. The sample period is from 2012 to 2021. In Panels A and B, the unit of analysis is the branch-year and bank-county-income type-year level, respectively. *Post* is an indicator variable set to one since the detection of misconduct committed by co-located affiliated RIA in the same county. In columns (3) and (4), the samples only include counties where the treatment bank branches are located. Controls include categorical variables of bank branch services. In Panel A (B), standard errors are in parentheses and are clustered at the bank branch (bank-income group and year) level. The variables are defined in Appendix Table A.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank Branch Deposits

Dependent Variable:	Bank Branch Deposits			
Sample of Counties:	Full Sample		Only Exposed	
	(1)	(2)	(3)	(4)
Post	-0.123***	-0.122***	-0.140***	-0.127***
	(0.032)	(0.030)	(0.035)	(0.032)
Controls	Yes	Yes	Yes	Yes
Fixed effects:				
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	429,912	429,912

Panel B: Origination of Small Business Loans

Dependent Variable:	Origination Amount of CRA Loans			
Sample of Counties:	Full Sample		Only Exposed	
	(1)	(2)	(3)	(4)
Post	-0.011***	-0.029***	-0.037	-0.030***
	(0.001)	(0.000)	(0.027)	(0.003)
Fixed effects:				
Income Group FE	Yes	Yes	Yes	Yes
Bank × County 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	0.770	0.776	0.909	0.796
Observations	440,612	440,600	64,980	70,532

Table 5: Quasi-natural experiment of Mutual Fund Scandal

This table reports the results of a Poisson regression of a difference-in-difference (DiD) test on the effect of advisory misconduct committed by RIAs on their affiliated bank branches using the mutual fund scandal in 2003. Section 6.2 outlines the sample construction. *Post* is a dummy that equals one for treated bank branches, during the years following the revelation of misconduct committed by affiliated RIAs involved in MFS. The sample period is 2000-2007. In columns (1) and (2), all counties are included in the sample. In columns (3) and (4), the samples only include counties where the treatment bank branches are located. Panel A shows the estimates of Eq. (1) on the volume of bank branch deposits in a given year using the DiD sample. The unit of analysis is the bank branch-level. Controls include categorical variables of bank branch services. Standard errors are in parentheses and are clustered at the bank branch level. Panel B presents estimates of Eq. (3) on the total volume of small business loan originations. The unit of analysis is the bank-county-borrower income group-year level. Standard errors are in parentheses and are clustered at the bank-income group and year level. The variables are defined in Appendix Table A.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank Branch Deposits

Dependent Variable:	Bank Branch Deposits			
Sample of Counties:	Full Sample		Only Exposed	
	(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
Fixed Effects:				
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	0.978	0.981	0.982	0.982
Observations	651,149	649,288	148,785	148,785

Panel B: Origination of Small Business Loans

Dependent Variable:	Origination Amount of CRA Loans			
Sample of Counties:	Full Sample		Only Exposed	
	(1)	(2)	(3)	(4)
Post	-0.121***	-0.079***	-0.097*	-0.095
	(0.024)	(0.020)	(0.058)	(0.066)
Fixed effects:				
Income Group	Yes	Yes	Yes	Yes
Bank × County 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	0.784	0.789	0.622	0.623
Observations	338,748	338,724	1,004	1,004

