Trust Busting: The Effect of Fraud on Investor Behavior*

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Abstract

We study the effects of trust on investor behavior and investment flows by exploiting the geographic dispersion of victims of a multi-billion dollar Ponzi scheme. Investors in communities that were more exposed to the fraud subsequently withdrew assets from investment advisers and increased cash deposits at banks. Exposed advisers were also more likely to close. Advisers who provide services that can build trust—such as financial planning—experienced much lower withdrawals. Our evidence suggests that the trust shock was transmitted through social networks. Taken together, our results show that trust is a critical determinant of asset allocation and has real economic effects.

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Trust underlies most financial transactions. In the presence of incomplete contracts, an investor must have some degree of trust in a financial intermediary before being willing to invest.[1]

In this paper, we empirically investigate the effects of trust on investor behavior and investment flows by exploiting a large shock to investor trust in financial advisers. In the framework of Gennaioli, Shleifer, and Vishny (2015), trust in financial intermediaries has two facets: first, confidence that one's assets will not be stolen; and second, feeling that one's assets are "in good hands," thereby reducing anxiety about taking risk. The trust shock we study could lead investors to update their beliefs about the risk of theft, causing them to withdraw investments from delegated managers in favor of the relative safety of banks. We find strong evidence that investors did precisely that, but, consistent with the predictions of Gennaioli et al. (2015), we also show that money managers who provide additional services that can build trust—such as providing financial planning advice—suffered very little from withdrawals.

To identify the causal effects of trust, we exploit the collapse of the multi-billion dollar Ponzi scheme orchestrated by Bernard Madoff, which was uncovered in December 2008. The Madoff fraud provides a particularly good testing ground to study trust for a number of reasons. First, the fraud was extremely large, and directly affected many geographically dispersed investors.[2] Second, the fraud was explicitly a shock to trust of at least some investors. This is made clear from the 113 victim impact statements that were submitted to the court, which mention "trust" 45 times and by Guiso (2010) who documents the large spillover effects on trust in Madoff afflicted areas using survey data and concludes that his evidence (p. 10), "...proves that the Madoff fraud has lowered trust in financial intermediaries..." Third, because the fraud targeted a particular group of investors, we are able to study how the trust shock is transmitted through social networks.

A common factor in the success of a Ponzi scheme is whether an "affinity" link is present between the perpetrator and the targeted victims. In a study of 367 Ponzi schemes, Deason, Rajgopal, and Waymire (2015) find that common religion is one of the most frequent affinity links cited by the SEC.

[1] Arrow (1969) writes: "It is useful for individuals to have some trust in each other's word. In the absence of trust it would become very costly to arrange for alternative sanctions and guarantees, and many opportunities for mutually beneficial cooperation would have to be foregone."

[2] The total amount of losses is difficult to determine. The original criminal complaint against Madoff alleged a $50 billion fraud, but later estimates were between $10 and $17 billion, and court-ordered restitution was $17 billion. Calculations vary depending on whether fictitious profits are included, for example. It is estimated that about half of Madoff's clients lost no money.

The Madoff scheme was an example of such a fraud, with many Jewish people and organizations becoming victims. The losses were widely felt in the Jewish community, with a number of charities being forced to cut back operations, and in some cases, close.[3] We therefore refer to the Jewish community as the "affinity group" for this episode of fraud.

In addition to the direct effect of a shock to trust on Madoff victims, we draw on evidence that social connections and geographic proximity influence investment behavior (Hong, Kubik, and Stein, 2005; Ivković and Weisbenner, 2007; Pool, Stoffman, and Yonker, 2015) to hypothesize that other investors who are socially connected to a victim or members of the same affinity group are also more likely to suffer a reduction in trust. We exploit the relative clustering of victims in certain areas to implement difference-in-difference tests that enable us to identify the causal effect of trust on investor behavior.

The firm through which the fraud was perpetrated, Bernard L. Madoff Investment Securities, LLC (BLMIS), was regulated by the Securities and Exchange Commission (SEC) under the Investment Advisors Act of 1940 as a registered investment adviser (RIA). Despite having received several tips of suspicious behavior, the SEC did not act until Madoff's son turned his father in.[4] Thus, in the eyes of some, the Madoff fraud was seen as a failure of the SEC.[5] People lost trust in the system. Indeed, using Gallup survey data, we confirm that people who were more exposed to the Madoff fraud reported larger declines in confidence in the criminal justice system than unaffected people; these results are confined to college-educated people and those with higher levels of income (see Table A.1 of the Internet Appendix).

Investors may have thought that if a former chairman of the NASDAQ could perpetrate such a fraud, how many other fraudsters might exist among investment advisers? Following this logic,

[3]One *New York Times* article notes that "...among the apparent victims of Mr. Madoff were many Jewish educational institutions and charitable causes that lost fortunes in his investments; they include Yeshiva University, Hadassah, the Jewish Community Centers Association of North America and the Elie Wiesel Foundation for Humanity. The Chais Family Foundation, which worked on educational projects in Israel, was recently forced to shut down because of losses in Madoff investments. Many of Mr. Madoff's individual investors were Jewish and supported Jewish causes, apparently drawn to him precisely because of his own communal involvement and because he radiated the comfortable sense of being one of them" (`http://www.nytimes.com/2008/12/24/us/24jews.html`). See also `http://blogs.wsj.com/deals/2008/12/15/madoff-the-atomic-bomb-for-jewish-charities/`.

[4]Markopolos (2010) documents three cases in which he provided evidence of the Madoff fraud to the SEC, beginning in 2000.

[5]For example, one victim writes in a statement to the court: "In addition to Madoffs [*sic*] actions, our own government has failed us completely. The failure of the SEC to act when they had all the information necessary to stop Madoff in his tracks. Now the SIPC and Mr. Picard is peforming [*sic*] in a manner to deny us our rights they were supposed to protect."

we expect to see abnormal outflows from SEC RIAs and inflows into safe bank deposits in treated areas. To test this, we use court documents to identify the direct victims of the Madoff fraud by name and address. We then aggregate the number of victims in a particular geographic area, and define the treatment as the relative concentration of victims in that area. We construct a panel of investment adviser flows using a data set that we construct to provide detailed information on annual assets under management (AUM) and the clientele locations for all SEC RIAs. We also collect branch-level cash deposits at banks from the FDIC's Summary of Deposits data. Together, these data allow us to use a difference-in-difference framework to estimate the effects of the shock to trust on both the amount invested in delegated assets held with RIAs as well as in relatively safe bank deposits.

The shock to trust led investors to move money out of risky investments to low-risk bank deposits. The results are strongest among those RIAs that are most similar to Madoff's firm—those that invested in pooled investment vehicles where the RIA had custody of the assets, and did not provide financial planning services. That is, consistent with the prediction of Gennaioli et al. (2015), "money doctors" who build trust with clients by providing "hand-holding" were able to substantially avoid the effects of this trust shock. Perhaps more importantly, our analysis shows that there is no evidence that the withdrawals are reversed, even up to four years after the fraud was revealed. These findings are consistent with the view that trust shocks have long lasting effects on investment environments.

Our full-sample results show that an adviser with clients in an area with one standard deviation more victims per capita experienced abnormal reductions in their AUM of 4.9%. Aggregating across all RIAs, our estimates indicate that the reduction in risky investments due to the trust shock was around $430 billion, which is 25 times of the estimated size of direct wealth loss (court-ordered restitution was $17 billion). In other words, direct wealth loss can explain less than 4% of the liquidation of risky assets from RIA accounts. The remaining funds were likely liquidated by investors who were not directly effected by the wealth shock. The investors may have simply updated their beliefs about the probability of fraud after learning of the fraud, either from media or through social networks. Consistent with this, the abnormal adviser withdrawals were concentrated in areas with large populations of the affinity group, suggesting that the trust shock was transmitted through social networks within this group.

While the Madoff fraud was national news, local media in areas with more victims and more members of the affinity group may have provided more extensive coverage. People in these areas may therefore have been more aware of the fraud, and felt its effects more directly, especially if they knew victims personally. Evidence from internet search patterns indicates that people in areas with more victims were more interested in the fraud: Looking at Google data for the search term "Madoff" in the year after the fraud, the rank correlation between the number of victims in a state and the Google interest index in that state is 0.77.[6] And since the fraud was national news, the fraud may also have affected investors more broadly, suggesting that our results—which are based on differences between affected and unaffected areas—could understate the true magnitude of the effect.

In subsequent analysis, we find evidence that money outflows from RIAs led to a significant increase in the number of firm exits from the financial intermediary market: RIAs with clients in regions affected by the trust shock were about 30% more likely to close following the Madoff event. We also show that bank branches located in zip codes with Madoff victims saw abnormal increases in cash deposits of about 4%.

While our shock to trust is particularly clean, the empirical setup does pose two additional challenges. First, Madoff's clients were not chosen randomly; he targeted older, wealthier investors in Jewish communities. It is possible that communities in which Madoff victims reside are relatively more conservative in the face of a crisis. We rule this out by using a placebo test to show that neither the treatment group nor the affinity group responded differently from control groups around another large market decline—the collapse of the Internet bubble, in which the broad S&P 500 index fell about as much it did in the aftermath of the financial crisis.

Second, the discovery of the Madoff fraud coincided with the 2008 financial crisis. Perhaps people living in areas with many Madoff victims withdrew money from RIAs due to another shock that happened to affect people living in these locations precisely at the same time of the Madoff crisis. For example, Florida—where several hundred Madoff victims resided—felt the subprime mortgage crisis more than other areas.[7] If investors in these areas reduced their holdings at RIAs to

[6] Google constructs a search index for any search term, which is available by over time by region. Results for the search term "Madoff" during 2009 are at `https://goo.gl/3QPpoN`.

[7] Between 2005 and 2007, the average mortgage default rate was 6.2% in Orlando and 9.7% in Miami, compared to an average of 4.8% in subprime zip codes (Mian and Sufi, 2009). Several papers investigate the causes and consequences

cope with potential negative consequences of the subprime mortgage crisis—and not due to the Madoff fraud—that would cast doubt on whether the Madoff trust shock *per se* generated the effect we document. Therefore, our regressions include time-varying fixed effects at various geographic levels and a battery of controls (including zip code level house price appreciation) to control for contemporaneous changes in the economic environment. We also show that our treatment and control groups exhibit parallel trends in observed characteristics prior to shock and find that our results are robust using different econometric specifications.

Our paper contributes to the literature on the role trust plays in economic activity. Trust is associated economic growth (Putnam, Leonardi, and Nanetti, 1994; Knack and Keefer, 1997; Zak and Knack, 2001), the size of firms (La Porta, Lopez-de Silanes, Shleifer, and Vishny, 1997; Bloom, Sadun, and Van Reenen, 2012), financial development (Guiso, Sapienza, and Zingales, 2004, 2008; D'Acunto, Prokopczuk, and Weber, 2015), and international trade and investments (Guiso, Sapienza, and Zingales, 2009). Sapienza and Zingales (2012) have also argued that a decline in trust amplified the adverse effects of Lehman Brothers default and AIG bailout on the overall economy.

Others have shown that corporate financial misconduct leads not only to significant value losses in the fraudulent companies (Karpoff, Lee, and Martin, 2008; Dyck, Morse, and Zingales, 2013), but also to lower levels of trust in the financial system. Giannetti and Wang (2014) study corporate financial misconduct and show that federal securities enforcement actions lead to reduced stock market participation of households in the fraudulent firm's state. Our findings complement those of the existing literature, especially Guiso et al. (2004, 2008), who document how variations in trust shape wealth allocations to risky investment both between and within countries. They find that individuals who exhibit a high level of trust are more likely than others to invest in risky financial assets and tend to invest larger shares of their wealth in such assets. By exploiting an exogenous shock to trust, we show a *causal* relationship between trust and portfolio allocation and investment flows; that trust is transmitted through social channels; and that trust has real economic effects—RIAs with trust-shocked investors were more likely to go out of business.

of the subprime crisis, including lax screening (Keys, Mukherjee, Seru, and Vig, 2010), misrepresentation of mortgages (Piskorski, Seru, and Witkin, 2015), deceptive advertising (Gurun, Matvos, and Seru, 2015), and the use of TARP funds to purchase assets from those financial institutions that were most affected by subprime mortgages (Calomiris and Khan, 2015).

1 Data and sample construction

The analysis relies on three main sources of data: court documents listing the victims of BLMIS; the Security and Exchange Commission's Form ADV; and the FDIC's Summary of Deposits (SOD) data. In this section we provide detail on each source.

1.1 Madoff victim data

We obtain the list of BLMIS's clients from court documents released by the U.S. federal bankruptcy court in February 2009.[8] This list contains approximately 14,000 investors, although some investors are mentioned multiple times, as they had more than one account. Victims are identified by names and address. In some cases, multiple victims have the same address, in which case the address is usually the office of a financial adviser. After cleaning the data to identify duplicates, we have 10,276 unique names at 5,907 unique addresses, which is similar to the 11,374 victims reported by Sander (2009).

Some investments were funneled to Madoff through "feeder" funds set up by investment firms. The largest of these, Fairfield Greenwich Advisors, had over $7.5 billion invested.[9] In the case of such feeder funds, the victim list has the name of the feeder fund, but not its individual investors. Since it is not possible to know how many investors are represented by these funds, we exclude them by removing corporate entities from our sample using filters on the investor names. We also exclude investors with foreign addresses, thereby removing some large foreign banks and investment funds headquartered in the Bahamas from our sample. Excluding these investors means that we are in some cases under-estimating the size of the trust shock in some areas, which means our estimates for the magnitude of the effects may be understated.

Madoff victims were particularly concentrated in certain geographic areas of the country, as shown in Figure 1. While some victims are found throughout the country, they are most concentrated in the Northeast from Philadelphia to Boston, in parts of California, and in southeast Florida, in particular around Miami. As we discussed in the introduction, we observe the same geographic concentration in internet searches for information about Madoff. Cities with the highest levels of

[8] Available at `http://www.scribd.com/doc/11705845/Bernie-Madoff-s-Clients-The-List`.

[9] `http://s.wsj.net/public/resources/documents/st_madoff_victims_20081215.html`

Google searching in the year after the fraud was revealed are also shown in Figure 1, with larger circles indicating more intense searching. The strong correlation between the location of victims and the intensity of searching suggests that the effect of the fraud was highest among people who live close to victims, or are socially connected to them.

1.2 Investment adviser data

We collect data on funds held at investment advisers from Part 1A of SEC Form ADV, which is also known as the Uniform Application for Investment Adviser Registration. Investment advisers regulated under the Investment Advisers Act of 1940 must file this form upon initial registration; annually in the form of an annual update; and any time there is a material change to their advisory business. The form and its schedules include detailed information about investment advisers including general information about the advisory business, control persons, client composition, conflicts of interest, and criminal behavior.

Legally, an investment adviser is "any person or firm that, for compensation, is engaged in the business of providing advice to others or issuing reports or analyses regarding securities."[10] We focus on money managers by excluding financial planners and investment consultants using disclosures from the form.

We obtain Part 1A of Form ADV data through a series of Freedom of Information Act (FOIA) requests made to the SEC.[11] The SEC provided us with all filings that were made subsequent to the beginning of electronic submission, which was mandated in 2001. Filings are made on the Investment Adviser Registration Depository (IARD) system, which is maintained by FINRA. Sensitive personal data, such as the social security numbers of the filers, have been removed from the files. Using these raw files, we construct a panel of U.S.-based adviser-year observations from 2006 to 2010, which straddles the December 2008 discovery of the Madoff fraud. Since the event occurred so close to the fiscal year end of many firms, we exclude 2008 from our sample.

[10] See p. 2 of "Regulation of Investment Advisers by the U.S. Securities and Exchange Commission" available at `http://www.sec.gov/about/offices/oia/oia_investman/rplaze-042012.pdf`

[11] A number of papers have used data from Form ADV to study hedge funds. See, for example, Brunnermeier and Nagel (2004), Brown, Goetzmann, Liang, and Schwarz (2008), Brown, Goetzmann, Liang, and Schwarz (2009), Dimmock and Gerken (2012), Brown, Goetzmann, Liang, and Schwarz (2012), Bollen and Pool (2012), and Clifford, Ellis, and Gerken (2014).

To construct the sample, we keep only filings that are "annual updating amendments." Some firms submit numerous updates throughout the year, but only the annual amendment requires firms to update their assets under management (AUM), and these filings must be made within 90 days of the adviser's fiscal year end, thereby producing consistent timing. We use these filings to construct a panel data set.[12] A few firms submit more than one annual update for a given fiscal year, in which case we keep the first annual update that was submitted.

We remove stale filings (those of firms whose AUM do not change from one fiscal year to the next) and also those with missing AUM. During the sample period, advisers had to register with the SEC if they managed over $25 million, however, many RIAs exist with very few assets under management. We exclude these small firms by requiring advisers to have AUM of at least $50 million in 2005. We also require advisers to be based in the U.S. and to exist in 2006 and survive until at least 2009. We remove outliers from the sample by removing firms that achieved astronomical growth in any year (the 99th percentile of firm maximum growth).[13] Finally, we drop two sets of managers from the sample: First, we remove BLMIS as well as any firm that was engaged in a lawsuit because of alleged investments with BLMIS. There are five such firms, which we identify using the "Disclosure Reporting Pages" of ADV filings, which requires advisers to report any litigation against them. Next, we exclude the RIAs of all feeder funds listed by the *Wall Street Journal* to have invested with Madoff.[14] Our final sample has 18,435 firm-year observations from 2006 to 2010, excluding 2008. The sample includes 4,685 unique investment advisers with main offices in every state and the District of Columbia.

We are interested in how exposure to Madoff victims is related to the investment flows of investment advisers. In item 5F of form ADV, investment advisers report their assets under management and the number of advisory accounts their clients have. We use the natural logarithm of each of these variables as outcome variables to capture investment advisor flows. Because changes in assets under management is a function of both asset flows and investment returns, in most specifications we include controls to remove the effect of investment returns. In particular, we

[12] There are 343,691 filings during the period 2000–2014, of which 37.4% are "annual updating amendments."

[13] An alternative way of dealing with this is to winsorize the data, but doing so on AUM does not make sense in this setting since firms with the largest assets will have their AUM set to some maximum percentile for the entire study period, which would give zero AUM growth throughout the study.

[14] The list of victims can be found `http://s.wsj.net/public/resources/documents/st_madoff_victims_20081215.html`

include fixed effects for the filing period to which an adviser's ADV report applies. These fixed effects are determined the month and year of both the current and previous ADV filings, so they capture the effect of the average investment return on changes in AUM during the period covered by a filing.

There are three important disclosures that we use to capture the exposure of the firm's clientele to Madoff victims. The first is the location of the advisory firm's main office, which is disclosed in item 1F. In schedule D, firms must also disclose the locations of their five largest offices (by number of employees) where their advisory business is conducted. (Many firms choose to disclose more than five.) Finally, in item 2C advisers must provide a list of any states in which they have at least five clients. (The SEC then sends a "notice filing" to the securities regulator in each state, except for Wyoming, which has no such regulator.)

We construct two measures of exposure to Madoff victims. The first is based on the location of the investment adviser and the second is based on the location of the clients of the adviser. For the first measure, we use the zip codes reported for the main office and any additional offices to compute the number of Madoff victims who live in the same zip code, or within various distances of the office zip codes. We construct the measure *Log(Num. victims)* as the number of victims within a given radius of the offices. When constructing the measure based on multiple offices, we compute this as the natural log of the average number of victims within the given radius of all reported domestic offices.

For the second measure, we begin by calculating the number of Madoff victims by state. We then sum the number of victims and the population across all the states with which the advisory firm notice files (i.e., has at least five clients). Based on these calculations, we construct a measure of exposure as the average number of victims per 1,000 people in states where the advisory firm has clients.