Table 6: Spillover Effects by Misconduct Characteristics

This table presents the results of the Poisson regression on the volume of deposits (columns (1) and (2)) and small business loan originations (columns (3) and (4)) of bank branches following the revelation of misconduct committed by their affiliated RIAs located in the same county as the bank branch. *Post* is an indicator variable set to one since the detection of misconduct committed by affiliated RIA located in the same county. The sample period is 2012-2021. Columns (1) and (2) show estimates using Eq. (1). Standard errors are clustered at the bank branch-level. Controls include categorical variables of bank branch services. Columns (3) and (4) show estimate using Eq. (3). Standard errors are clustered at the bank-income group and year level. In columns (2) and (4), the samples only include counties where treated bank branches are located. Panels A and B present results using the amount of monetary fine charged against RIA misconduct cases and the types of RIA misconduct, respectively, interacting these measures with the *Post* indicator variable. The variables are defined in Appendix Table A.1. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Bank Branch Deposits		CRA Loan Origination	
Sample of Counties:	Full sample	Only Exposed	Full sample	Only Exposed
	(1)	(2)	(3)	(4)
Panel A: Monetary Fine Amount				
Post × *Fine Amount*	-0.022***	-0.022***	-0.013***	-0.011***
	(0.005)	(0.005)	(0.001)	(0.000)
Controls	Yes	Yes	No	No
Fixed Effects:				
Income group FE	–	–	Yes	Yes
Bank × County FE	–	–	Yes	Yes
Branch FE	Yes	Yes	–	–
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.986	0.986	0.776	0.796
Observations	853,595	429,912	440,600	70,532
Panel B: Misconduct Type				
Post × *Transaction*	-0.223***	-0.234***	0.010***	0.005
	(0.058)	(0.061)	(0.002)	(0.020)
Post × *Disclosure*	0.063	0.048	-0.014***	-0.011
	(0.056)	(0.060)	(0.001)	(0.031)
Post × *Compliance*	0.047	0.058	-0.012***	-0.013
	(0.052)	(0.056)	(0.001)	(0.047)
Post × *Other*	-0.217***	-0.210***	-0.070***	-0.075***
	(0.057)	(0.059)	(0.008)	(0.011)
Controls	Yes	Yes	No	No
Fixed Effects:				
Income group FE	–	–	Yes	Yes
Bank × County FE	–	–	Yes	Yes
Branch FE	Yes	Yes	–	–
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.986	0.986	0.776	0.796
Observations	853,595	429,912	440,600	73,876

Table 7: Spillover Effects by Bank Characteristics

This table presents the results of the Poisson regression on the volume of deposits (columns (1) and (2)) and small business loan originations (columns (3) and (4)) of bank branches following the revelation of misconduct committed by their affiliated RIAs located in the same county as the bank branch. *Post* is an indicator variable set to one since the detection of misconduct committed by affiliated RIA located in the same county. The sample period is 2012-2021. Columns (1) and (2) show estimates using Eq. (1). Standard errors are clustered at the bank branch-level. Controls include categorical variables of bank branch services. Columns (3) and (4) show estimate using Eq. (3). Standard errors are clustered at the bank-income group and year level. In columns (2) and (4), the samples only include counties where the treatment bank branches are located. Panel A (B) presents results using the ratio of uninsured deposits (*Top 10 Banks* indicator variable, which equals one if the bank belong to the top ten in terms of asset size in a given year), interacting these measures with the *Post* indicator variable. The variables are defined in Appendix Table A.1. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Bank Branch Deposits		CRA Loan Origination	
Sample of Counties:	Full sample	Only Exposed	Full sample	Only Exposed
	(1)	(2)	(3)	(4)
Panel A: Uninsured Deposits				
Post × *Uninsured Deposit Ratio*	-0.163***	-0.172***	-0.078***	-0.112***
	(0.056)	(0.059)	(0.001)	(0.007)
Controls	Yes	Yes	No	No
Fixed Effects:				
Income group FE	–	–	Yes	Yes
Bank × County FE	–	–	Yes	Yes
Branch FE	Yes	Yes	–	–
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.986	0.986	0.777	0.796
Observations	644,233	378,635	426,036	71,256
Panel B: Bank Asset Size				
Post	-0.202***	-0.237***	-0.032***	-0.035***
	(0.072)	(0.085)	(0.000)	(0.003)
Post × *Top 10 Banks*	0.106	0.144	0.007***	-0.005
	(0.081)	(0.094)	(0.001)	(0.004)
Controls	Yes	Yes	No	No
Fixed Effects:				
Income group FE	–	–	Yes	Yes
Bank × County FE	–	–	Yes	Yes
Branch FE	Yes	Yes	–	–
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.986	0.986	0.776	0.796
Observations	853,595	429,912	440,600	73,876