We then construct a measure of adviser closures using data on RIA withdrawals from SEC registration. RIAs must file form ADV-W when withdrawing from registration and must specify their reason for withdrawal. We obtain all ADV-W filings from 2001 to 2014 from the SEC through an additional FOIA request. Firms can withdraw either partially or fully, but since we are interested in firm closures we keep only full withdrawals from registration. While there are many reasons firms withdraw from registration, the most common include going out of business, mergers, and relying on an exemption to deregister. Table 1 shows that about 5.5% of firms that were registered with the SEC in 2007 withdrew from registration in 2009 or 2010. We are interested in investigating whether abnormal withdrawals due to the trust shock forced some RIAs out of business. We therefore create a variable that indicates whether the RIA went out of business or discontinued its advisory business in 2009 or 2010 by manually examining the stated reason for withdrawal. Almost half of all full withdrawals fall into this category (2.4% overall). The most common withdrawal reasons cited are simply "No longer in business" or "closing business," but other examples include "Winding up investment adviser due to bankruptcy" and "Not enough business."

1.3 Branch-level deposit data

We collect data from FDIC Summary of Deposits (SOD) database to measure the spatial distribution of bank deposits. The FDIC collects this data from each institution through a survey. All institutions with branch offices are required to submit the survey, while institutions with only a main office are exempt from filing. The SOD data contain information about the location, ownership, and deposit amounts booked at all offices of FDIC-insured bank and thrift institutions as of June 30 of each year.

The data links each bank branch to a complete street address and the branch's latitude and longitude (beginning in 2008). The FDIC requires institutions to use actual address locations to ensure consistency with U.S. Postal Service standards. The FDIC survey also explicitly prohibits use of post office boxes, mailing addresses other than the actual physical address, street names without actual numbers, intersections, or any other general locations when filing branch office location information. Institutions are also given the opportunity to change branch office information because of a merger or branch office purchase after disclosing the name, city, and state of the other institution involved in the transaction and the effective date of the transaction. This ensures that the branch location data are of high quality.

We aggregate deposits at each branch for each zip code. We drop observations if the street address cannot be unambiguously matched to a zip code. Nguyen (2014) reports that the percentage of unmapped observations is 7.5% in 1999 and declines to less than 1% during the sample period we are using in our study. Most of our analysis is conducted using data from 2007 through 2010. Over this period the data include aggregated deposit data from 97,756 unique bank branches from 21,126 unique zip codes. In total there are 80,478 zip code-year observations spanning 2007 to 2010.

Panel B of Table 1 displays summary statistics for the panel of of zip code level branch deposits. The median zip code has over $80 million in deposits, but there is large variation. Madoff victims are present in about 7% of zip codes. Also included are statistics on demographic controls at the zip code and county levels. One important control variable is Log(RIA AUM in main office zip), which is the natural log of all assets held in RIA accounts in the zip code. The summary statistics in Panel A shows that over 59% of RIAs have at least one Madoff victim. This is because RIAs tend to locate near very wealthy areas. Therefore, this variable is an important control for the location of high-net-worth individuals.

1.4 Additional data sources

We use a number of additional data sources to construct geographic control variables. Age, income, and population data are from the 2000 U.S. Census. Data on religious affiliation are from the Religious Congregations and Membership Study, 2000. These data are available at both the county and state level, and can be downloaded from the Association of Religious Data Archives (ARDA) website.[15]

2 Empirical methodology

We estimate the impact of trust on financial outcomes using a difference-in-differences framework surrounding the Madoff fraud. Since some areas of the country were more exposed to the fraud than others, we are able to estimate differences in the changes in aggregate investment behavior between areas with differential exposure. As discussed in the introduction in detail, our main hypothesis is that those areas with higher exposure will experience greater effects of the trust shock. We are not interested in the "wealth" effects of the Madoff fraud—that is, the reduction in investments due directly to the destruction of wealth by the fraud—but rather the impact of the reduction in

[15] Available at `http://www.thearda.com/Archive/Files/Descriptions/RCMSCY.asp`.

trust induced by the fraud. Our notion is that knowing others who were affected by the fraud could reduce investors' trust in investment advisers and, in turn, assets will flow from these advisers into safe assets such as bank deposits.

We face two important challenges with this empirical setup. First, Madoff did not choose his clients randomly; rather, he targeted older, wealthier investors within the affinity group and it is well-documented that both age and wealth affect risk taking in individuals (Malmendier and Nagel, 2011). Second, the collapse of the fraud coincided with the financial crisis.[16] Because our methodology differences out the time effect, this should not be a major concern unless one believes that the financial crisis—and not the shock to trust—caused people nearer to Madoff victims to respond differently. Considering these issues together, the most plausible alternative that we must be careful to rule out is that differences in age and wealth across areas with differential exposure to Madoff led to differential responses to the financial crisis. This makes it important to control for the effects of demographic characteristics.[17]

To investigate fund flows at investment advisers, we estimate various forms of the regression equation

$$\log(\text{AUM})_{i,j,t} = \alpha_i + \gamma_{j,t} + \beta_M \text{Post}_t \times \text{Madoff Exposure}_i + \sum_m (\beta_{C,m} \text{Post} \times \text{Control}_{i,m}) + \epsilon_{i,t}, \quad (1)$$

where $\log(\text{AUM})_{i,j,t}$ is the natural logarithm of the assets under management at RIA i with its main office in state j, in year t. Post is a dummy variable for the years following the December 2008 event (2009 and greater). Our base model includes RIA fixed effects as well as fixed effects for either state–year or the ADV filing period (explained in the data section). This controls for time-varying geographic-specific omitted variables, such as changes in local economic conditions. Including fixed effects of this nature makes our specification analogous to that recommended by Gormley and Matsa (2014) to control for unobserved heterogeneity.

[16]Since Ponzi schemes rely on new investors to pay off existing investors, such schemes tend to collapse when new investors dry up or when many existing investors want to withdraw funds. Both of these happened in the aftermath of the financial crisis.

[17]Alesina and La Ferrara (2002) show that trust is not only related education, gender, or income of the individual, but also community characteristics such as the level of income inequality where the investor lives. These findings are particularly important for our paper, as our interest lies in comparisons of different geographic regions after controlling for community characteristics that can influence level of trust.

Defining the location of an adviser is made difficult, however, by the fact that not all clients are physically close to an adviser's office. Therefore, as discussed in the data section, we measure the Madoff Exposure of RIA i in two ways: First, we use the log of one plus the number of Madoff victims in the zip code(s) where the RIA has an office. This is a measure of the RIA's proximity to victims. Second, we use a measure of the proximity of an RIA's *clients* to victims using the number of victims in states where the RIA has at least five clients, and is therefore required to "notice file" in Form ADV. We refer to the first measure as "adviser proximity" and the second measure as "client proximity."

The coefficient of interest in equation (1) is β_M. If a reduction in trust causes investors to move money out of investment adviser accounts, then β_M should be negative, indicating that people who are more exposed to the Madoff fraud abnormally decreased their RIA investments following the Madoff fraud.

A valid difference-in-differences estimation must satisfy the "parallel trends" assumption; that is, the control and treated groups must not behave differently prior to the event—they must exhibit parallel trends in the dependent variable. In Figure 2 we plot the coefficient estimates of year interactions with the measure of client exposure to Madoff victims (number of victims per 1000 population in client states). Also included are 95% confidence bands around these estimates. These coefficients estimate the change in the difference between assets under management at RIAs whose clients are exposed to Madoff victims to varying degrees in each year relative to the initial difference in 2005. The plot shows that exposure levels do not affect investment adviser AUM until after the Madoff event, confirming the validity of the parallel trends assumption in our tests. In 2009 and 2010, RIAs with clients in more exposed states lose an abnormal percentage of their AUM. The figure also shows the persistence of the effect. By 2012 there is no sign of reversal. We revisit these finding in section 3.1.

After studying flows from investment advisers, we turn next to bank deposits using the branch-level FDIC data. Our regressions follow the same structure as those for the RIA data, although we now use zip code–year observations (measured at June 30th). In contrast to investment advisers, banks are located in virtually every zip code in the country, so we have more zip code level observations in this analysis. And since individuals are likely to bank at a branch near where they live,[18] we define the exposure to the trust shock for banks in a zip code simply as whether any victims live in the zip code, or the log of the number of victims. Similar to the numerous fixed effects we include in the RIA regressions, our bank deposit regressions include fixed effects for the zip code and either state–year or county–year fixed effects.

3 Results

3.1 Investment adviser flows

We begin by our main empirical analysis by by showing that trust-shocked investors withdrew funds from accounts held at registered investment advisers. We examine the effect on advisers of being located close to victims of the Madoff fraud or of their clients being located close to victims. We do so by investigating changes in their assets under management. As discussed in the methodology section, we include a variety of fixed effects and numerous other controls to rule out alternative explanations related to the financial crisis.

Our first set of results is reported in Table 2, where we present results from difference in difference regressions of assets under management on an adviser's exposure to Madoff victims. In this analysis, we measure victim exposure as the log of the average number of Madoff victims in each of the zip codes where an adviser has an office. Our panel includes annual observations during the period 2006–2010, with 2008 excluded, as discussed above. The dummy variable "Post" is an indicator for observations occurring after the Madoff fraud was uncovered in 2008, so it is activated for observations in 2009 and 2010.

We include a number of demographic control variables, all of which are measured as the average demographic statistic in the zip code or county around each of the advisers' offices. These control variables include measures of the size of the adviser's business (AUM before the fraud began, number of offices, and number of states in which it operates) as well as zip code characteristics such as average age and median income. We also include the log of the total funds invested across all RIAs in a zip code as a measure of total wealth, especially of high net worth individuals. In some specifications, we also include the percentage of the county population that is in the affinity group.

[18] Gilje (2011) shows that local bank deposits increase with local natural gas discoveries.

These controls are time-invariant. In addition, all regression specifications include adviser fixed effects, which absorb any time-invariant variables, so all variables are only included when interacted with the Post dummy. Finally, we include filing period or state–year fixed effects, where the state corresponds to the state in which an adviser maintains its main office and the filing period is described in the data section. Standard errors are clustered to allow correlation within an adviser and filing period (in models 1 and 2), or by adviser and state-year (models 3–6).