Table 8: Spillover Effects by Social Capital Index

This table presents the results of the Poisson regression on the volume of deposits (columns (1) and (2)) and small business loan originations (columns (3) and (4)) of bank branches following the revelation of misconduct committed by their affiliated RIAs located in the same county as the bank branch. *Post* is an indicator variable set to one since the detection of misconduct committed by affiliated RIA located in the same county. *High Social Capital* equals one if the social capital index of the county is above the median of the measure. The sample period is 2012-2021. Columns (1) and (2) show estimates using Eq. (1). Standard errors are clustered at the bank branch-level. Controls include categorical variables of bank branch services. Columns (3) and (4) show estimate using Eq. (3). Standard errors are clustered at the bank-income group and year level. In columns (2) and (4), the samples only include counties where the treatment bank branches are located. *High Social Capital* equals one if the county has a social capital index value above its median, and I interact this measure with the *Post* indicator variable. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Bank Branch Deposits		CRA Loan Origination	
Sample of Counties:	Full sample	Only Exposed	Full sample	Only Exposed
	(1)	(2)	(3)	(4)
Post	-0.086***	-0.092***	-0.018***	-0.029***
	(0.028)	(0.029)	(0.002)	(0.011)
Post × *High Social Capital*	-0.184**	-0.176**	-0.029***	-0.007
	(0.074)	(0.075)	(0.003)	(0.009)
Controls	Yes	Yes	No	No
Fixed Effects:				
Income group FE	–	–	Yes	Yes
Bank × County FE	–	–	Yes	Yes
Branch FE	Yes	Yes	–	–
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.985	0.985	0.776	0.793
Observations	845,989	428,289	428,972	68,964

Table 9: Effects on Bank Branch Deposit Rates

This table presents the results of the OLS regression on the interest rates of deposit products in bank branches following the revelation of misconduct committed by affiliated RIA located in 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 interest rates (%×100) of deposit accounts (for example, 1% interest rate is calculated as 100). *Post* is an indicator variable set to one since the detection of misconduct committed by a co-located affiliated RIA in the same county. 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. Standard errors are in parentheses and are clustered at the bank branch level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Interest Rate of Bank Deposit Accounts (%×100)			
	CD 6m (10K)	CD 12m (10K)	MM (10K)	MM (25K)
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Post	0.042	0.246***	0.253***	0.332***
	(0.044)	(0.058)	(0.048)	(0.049)
Controls	Yes	Yes	Yes	Yes
Fixed effects:				
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
R^2	0.980	0.980	0.967	0.969
Observations	784,639	786,233	740,953	743,060
Dep. Var. Mean	18.271	29.359	10.833	13.28
Panel B: Only Misconduct-Exposed Counties				
Post	-0.071	0.100*	0.199***	0.291***
	(0.046)	(0.060)	(0.049)	(0.050)
Controls	Yes	Yes	Yes	Yes
Fixed effects:				
Branch FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
R^2	0.979	0.977	0.962	0.964
Observations	394,053	394,552	367,131	368,103
Dep. Var. Mean	18.271	29.359	10.833	13.28

Appendix

Table A.1: Variable Definitions

Variable	Definition	Source
Deposits	Deposits of Bank branch office as of June 30th (in thousand $).	FDIC Summary of Deposits
Deposit rates	APY(%)×100 of bank deposit products (in percentage).	RateWatch
CD 6m (10k)	APY(%)×100 of $10k Certificate of Deposits (CD) of 6 months maturity.	RateWatch
CD 12m (10k)	APY(%)×100 of $10k CD of 12 months maturity.	RateWatch
MM (10k)	APY(%)×100 of $10k Money market account (MM).	RateWatch
MM (25k)	APY(%)×100 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
Low Income	Group of borrowers with incomes less than 50% of the median family income (MFI) in the metropolitan statistical division of their residency.	FFIEC CRA
Moderate Income	Group of borrowers with incomes between 50% and 80% of MFI.	FFIEC CRA
Middle Income	Group of borrowers with incomes between 80% and 120% of MFI.	FFIEC CRA
High Income	Group of borrowers with incomes greater than or equal to 120% of MFI.	FFIEC CRA
Fine Amount	Total amount of monetary fine imposed against a RIA at a given year.	SEC Form ADV
Transaction Misconduct	Indicator variable that equals to one if the misconduct case is related to investment transaction activity.	SEC Form ADV
Disclosure Misconduct	Indicator variable that equals to one if the misconduct case is related to information disclosure.	SEC Form ADV
Compliance Misconduct	Indicator variable that equals to one if the misconduct case is related to fund operation.	SEC Form ADV
Others	Indicator variable that equals to one if the misconduct case is not classified either as Transaction, Information, or Compliance Misconduct.	SEC Form ADV
Ratio of Retail Clients	Ratio of number of retail clients, individuals other than high net work individuals, to total number of clients for a RIA at a given year.	SEC Form ADV
Top 10 Banks	Indicator variable that equals to one if the bank belonged to the top ten in terms of total assets at a given year.	FDIC Summary of Deposits
Uninsured Deposit Ratio	Ratio of estimates of uninsured deposits amounts to total deposits.	FFIEC Call Reports
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
Misconduct	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
Misconduct(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
Social capital	The county-level weighted sum of standardized scores based on principal components analysis using data on various variables, such as the share of births to unmarried women, the share of own children living in single-parent families, registered non-religious non-profits, religious congregations, voter turnout, mail-back response rates, and violent crimes collected between 2006 and 2016.	Social Capital Project (U.S. Congress)