Table 2 shows a consistent negative relation between exposure to Madoff victims and the growth rate of funds invested in risky assets. We begin with no control variables (aside from the adviser and filing period fixed effects), and then add additional controls. Coefficient estimates on Post×Log(Num. victims) are all significant at the 1% level. In model 4, we see that a one standard deviation increase in the log number of victims leads to a decrease of assets under management of $0.0436 \times 1.55 = 6.8\%$. Compared with the median AUM growth rate in the sample of 13%, this is an economically large result. In model 5 we add the percent of the population in the RIA office's county that is in the affinity group. The negative estimate of this coefficient suggests that social connections within the affinity group may contribute to the abnormal outflows from advisers.

Coefficient estimates on control variables indicate that advisers with larger investment balances or fewer locations see larger outflows after 2008. Areas with older people or more wealth also have more outflows. After controlling for wealth, however, the level of average income in the RIA office zip code has no significant effect on flows.

In Table A.2 of the Internet Appendix, we report several specifications with two additional controls: (1) the change in high-end home prices from February 2007 to December 2008 in a zip code;[19] and (2) the percent of households with income above $200 thousand, averaged across zip codes where the RIA has offices. The first variable, which provides a control for the effects of the housing crisis, enters weakly significant in the regression, but including this control has little effect on our main coefficient of interest. The second variable, which provides another control for wealth, is insignificant and has no effect on the other estimates. (We confine these results to the appendix because data limitations for these variables lead to a loss of about one-third of the observations.)

[19] We use the Zillow Home Value Index (ZHVI) for top-tier residences by zip code, provided by the real estate data firm Zillow. This index uses houses with prices in the top third of the price distribution. Data available at `http://www.zillow.com/research/data/`.

In model 6, we interact Log(Num. victims) with the Log(Num. client states). While our office-based measure for Madoff exposure may be good for RIAs whose clients are local, it may not be a good measure for advisers who have clients in many states. Indeed, the coefficient estimate of the interaction term confirms this conjecture: operating in many states mitigates the effect of Log(Num. victims) on RIA flows. This suggests that a clientele-based measure of exposure may be more appropriate. We address this by creating the clientele-based exposure measure, using the number of victims in a state where an RIA has clients (see section 1.2 for details). For this analysis, we include a similar set of control variables as in Table 2, although we must now aggregate these at the state-level rather than zip code or county. In addition, since our measure is clientele-based and not based on the location of the RIA we include county-year fixed effects for the adviser's main office in some specifications.

The regression results are reported in Table 3. Again, we see strong investment flows out of investment advisers whose clients are more exposed to fraud victims. Taking the standard deviation of "Avg. victims per 1000 pop. in client states" of 0.05 from Table 1, the magnitude of the effect in model 4 is $-0.97 \times 0.05 = -4.9\%$. Alternative specifications in models 1–3 yield similar results.

In models 5–7 we see additional evidence that the trust shock was transmitted via social connections or media within the affinity group. This can be seen in the fact that the effect of negative flows is actually restricted to states in which there are both more victims and higher populations of the affinity group. In each of the three specifications the interaction term between Avg. victims per 1000 pop. in client states and Avg. pct. affinity group in client states is significantly negative at the 1% significance level.

3.2 Adviser characteristics

Gennaioli et al. (2015) observe that many investment managers advertise their services based on trust, experience, and dependability, rather than just past performance. They model a money management industry in which money managers compete for investors not only on the basis of performance, but also of being trustworthy. This model predicts that investors would prefer to use a money manager whom they trusts, enabling trusted managers to charge investors a higher fee without having them take their business to a less expensive competitor. The Form ADV data allow us to observe different types of services provided by RIAs including client type, fee structure, and whether they take custody of assets. In this section, we examine how these RIA characteristics affect their susceptibility to the Madoff trust shock.

RIAs include hedge funds, private equity, real estate, and venture capital advisory firms, but also include what we might consider as wealth managers. We broadly classify RIAs as either "wealth managers" or "private fund advisers" by defining private fund advisers as those RIAs that disclose that they advise a private fund in Form ADV in 2007. While many RIAs provide both wealth management services and advise private funds, this coarse definition captures two different types of firms, and defining the firms this particular way is more likely to capture "pure" wealth managers. Table A.3 in the Internet Appendix shows large differences in client composition, fee structure, and services provided between these two types of RIAs. Wealth managers have a much greater concentration of individual clients (76% vs. 43%), are much more likely to provide financial planning services (54% vs. 22%), and charge performance-based fees less frequently (8% vs. 59%). They are also much less likely to have custody of client assets (13% vs. 48%). The table also shows that BLMIS looked much more like a private fund adviser than a wealth manager; the RIA disclosed few individual clients, did not provide financial planning services, and importantly, had custody of client assets.

In Table 4, we report results from regressions following those in model 2 in Table 3, but we add various RIA characteristics interacted with the post period dummy as well as the interaction of the post period dummy, the RIA characteristic, and the measure of Madoff victim exposure. The coefficient estimate on the RIA characteristic interacted with the post period estimates the abnormal change in AUM over the event period associated with that particular characteristic, while the triple interaction terms estimate the degree to which the characteristic mitigates or exacerbates the effects of the trust shock. For these regressions, we use the client-based measure of exposure. Results using the adviser-based exposure are reported in Table A.4 of the Internet Appendix.

The table reports three coefficient estimates for each regression: Post $\times$ Victim exposure, Post $\times$ RIA characteristic, and Post $\times$ Victim exposure $\times$ RIA characteristic. We report results for separate regressions using six adviser characteristics, with three different sampless each (the full sample, just wealth managers, and just private fund advisers). For example, looking at the first row estimated using the "Full sample", we see that when an RIA has clients in states with more victims, they see abnormal outflows, as we saw above. We also see that if the RIA tends to have individual clients (excluding high net worth individuals) they experienced small abnormal outflows during the post period when we condition out the effect of victim exposure. But interestingly, the negative flow effect of victim exposure is mitigated by having more individual investors, as seen in the positive interaction term estimate.

The results for the full sample of RIAs show that the trust shock was less severe for RIAs with a greater percentage of individual and high net worth individual clients, and those that provide financial planning services. In fact, conditioning out the effect of victim exposure indicates that providing financial planning services reduces outflows during the post period (note the strong positive coefficients in the "RIA char." column in each model). This result provides strong empirical evidence consistent with the predictions of Gennaioli et al. (2015) which we outlined at the beginning of this section. We also find that RIAs compensated by performance-based fees or those who had custody of client assets saw greater trust shock-related outflows. It is not surprising that custody is important, as RIAs without custody of customer assets would find it very difficult to steal from them.

Of course, many of these characteristics are correlated with different types of advisory businesses. We therefore estimate these same regressions restricting our sample first to wealth managers and then to private fund advisers. Within the set of wealth managers, providing financial planning services substantially mitigates the effect of the trust shock on outflows. Additionally, for both groups of RIAs there is evidence that having an individual-based client base reduces the effects of the trust shock on flows, while charging performance-based fees increases the effect of trust-based outflows.

3.3 RIA closures

We now investigate whether RIAs with clients more exposed to the trust shock were more likely to go out of business following the Madoff event. Table 5 displays the results of linear probability models predicting the probability that an RIA goes out of business in either 2009 or 2010. The sample is composed of all U.S.-based RIAs in existence in 2007, subject to the filters discussed in section 1 with one exception: RIAs are not required to exist in 2009, since we are trying to predict whether they go out of business in 2009 or 2010. Data on RIA closures come from Form ADV-W, as discussed earlier in section 1.2. The dependent variable is an indicator variable that is one if the RIA withdraw from SEC registration due to business closure and the variable of interest is "Avg. victims per 1000 pop. in client states."

The table shows that RIAs with clients more exposed to Madoff victims are more likely to go out of business following the trust shock. Since about 2.4% of RIAs were driven out of business in 2009 or 2010, the coefficient estimates suggest that a one standard deviation increase in Madoff victim exposure increases the probability of going out of business by 0.011, which is a 46% increase in the unconditional probability of closure. When splitting the sample between wealth managers and private fund advisers, the primary effect is through the private fund advisers. These advisers had a higher probability of closures during the period at 0.034 and the estimated effect of the trust shock is also much larger. A one standard deviation increase in Madoff exposure leads to a 0.018 greater probability of closure, which means firms with greater exposure are over 50% more likely to close. Table A.5 in the Internet Appendix shows that these results continue to hold when estimated using probit regressions.

3.4 Bank deposits

Having shown that funds are withdrawn from investment advisers, we turn next to examine changes in deposits at banks following the uncovering of the Madoff fraud. We use data from 2007 to 2010 to analyze the change in deposits around the trust shock. (The deposit data are as of June 30th each year.) The main variable of interest is a dummy variable for whether at least one victim of the Madoff fraud lives in the same zip code as the bank branch (models 1–4), or the log number of victims in the zip code (models 5–6). Results are reported in Table 6.

We define the Post indicator variable to take a value of one in 2009 and 2010, and zero in other years. All specifications consistently show greater increases in cash deposits in zip codes that suffer the trust shock. In model 1, without controls, the estimate on the Post coefficient indicates that cash deposits increased by 9.5% in the period 2009–2010 across all zip codes. Remarkably, we see an *additional* 10.0% increase if there is at least one fraud victim in the zip code. This coefficient estimate declines to 4.1% when estimating models 2–4, which include additional controls and county-year fixed effects. However, all estimates remain statistically significant at better than the 1% level, with t-statistics greater than 3.5.[20] Similar to the RIA regressions above, the control variables interacted with the post period include average age and income in the zip code, total assets held at RIAs, percentage of the population that is in the affinity group, and the population in the zip code[21], and cash deposits in 2006. The total wealth measure is a particularly important control in these regressions (t-statistics are in between 10 and 20) because, in contrast to the RIA sample where investment advisers will tend to be located only in wealth areas, bank branches are located in most zip codes in the country.