Table A.2: Example of Advisory Misconduct

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.

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	NC State	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.

Table A.3: Robust to Log Specification: Bank Branch Deposits

The Panels A and B present the estimates of the log-linear model specified in Eq. (1) and Eq. (3), respectively. To deal with the large number of zeros in the sample, I use a log(0.00001 + x) transformation. The sample period is from 2012 to 2021. In Panels A and B, the unit of analysis is the branch-year and bank-county-income type-year level, respectively. *Post* is an indicator variable set to one since the detection of misconduct committed by co-located affiliated RIA in the same county. In columns (3) and (4), the samples only include counties where treated bank branches are located. Controls include categorical variables of bank branch services. In Panel A (B), standard errors are in parentheses and are clustered at the bank branch (bank-income group and year) level. The variables are defined in Appendix Table A.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank Branch Deposits				
Dependent Variable:	Bank Branch Deposits			
Sample of Counties:	Full sample		Only exposed counties	
	(1)	(2)	(3)	(4)
Post	-0.017	-0.030**	-0.025**	-0.025*
	(0.012)	(0.013)	(0.012)	(0.013)
Controls	Yes	Yes	Yes	Yes
Fixed effects:				
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
R^2	0.958	0.960	0.950	0.951
Observations	883,095	881,031	440,637	440,637

Panel B: Origination of Small Business Loans				
Dependent Variable:	Origination Amount of CRA Loans			
Sample of Counties:	Full sample		Only exposed counties	
	(1)	(2)	(3)	(4)
Post	-0.278**	-0.363**	-0.316**	-0.366**
	(0.133)	(0.142)	(0.158)	(0.162)
Fixed effects:				
Income Group FE	Yes	Yes	Yes	Yes
Bank × County 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
R^2	0.565	0.580	0.750	0.579
Observations	440,632	440,632	70,532	70,532

Table A.4: List of Mutual Fund Families involved in Mutual Fund Scandal

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 rectangular boxes on the name of that company in Table A.4 and used at the analysis looking at individual banks. The sources are from Houge and Wellman (2005) and Qian (2011).

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	Bank of America
One Group Funds	9/3/03	Market timing	SEC/NY State AG	Bank One
Strong Capital	9/3/03	Market timing	SEC/NY State AG	Private
Franklin Templeton	9/3/03	Market timing	California AG	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	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	FleetBoston Financial
Scudder Investment	1/23/04	Market timing	SEC/NY State AG	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	Wachovia
Sentinel	10/7/04	Market timing	SEC	Private

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

This table reports the difference-in-difference (DiD) test results on sample constructed as Section 6.2. *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 the interest rates of deposit products in bank branches. 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 variables of bank branch services. Standard errors are clustered at the bank branch level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample

	CD 6m (10k)	CD 12m (10k)	MM (10k)	MM (25k)
	(1)	(2)	(3)	(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

Panel B: Only exposed counties

	CD 6m (10k)	CD 12m (10k)	MM (10k)	MM (25k)
	(1)	(2)	(3)	(4)
Post	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

Figure A.1: Example of Form ADV

This figure presents a part of Form ADV filed by EAGLE ASSET MANAGEMENT INC on December 8, 2023 for the fiscal year 2023. Section 7.4 shows detailed information regarding the financial industry affiliation of the advisory firm.