Using the dose of the treatment as our variable of interest, Log(Num. victims), we find that banks in areas with more Madoff victims experienced greater increases in deposits. The coefficient estimate on Log(Num. victims) is 0.028 in model 5, which indicates that a one standard deviation increase in the Log(Num. victims) is associated with a 1.2% increase in cash deposits.

As with the RIA results, we also report additional regression results in Table A.6 of the Internet Appendix with additional controls for home price changes and wealth. Our results remain qualitatively unchanged.

Since the locations of Madoff victims are not randomly distributed, it is also useful to estimate our regressions using only the set of zip codes targeted by Madoff. We report this in column 6, where the analysis is restricted to those zip codes where at least one victim of the Madoff fraud resides. Even within these zip codes, we continue to see that areas with more victims have a greater increase in cash deposits following the trust shock. And despite a much smaller sample (5575 observations in 1438 zip codes), the coefficient estimates remain strongly statistically significant.

In Table A.7 of the Internet Appendix, we provide an alternative approach to this analysis by using a matched sample approach. We run a probit regression with 2006 data to predict which zip codes will be treated—that is, have at least one victim. All coefficients are significant at the 1% level, and the pseudo-R^2 is 0.40. We use predicted values from this regression to do a propensity score match, where, for each treated zip code, we identify the most-similar untreated zip code by using

[20]Standard errors are clustered by zip code in models 1 and 2, by zip code and state-year in model 3, and by zip code and county-year in models 4 through.

[21]Rather than using population to scale the number of victims in the zip code, we include it as a control variable. There is not much variation in population between zip codes, but a some of zip codes have small populations that make it a poor scaling variable.

a nearest-neighbor match without replacement. We estimate difference-in-differences regressions using these matches. Our finding that bank deposits increase in treated zip codes is confirmed in all specifications.

Our measure of exposure has so far been based on victims within the zip code of each branch. We now investigate the effect of distance between branches and Madoff victims on changes in bank deposits. We use model 3 of Table 6, but also include indicator variables that indicate whether the closest Madoff victim is in the same zip code, within 10 miles of the zip code, from 10 to 25 miles of the zip code, or from 25 to 50 miles of the zip code. The coefficient estimates on these indicators, interacted with the post period indicator, are plotted in Figure 3 along with their 95% confidence intervals. The figure shows that deposits abnormally increase with shorter distances from Madoff victims. Banks in zip codes with Madoff victims experienced abnormal deposit growth of over 5% following the Madoff event, while those with the nearest Madoff victim within 10 miles saw deposit growth of almost 3%. Banks with Madoff victims greater than 10 miles away did not experience abnormal deposit growth.

3.5 Placebo test

In this section, we conduct a placebo test to see whether investors in areas that later suffer the trust shock also behaved similarly during another market downturn. Specifically, we use the bursting of the bubble in technology stocks in 2000 to test whether areas that were later exposed to the Madoff fraud also behaved differently from other areas during another time of financial stress. If we were to find that investments of trust-shocked areas were disproportionately transferred from risky to less-risky assets, then we would conclude Madoff trust shock *per se* is not the primary reason of the results we have documented.

To do so, we estimate the exact same regressions as in Table 6, but use bank deposit data from 1999 to 2002. (The RIA data are not available during this time period, so we focus only on bank deposits.) The market reached its peak in March 2000, and by June of 2000 it was only slightly down from that peak. It then plummeted until October 2002. Thus, we use 1999 and 2000 as the pre period in our analysis and 2001 and 2002 as the post period (all observations are as of June 30).

Table 7 presents the results. Column 1 of the table shows that unconditionally, growth in deposits in zip codes with at least one Madoff victim were 2.8% higher. However, zip codes that were exposed to the Madoff fraud are also wealthier and older. Once we control for these observable differences, Madoff exposed areas show no difference in deposit growth in response to the tech bust. The estimates in columns 2 through 5 confirm this.

In column 6, the model excludes the Madoff exposure variable from the regression in order to compare the coefficient estimates on the other control variables with those estimated around the financial crisis in Table 6. Most of the coefficient estimates on these controls are similar around both downturns, but only following the financial crisis—which coincided with the Madoff fraud—do we see evidence of a positive relationship between the percentage of affinity group population around banks and bank deposit growth rates. This effectively rules out an alternative explanation for our results: that people in these areas respond to financial crises more conservatively than those in other areas, and that this response had nothing to do with Madoff. Clearly this is not the case.

3.6 Instrumental variables regressions

We have so far addressed endogeneity due to omitted variables using numerous fixed effects specifications. As a final test, we use an instrumental variables approach to verify that our results remain unchanged.

Our main instrument for the number of victims in a zip code is simply the average percentage of the county population that is in the affinity group in counties where the RIA has offices. Areas with more members of the affinity group are more likely to have victims, making this a good candidate for an instrument. To be a valid instrument, the exclusion restriction requires that the variable also not be related to either RIA investments or bank deposits other than through its effect on the number of Madoff victims. As we just showed with the placebo analysis, there is no evidence that members of the affinity group behave differently following stock market declines. Therefore, after controlling for demographic characteristics, this restriction is satisfied.

We report results from this IV approach in Table 8. First-stage regressions in columns (1) and (3) confirm that the instrument is highly correlated with exposure to the trust shock: coefficient estimates on Avg. pct. affinity group are highly significant ($t > 9$) and the R^2s are about 0.33. In column (1), where we use the RIA sample, the only other variable that is related to the number of victims is zip code age. In column (3), the sample includes a more heterogeneous group of zip codes than the RIA data due to the prevalence of bank branches, so other variables such as wealth, age, and income are important in identifying which zip codes will have more victims.

Results from the second stage regressions are reported in column (2) for RIA assets and column (4) for bank deposits. In both cases, estimates are similar to what we found in the earlier tests, although somewhat larger in magnitude.

4 Conclusion

Using events surrounding the Madoff scandal, we present evidence that a shock to trust led investors to move money from risky to low-risk assets. In conjunction with the previous research that has used cross-sectional variation in measures of trust to identify its effect on a variety of economic behavior outcomes, our results are consistent with the view that investor perceptions are important for resource allocation in the economy.

Since Madoff victims were primarily targeted due to their affinity to the perpetrator of the fraud, we are able to use the ethnic composition of communities as an instrument to test whether changes in trust caused the shift in asset allocation, and find that they do. RIAs with clients in areas affected more by the trust shock experienced more than 30% closure rates suggesting trust shocks can lead to adverse real effects in the economy.

While the results in our paper are identified from one particular ethnic group that comprises the affinity group for the fraud, the implications for how a shock to trust can be transmitted through social connections would likely apply to any group.

Our study offers several new directions for future research. First, our analysis focuses on aggregate investment by geographic areas. Another study could perform a similar analysis at the individual investor level and study how past experiences interacted with trust shocks affect investment behavior in financial markets.[22] Another direction for future research could be to investigate other real effects of trust shocks on the economy: Do individuals' portfolio rebalancing

[22]Malmendier and Nagel (2011) show that generation that experienced the Great Depression report lower willingness to take financial risk, after controlling for age, year effects, and household characteristics.

due to sudden trust shocks affect both risk and resource allocation both at aggregate market and local levels? Finally, how does trust in financial intermediaries evolve or is rebuilt after being diminished?

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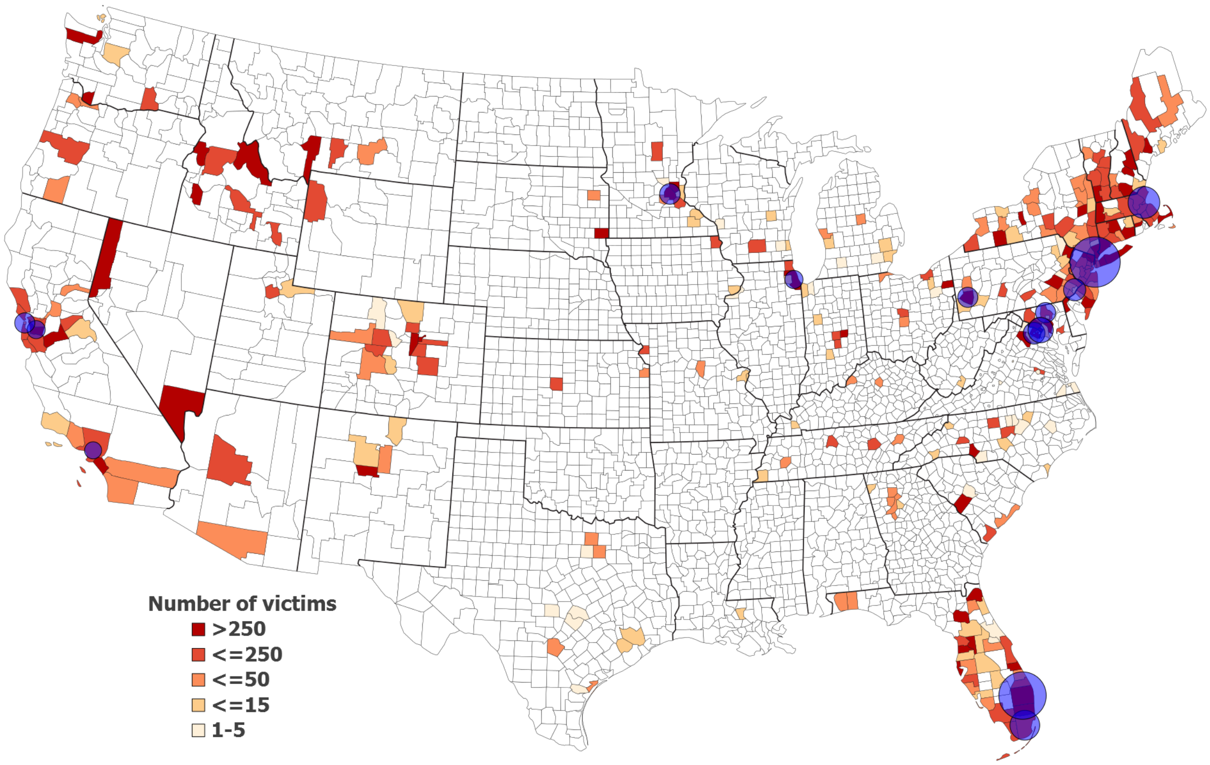

Figure 1: Number of Madoff victims by county

The map shows the number of victims of the Madoff fraud by county. We count victims as the number of unique names on the list of victims supplied to the court. In some cases, the address corresponds to that of an investment advisory or accounting firm, in which case the victim may reside elsewhere. Counting victims by number of unique addresses—and therefore putting less weight on locations of firms representing victims—provides a very similar picture of the distribution of victims. Cities with high levels of Google searching for the term "Madoff" during 2009 are denoted with circles; larger circles indicate more intense search interest. At the state level, the rank correlation between the Google search index and the number of victims is 0.77.

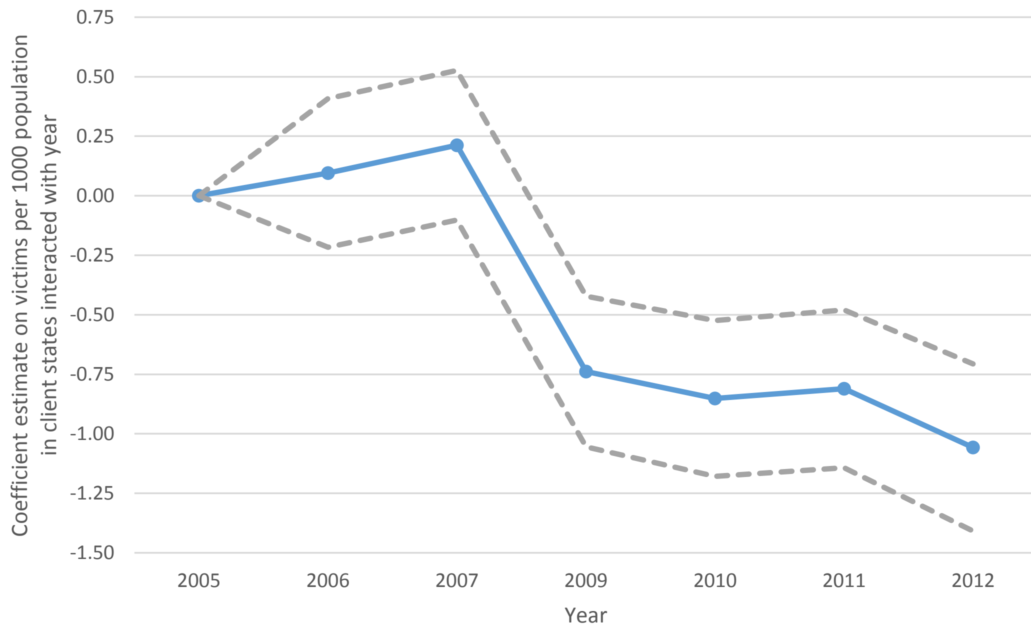

Figure 2: Changes in investment adviser AUM by year based on victims per 1000 in client states

The figure displays coefficient estimates measuring differences in the changes in log (AUM) of investment advisers attributed to the number of Madoff victims per 1000 population in the states in which the RIA operates by year. The base year is 2005 and the Madoff Ponzi scheme was uncovered on December 10, 2008. The AUM data are as of the RIA's fiscal year end. Specifically, plotted are the γ coefficient estimates and their 95% confidence interval (based on heteroscedasticity-consistent standard errors clustered by firm and year) from the following adviser-level regression:

$$\log(\text{AUM})_{i,t} = \sum_{j} (\beta_j I_t(t=j) + \gamma_j I_t(t=j) \times \text{Victims per 1000 pop}_i) + \delta_i + \epsilon_{i,t},$$

where $\log(\text{AUM})_{i,t}$ is the natural logarithm of AUM for adviser i, j takes the values 2006, 2007, 2009, 2010, 2011, and 2012, $I_t(t=j)$ indicates whether the observation occurs during year j, and Victims per 1000 pop_i is the number of victims per 1000 population in the states in which adviser i operates. The sample includes all U.S.-based, SEC-registered money managers outlined in section 1.2 from 2005 through 2012, excluding 2008.

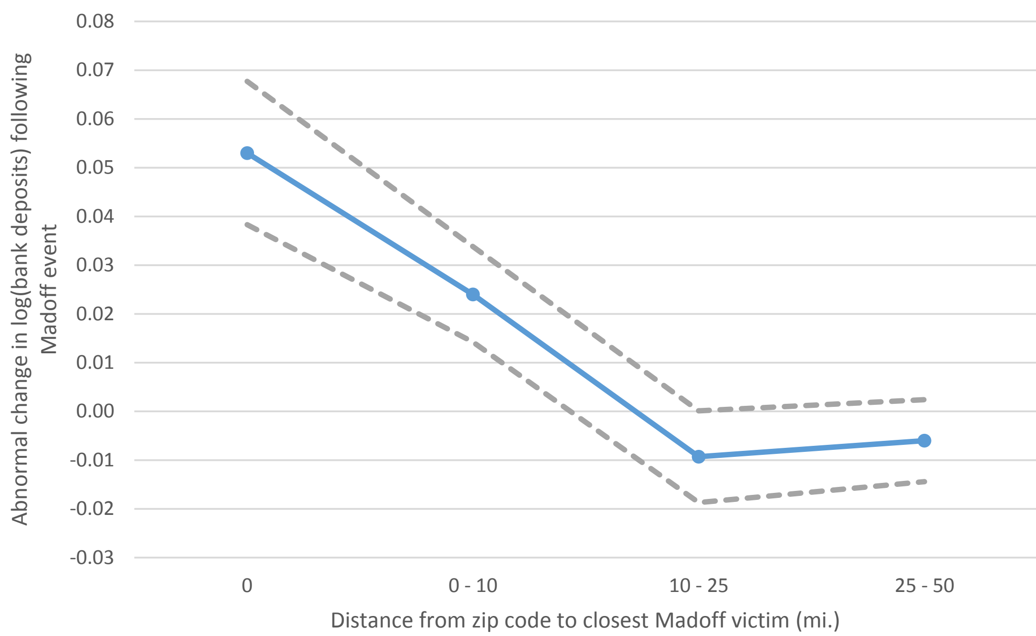

Figure 3: Change in bank deposits and distance from Madoff victims

The figure displays estimates of distance from Madoff victims on changes in bank deposits around the Madoff event. Estimates and standard errors are estimated using the model estimated in column 3 of Table 6, which includes zip code and state-year fixed effects and is estimated using data from 2007 through 2010. Also included in the model are indicator variables that indicate the closest victim to the zip code. Specifically, variables that indicate whether the closest Madoff victim is within 10 miles of the zip code,from 10 to 25 miles of the zip code, or from 25 to 50 miles of the zip code. The coefficient estimates on these indicators interacted with the post period indicator are plotted along with their 95% confidence intervals (based on heteroskedasticity-consistent standard errors clustered by zip code).

Table 1:

Summary statistics

The table displays summary statistics for the investment adviser data (Panel A) and the bank branch data (Panel B). Panel A includes data from the years 2007 through 2010, while in panel B the sample includes the years 2006 through 2010, excluding 2008. Bank branch deposit data is reported as of June 30th of each year. Investment advisor data are from annual updating amendments to form ADV, which are reported within 90 days of the adviser's fiscal year end. Data on SEC registration withdrawals and RIA closures are from SEC form ADV-W.

Panel A: Investment adviser sample summary statistics

	Mean	Median	St. Dev.	N
AUM ($s millions)	5,283.010	293.173	37,447.950	18,435
AUM growth rate	0.199	0.132	0.583	18,326
Number of Madoff victims in zip code	18.634	1.000	56.868	18,435
Number of domestic offices	1.835	1.000	7.077	18,435
Number of client states	8.261	3.000	13.345	18,435
Log(AUM)	6.106	5.684	1.777	18,435
At least one victim in zip	0.592	1.000	0.492	18,435
Log(Num. victims)	1.247	0.693	1.552	18,435
Log(Num. victims) if Num. victims > 0	2.106	1.609	1.503	10,919
Avg. victims per 1000 pop. in client states	0.046	0.034	0.050	17,301
Log(Beg. AUM)	5.927	5.447	1.707	18,329
Log(Num. of offices)	0.291	0.000	0.560	18,435
Avg. age in office zips	43.167	41.417	10.183	18,352
Avg. age in client states	35.334	35.504	1.360	17,301
Log(Avg. income in office zips)	11.283	11.344	0.481	18,272
Log(Avg. income in client states)	10.669	10.667	0.081	17,301
Log(RIA AUM in main office zip)	24.467	24.220	2.878	18,427
Avg. pct. affinity group in office counties	5.382	3.465	5.924	18,427
Avg. pct. affinity group in client states	2.386	2.005	1.683	17,301
Log(Num. client states)	1.557	1.386	1.056	18,435
Pct. clients individuals (not high net worth)	26.749	18.000	29.738	18,435
Pct. clients high net worth individuals	36.181	38.000	31.682	18,435
Provide financial planning services	0.413	0.000	0.492	18,435
Advise a private fund	0.399	0.000	0.490	18,435
Compensated by performance-based fee	0.280	0.000	0.449	18,435
Custody of cash or securities	0.268	0.000	0.443	18,435
2007 RIA filed ADV-W between 2009-2010	0.055	0.000	0.228	4,744
2007 RIA closure between 2009-2010	0.024	0.000	0.154	4,744

Table 1 continues on the following page.

Table 1 continued from the previous page.