FORM ADV

UNIFORM APPLICATION FOR INVESTMENT ADVISER REGISTRATION AND REPORT BY EXEMPT REPORTING ADVISERS

Primary Business Name: EAGLE ASSET MANAGEMENT INC	**CRD Number: 110653**
Annual Amendment - All Sections	**Rev. 10/2021**
12/8/2023 10:41:40 AM	

WARNING: Complete this form truthfully. False statements or omissions may result in denial of your application, revocation of your registration, or criminal prosecution. You must keep this form updated by filing periodic amendments. See Form ADV General Instruction 4.

Item 1 Identifying Information

Responses to this Item tell us who you are, where you are doing business, and how we can contact you. If you are filing an *umbrella registration*, the information in Item 1 should be provided for the *filing adviser* only. General Instruction 5 provides information to assist you with filing an *umbrella registration*.

A. Your full legal name (if you are a sole proprietor, your last, first, and middle names):
EAGLE ASSET MANAGEMENT INC

B. (1) Name under which you primarily conduct your advisory business, if different from Item 1.A.
EAGLE ASSET MANAGEMENT INC

SECTION 7.A. Financial Industry Affiliations

1. Legal Name of *Related Person*:
RAYMOND JAMES BANK, N.A.

2. Primary Business Name of *Related Person*:
RAYMOND JAMES BANK

3. *Related Person's* SEC File Number (if any) (e.g., 801-, 8-, 866-, 802-)
-
or
Other

4. *Related Person's*
(a) *CRD* Number (if any):

(b) CIK Number(s) (if any):

5. *Related Person* is: (check all that apply)
(a) ☐ broker-dealer, municipal securities dealer, or government securities broker or dealer
(b) ☐ other investment adviser (including financial planners)
(c) ☐ registered municipal advisor
(d) ☐ registered security-based swap dealer
(e) ☐ major security-based swap participant
(f) ☐ commodity pool operator or commodity trading advisor (whether registered or exempt from registration)
(g) ☐ futures commission merchant
(h) ☑ banking or thrift institution
(i) ☐ trust company
(j) ☐ accountant or accounting firm
(k) ☐ lawyer or law firm
(l) ☐ insurance company or agency
(m) ☐ pension consultant
(n) ☐ real estate broker or dealer
(o) ☐ sponsor or syndicator of limited partnerships (or equivalent), excluding pooled investment vehicles
(p) ☐ sponsor, general partner, managing member (or equivalent) of pooled investment vehicles

Figure A.2: Distribution of Social Capital Index

This figure shows the spatial distribution of social capital degree at the county level from the Social Capital Project by the Joint Economic Committee of the U.S. Congress. The darker the shading on the county, the higher is the degree of social capital.

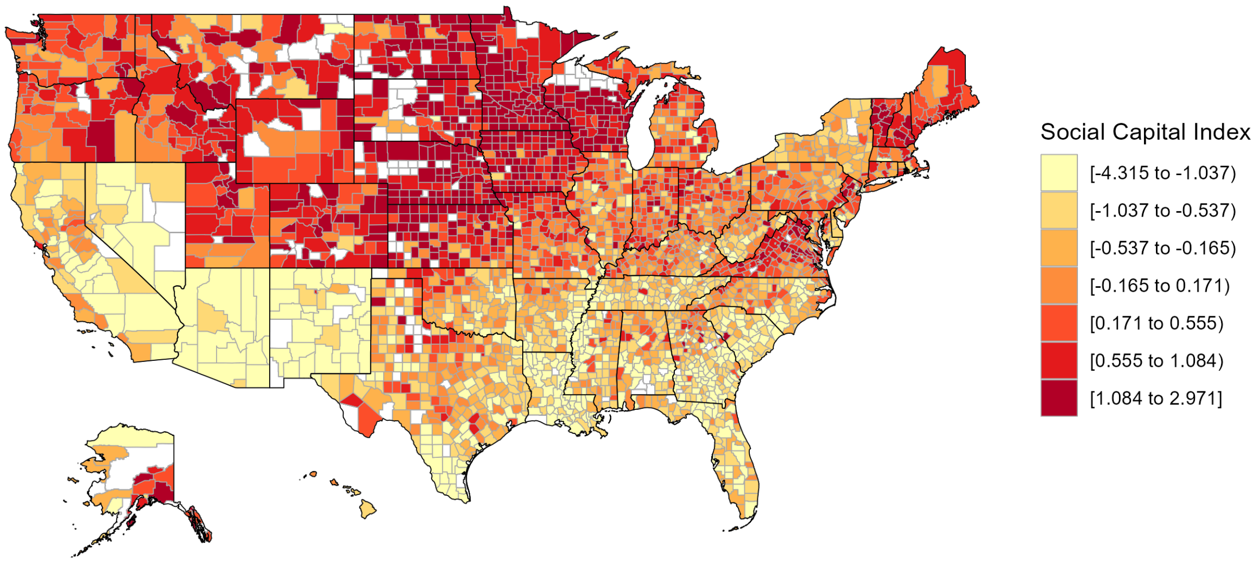


Figure A.3: Histograms of Bank Branch Deposits

This figure presents histograms for the deposit amounts in a bank branch-year from SOD from 2012 to 2021.

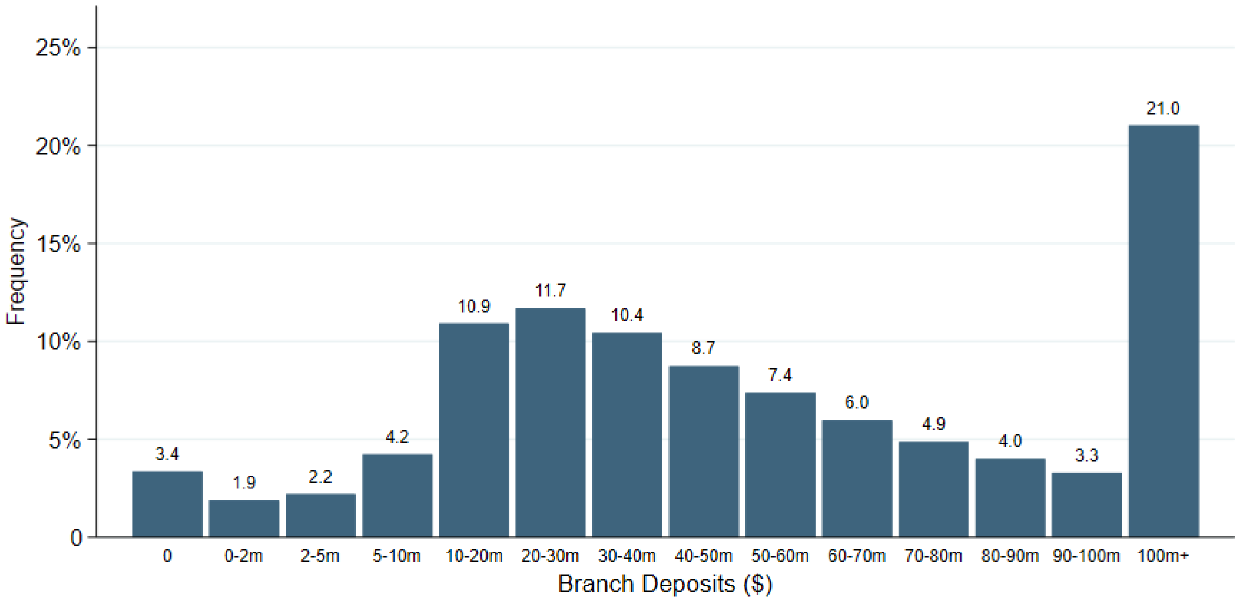


Figure A.4: Histograms of CRA Loan Origination Amounts

This figure presents histograms for the total amounts of CRA loan origination in a bank-county-borrower income group-year over the period from 2012 to 2021.