Panel B: Bank branch sample summary statistics

	Mean	Median	St. Dev.	N
Deposits ($s thousands)	312,854.600	79,509.990	2,344,202.000	81,194
Number of Madoff victims in zip code	0.454	0.000	7.172	81,748
Log(Deposits)	11.301	11.284	1.566	81,194
At least one victim in zip	0.071	0.000	0.256	81,748
Log(Num. victims)	0.096	0.000	0.414	81,748
Log(Num. victims) if Num. victims > 0	1.357	1.099	0.841	5,784
Avg. age in zip	38.462	40.000	10.068	81,649
Log(Avg. income in zip)	10.825	10.801	0.371	77,894
Log(RIA AUM in main office zip)	2.843	0.000	7.261	81,748
Log(zip population)	8.856	9.017	1.389	78,292
Log(Beg. Deposits)	11.216	11.209	1.542	80,139
Pct. affinity group in county	1.272	0.092	2.821	81,743

Table 2: RIA flows and adviser proximity to Madoff victims

The table displays regression results of the log of investment adviser AUM on exposure to Madoff victims following the Madoff fraud in December of 2008. Victim exposure is measured as the log of the average number of Madoff victims in the zip codes as each of the advisers' offices. The analysis is conducted using the sample of U.S.-based SEC registered investment advisers for the years 2007 through 2010, excluding 2008. Observations are at adviser-year level. The Madoff Ponzi scheme was uncovered on December 10, 2008, thus 2009–2010 is the post periods in the regressions. All regressions include adviser fixed effects. In addition, models include filing-period fixed effects and main office state-year fixed effects where indicated. Demographic control variables are measured as the average demographic around each of the advisers' disclosed offices. Control variables include beginning assets under management (measured in 2005), the log of the number of states in which the adviser has at least five clients, average age, log of median income, log of RIA AUM in the zip code, and the percentage of the county population that is in the affinity group. Also reported are the number of observations used in the estimation as well as the R^2. The table reports standard errors clustered by adviser and filing period in models 1 and 2 and by adviser and state-year in the remaining models. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Post ×						
Log(Num. victims)	-0.0474^a	-0.0386^a	-0.0371^a	-0.0436^a	-0.0390^a	-0.0572^a
	(0.0041)	(0.0042)	(0.0056)	(0.0064)	(0.0070)	(0.0088)
Log(Beg. AUM)		-0.0399^a	-0.0425^a	-0.0476^a	-0.0474^a	-0.0559^a
		(0.0040)	(0.0039)	(0.0044)	(0.0044)	(0.0046)
Log(Num. of offices)		0.0969^a	0.0947^a	0.1082^a	0.1085^a	0.0801^a
		(0.0116)	(0.0115)	(0.0126)	(0.0126)	(0.0132)
Avg. age in office zips				-0.0017^b	-0.0016^b	-0.0014^c
				(0.0008)	(0.0008)	(0.0008)
Log(Avg. income in office zips)				0.0180	0.0206	0.0198
				(0.0175)	(0.0176)	(0.0176)
Log(RIA AUM in main office zip)				0.0076^b	0.0086^a	0.0087^a
				(0.0031)	(0.0032)	(0.0032)
Avg. Pct. affinity group in office counties					-0.0037^c	-0.0029
					(0.0022)	(0.0022)
Log(Num. client states)						0.0304^a
						(0.0089)
Log(Num. victims) × Log(Num. client states)						0.0146^a
						(0.0036)
Adviser FE	Y	Y	Y	Y	Y	Y
Filing period FE	Y	Y	N	N	N	N
Main office state-year FE	N	N	Y	Y	Y	Y
R^2	0.9591	0.9595	0.9589	0.9584	0.9584	0.9587
N	18,321	18,321	18,321	18,147	18,147	18,147

Table 3: RIA flows and client proximity to Madoff victims

The table displays regression results of the log of investment adviser AUM on client exposure to Madoff victims following the Madoff fraud in December of 2008. Client victim-exposure is measured as the average number of Madoff victims per 1000 population in the states in which the firm has at least five clients. The analysis is conducted using the sample described in Table 2. All regressions include adviser fixed effects. In addition, models include filing-period fixed effects, main office state-year fixed effects, and main office county-year fixed effects where indicated. Demographic control variables are measured as the average demographic in the states in which the firm has at least five clients. Control variables include beginning assets under management (measured in 2005), the log of the number of states in which the adviser has at least five clients, average state-level age, log of median income, log of RIA AUM in the main office zip code, and the percentage of the state population that is in the affinity group. Also reported are the number of observations used in the estimation as well as the R^2. The table reports standard errors clustered by adviser and filing period in models 1, 2, and 5, by adviser and state-year models 2 and 6, and by adviser and county-year in the remaining models. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post ×							
Avg. victims per 1000 pop. in client states	-0.7708^a	-1.0563^a	-0.8617^a	-0.9716^a	-0.2917	-0.1175	-0.4051
	(0.1274)	(0.1427)	(0.1813)	(0.1929)	(0.3140)	(0.3731)	(0.3999)
Log(Beg. AUM)	0.0694^a	0.0633^a	0.0604^a	0.0565^a	0.0577^a	0.0554^a	0.0537^a
	(0.0069)	(0.0071)	(0.0072)	(0.0077)	(0.0074)	(0.0078)	(0.0083)
Log(Num. client states)	-0.0581^a	-0.0618^a	-0.0609^a	-0.0588^a	-0.0606^a	-0.0594^a	-0.0576^a
	(0.0042)	(0.0048)	(0.0047)	(0.0049)	(0.0048)	(0.0047)	(0.0049)
Avg. age in client states		0.0226^a	0.0103	0.0136^c	0.0177^a	0.0027	0.0070
		(0.0052)	(0.0074)	(0.0080)	(0.0054)	(0.0076)	(0.0082)
Log(Avg. income in client states)		-0.1570^c	-0.1346	-0.1362	-0.3473^a	-0.4152^a	-0.4050^a
		(0.0803)	(0.1188)	(0.1276)	(0.0971)	(0.1335)	(0.1433)
Log(RIA AUM in main office zip)		0.0055^b	0.0035	0.0121^a	0.0058^b	0.0035	0.0121^a
		(0.0027)	(0.0029)	(0.0038)	(0.0027)	(0.0029)	(0.0038)
Avg. pct. affinity group in client states					0.0254^a	0.0458^a	0.0468^a
					(0.0097)	(0.0123)	(0.0130)
Avg. victims per 1000 pop. in client states × Avg. pct. affinity group in client states					-0.2180^a	-0.2950^a	-0.2681^a
					(0.0578)	(0.0656)	(0.0697)
Adviser FE	Y	Y	Y	Y	Y	Y	Y
Filing period FE	Y	Y	N	N	Y	N	N
Main office state-year FE	N	N	Y	N	N	Y	N
Main office county-year FE	N	N	N	Y	N	N	Y
R^2	0.9597	0.9598	0.9589	0.9620	0.9598	0.9590	0.9621
N	17,200	17,192	17,192	17,192	17,192	17,192	17,192

Table 4: RIA characteristics and flows

The table displays regression results of the log of investment adviser AUM on client exposure to Madoff victims following the Madoff fraud in December of 2008. Regressions follow those in column 2 of Table 3, but also include the listed RIA characteristic interacted with the post period and the interaction of the post period, the RIA characteristic, and the measure of Madoff victim exposure. Coefficient estimates and their standard errors clustered by RIA and filing period are reported for these three variables for three different samples; the full sample, the sample of wealth managers, and the sample of private fund advisers. Private fund advisers are those RIAs that disclosed in 2007 that they advise a private fund. Wealth managers are RIAs that did not make this disclosure. Characteristics included are the percentage of clients that are individuals, but not high net worth, the percentage of clients that are high net worth individuals, a dummy variable indicating whether the RIA provides financial planning services, a dummy variable indicating whether the RIA advises a private fund, a dummy variable that indicates whether the RIA is compensated by a performance-based fee, and a dummy variable that indicates whether the firm has custody of cash or securities. All characteristics are disclosures made in form ADV during fiscal year 2007. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively

	Full sample			Wealth managers			Private fund advisers		
	Post×			Post×			Post×		
RIA characteristic	Victim exposure	RIA char.	Interact. term.	Victim exposure	RIA char.	Interact. term.	Victim exposure	RIA char.	Interact. term.
Pct. clients individuals (not high net worth)	-1.5154^{a}	-0.0005^{c}	0.0230^{a}	-1.1822^{a}	-0.0013^{a}	0.0217^{a}	-1.6231^{a}	0.0015^{c}	0.0053
	(0.1683)	(0.0003)	(0.0048)	(0.2291)	(0.0003)	(0.0050)	(0.2767)	(0.0008)	(0.0138)
Pct. clients high net worth individuals	-1.5091^{a}	-0.0004	0.0141^{a}	-0.3206	-0.0008^{a}	-0.0031	-1.8404^{a}	0.0009	0.0163^{b}
	(0.1857)	(0.0003)	(0.0039)	(0.2699)	(0.0003)	(0.0049)	(0.2999)	(0.0006)	(0.0076)
Provide financial planning services	-1.3680^{a}	0.0813^{a}	0.9970^{a}	-0.8655^{a}	0.0487^{a}	0.7225^{b}	-1.5730^{a}	0.1851^{a}	0.3828
	(0.1651)	(0.0181)	(0.2710)	(0.2214)	(0.0182)	(0.2887)	(0.2742)	(0.0448)	(0.6988)
Compensated by performance-based fee	-0.5077^{a}	-0.0399^{c}	-1.2591^{a}	-0.4070^{b}	0.0514	-1.2120^{b}	-0.7420^{c}	-0.0740^{b}	-1.1006^{b}
	(0.1755)	(0.0208)	(0.2642)	(0.1677)	(0.0356)	(0.5509)	(0.4482)	(0.0377)	(0.5179)
Custody of cash or securities	-0.8090^{a}	0.0058	-0.7838^{a}	-0.4321^{b}	0.0547^{c}	-0.4808	-1.4202^{a}	-0.0292	-0.3250
	(0.1688)	(0.0199)	(0.2683)	(0.1719)	(0.0281)	(0.4490)	(0.3684)	(0.0365)	(0.4656)
Advise a private fund	-0.5566^{a}	-0.0154	-0.9643^{a}						
	(0.1925)	(0.0190)	(0.2581)						

Table 5: RIA Closures and client proximity to Madoff victims

The table displays linear probability regression results predicting the probability of RIAs going out of business following the Madoff event in either 2009 or 2010. The full sample (column 1) is composed of all U.S.-based RIAs in existence in 2007, subject to the filters discussed in section 1 with one exception - RIAs are not required to exist in 2009 (we are trying to predict whether they go out of business in 2009 or 2010). The regresssions in columns 2 and 3 include only RIAs that are categorized as "wealth managers" and "private fund advisers," respectively. Private fund advisers are those RIAs that disclosed in 2007 that they advised a private fund. If they did not make this disclosure, the RIA is categorized as a wealth manager. Data on RIA closures come from Form ADV-W, which is the registration withdrawal statement. In this statement, firms list the reason for their withdrawal from SEC registration. The dependent variable is an indicator variable that is one if the RIA withdraw from SEC registration due to business closure. Coefficients and heteroscedastic robust standard errors are reported as well as the probability of the RIA going out of business.. Significance levels are denoted by *c*, *b*, and *a*, which correspond to 10%, 5%, and 1% levels, respectively.