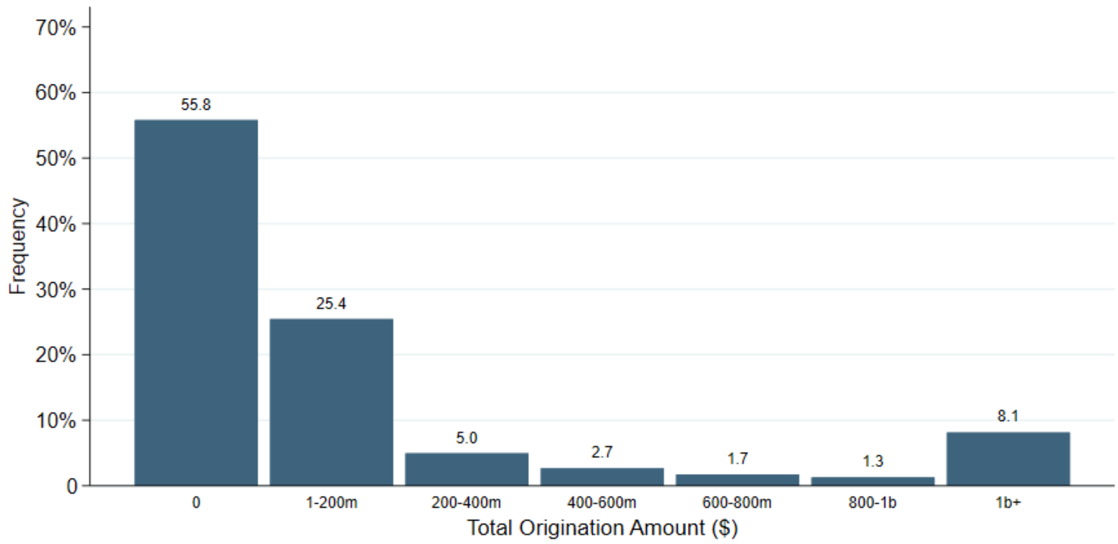


Figure A.5: Geographic Distribution of RIAs involved in MFS

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 6.2. Data on the location of major branches for each RIA are obtained from SEC Form ADV Schedule D. Counties where bank-affiliated fraudulent RIAs involved in MFS are classified as the treatment group and otherwise as control group.

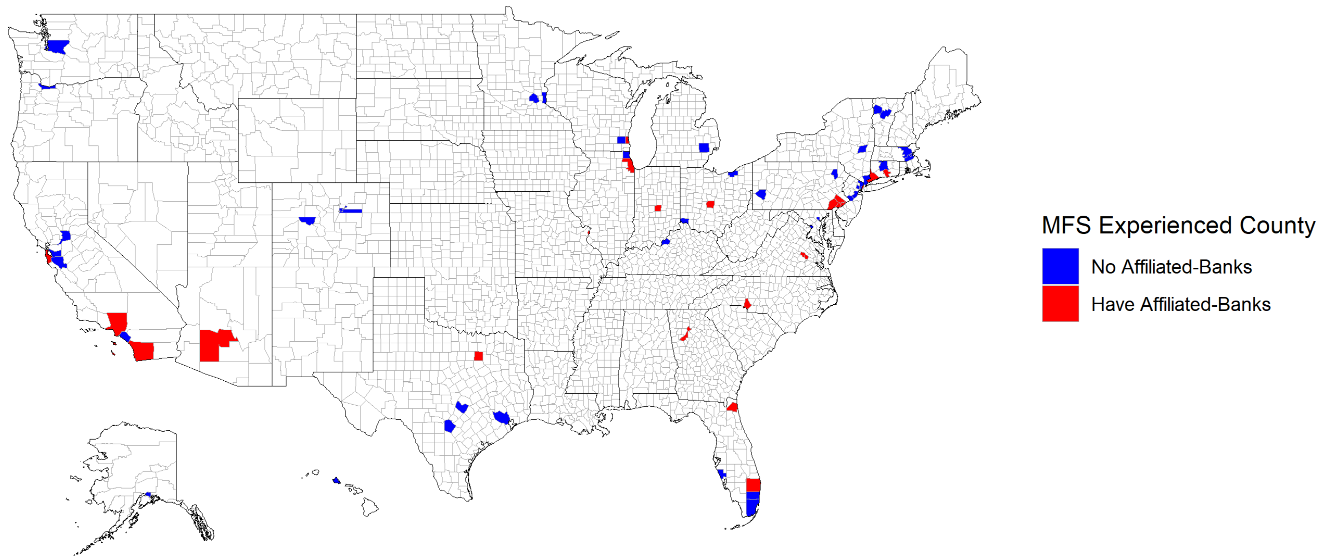


Figure A.6: RIA Monetary Fine Amount

This figure displays the distribution of monetary fines charged against RIA misconduct reported in Form ADV from 2012 to 2021.