Sample:	Full	Wealth mgrs.	Prvt. fund advisers
	(1)	(2)	(3)
Avg. victims per 1000 pop. in client states	0.2211^a	-0.0019	0.3639^a
	(0.0730)	(0.0731)	(0.1227)
Log(Beg. AUM)	-0.0027^c	-0.0015	-0.0061^b
	(0.0016)	(0.0021)	(0.0026)
Log(Num. client states)	-0.0029	0.0006	-0.0048
	(0.0025)	(0.0028)	(0.0042)
Avg. age in client states	-0.0037	-0.0023	-0.0032
	(0.0023)	(0.0025)	(0.0045)
Log(Avg. income in client states)	-0.0050	-0.0066	-0.0090
	(0.0440)	(0.0489)	(0.0811)
Log(RIA AUM in main office zip)	0.0017^c	-0.0011	0.0039^c
	(0.0010)	(0.0010)	(0.0021)
Main office state-year FE	Y	Y	Y
Prob. of RIA closure	0.0237	0.0167	0.0345
R^2	0.0179	0.0214	0.0385
N	4,726	2,872	1,854

Table 6: Bank deposits and Madoff victims

The table displays the results of difference-in-difference regressions of the natural logarithm of zip code-level total bank deposits on the "treatment" and various control variables for all U.S. zip codes within the 50 states that are included in the FDIC Summary of Deposits data for the years 2007 to 2010. The deposit data are as of June 30th each year. The treatment variable in columns 1 through 4 is dummy variable, indicating whether at least one of Madoff's victims resides in the zip code and in columns 5 and 6 the treatment variable is the natural logarithm of the number of Madoff victims residing in the zip code. The Madoff Ponzi scheme was uncovered on December 10, 2008, thus 2009–2010 is the post periods in the regressions. All regressions include zip code-level fixed effects. In addition, models include state-year and county-year fixed effects where indicated. The model estimated in column 6 includes only zip codes with at least one Madoff victim. Control variables include zip code-level mean age, log of mean income, log of population, log of RIA AUM, and log of lag bank deposits. In addition, the percentage of the county population that is in the affinity group is included for models not including county-year fixed effects. Also reported are the number of observations used in the estimation as well as the R^2. The table reports standard errors clustered by zip code in models 1 and 2, by zip code and state-year in model 3 and by zip code and county-year in models 4 through 6. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Post ×						
At least one victim in zip	0.0999^a	0.0402^a	0.0410^a	0.0406^a		
	(0.0106)	(0.0114)	(0.0062)	(0.0068)		
Log(Num. victims)					0.0283^a	0.0357^a
					(0.0045)	(0.0092)
Avg. age in zip		0.0004	0.0006^b	0.0006	0.0005	-0.0003
		(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0011)
Log(Avg. income in zip)		0.0949^a	0.0869^a	0.0900^a	0.0892^a	0.0791^a
		(0.0074)	(0.0043)	(0.0057)	(0.0057)	(0.0210)
Log(RIA AUM in zip)		0.0044^a	0.0042^a	0.0039^a	0.0039^a	0.0032^a
		(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0007)
Log(zip population)		0.0473^a	0.0456^a	0.0469^a	0.0472^a	0.0310^a
		(0.0042)	(0.0017)	(0.0021)	(0.0021)	(0.0094)
Log(Beg. deposits)		-0.0467^a	-0.0453^a	-0.0448^a	-0.0450^a	-0.0761^a
		(0.0044)	(0.0014)	(0.0015)	(0.0015)	(0.0062)
Pct. affinity group in county		0.0016	0.0017^a			
		(0.0010)	(0.0007)			
Post	0.0952^a	-0.8630^a				
	(0.0025)	(0.0821)				
Zip code FE	Y	Y	Y	Y	Y	Y
State-year FE	N	N	Y	N	N	N
County-year FE	N	N	N	Y	Y	Y
Zip codes with at least 1 victim	N	N	N	N	N	Y
R^2	0.984	0.9888	0.9892	0.9906	0.9906	0.9841
N	81,194	76,564	76,564	76,569	76,569	5,607

Table 7: Bank deposits and Madoff victims—Placebo Test

The table displays the results of difference-in-difference regressions of the natural logarithm of zip code-level total bank deposits on the "treatment" and various control variables for all U.S. zip codes within the 50 states that are included in the FDIC Summary of Deposits data for the years 1999 to 2002. The deposit data are as of June 30th each year. The treatment variable in columns 1 through 4 is dummy variable, indicating whether at least one of Madoff's victims resides in the zip code and in columns 5 and 6 the treatment variable is the natural logarithm of the number of Madoff victims residing in the zip code. The peak of the tech bubble was March of 2000 and the Nasdaq continued to fall until October 2002, thus 2001–2002 is the post periods in the regressions. All regressions include zip code-level fixed effects. In addition, models include state-year and county-year fixed effects where indicated. The model estimated in column 5 includes only zip codes with at least one Madoff victim. In addition, the percentage of the county population that is in the affinity group is included for models not including county-year fixed effects. Also reported are the number of observations used in the estimation as well as the R^2. The table reports standard errors clustered by zip code in models 1 and 2, by zip code and state-year in model 3 and by zip code and county-year in models 4 through 6. The models in Panel A categorize 2009 and 2010 as the post period, while in panel B the post period is broken down into 2009 and 2010. Only the coefficients on the variables of interest are reported in Panel B, however controls analogous to those reported in Panel A are included where indicated. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Post ×						
At least one victim in zip	0.0277^b	0.0074	0.0038	0.0046		
	(0.0123)	(0.0137)	(0.0088)	(0.0095)		
Log(Num. victims)					0.0070	
					(0.0062)	
Avg. age in zip		0.0012^c	0.0012^a	0.0009^c	0.0008^c	0.0012^a
		(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Log(Avg. income in zip)		0.0717^a	0.0824^a	0.0856^a	0.0850^a	0.0827^a
		(0.0106)	(0.0065)	(0.0083)	(0.0083)	(0.0064)
Log(RIA AUM in zip)		0.0034^a	0.0032^a	0.0032^a	0.0032^a	0.0032^a
		(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(zip population)		0.0500^a	0.0454^a	0.0399^a	0.0400^a	0.0453^a
		(0.0050)	(0.0025)	(0.0029)	(0.0029)	(0.0025)
Log(Beg. deposits)		-0.0389^a	-0.0364^a	-0.0334^a	-0.0336^a	-0.0363^a
		(0.0051)	(0.0021)	(0.0023)	(0.0023)	(0.0021)
Pct. affinity group in county		-0.0052^a	-0.0033^a			-0.0032^a
		(0.0012)	(0.0009)			(0.0009)
Post	0.1148^a	-0.7006^a				
	(0.0032)	(0.1154)				
Zip code FE	Y	Y	Y	Y	Y	Y
State-year FE	N	N	Y	N	N	Y
County-year FE	N	N	N	Y	Y	N
Zip codes with at least 1 victim	N	N	N	N	N	Y
R^2	0.9748	0.9782	0.979	0.9831	0.9831	0.9790
N	69,054	64,646	64,646	64,647	64,647	64,646

Table 8: Instrumented Madoff victim exposure

The table displays instrumental variable regression results of the log of investment adviser AUM (log of zip code-level total bank deposits) on Madoff victim exposure measures and control variables. The endogenous regressor is the Madoff victim exposure measure ("Avg. victims per 1000 pop. in client states" in columns 1-2 and "Log(Num. victims)" in columns 3-4). The instrument is the average of the percent of the affinity group population residing in the counties in which the firm has offices in columns 1-2 and the percentage of population in the zip codes' county composed of members of the affinity group in columns 3-4. Columns 1 and 3 show the results of the first stage regressions which is estimated for all firms (zip codes) in 2006. Predicted values of the Madoff victim exposure are then used in columns 2 and 4 in the instrumented regresssions. In second stage regressions, coefficients and standard errors are only reported for the variables of interest, however, these regressions include controls reported in column 2 of Table 3 (for column 2) and column 2 of Table 6 (for column 4) with the instrumented Madoff exposures substituted. The table reports standard errors clustered by the adviser's main office state in column 1, adviser and filing period in model 2, branch state in column 3, and by branch zip code in column 4. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	RIA flows		Bank branch deposits	
	First stage	Second stage	First stage	Second stage
	(1)	(2)	(3)	(4)
Avg. pct. affinity group	0.0037^a		0.0665^a	
	(0.0004)		(0.0072)	
Avg. age	0.0138^a		0.0054^b	
	(0.0031)		(0.0024)	
Log(Avg. income)	-0.0089		0.0796^b	
	(0.0611)		(0.0306)	
Log(RIA AUM in main office zip)	0.0003		0.0096^a	
	(0.0004)		(0.0015)	
Log(Beg. AUM)	-0.0005			
	(0.0006)			
Log(Num. client states)	-0.0068			
	(0.0074)			
Log(zip population)			-0.0219^b	
			(0.0096)	
Log(Beg. deposits)			0.0335^a	
			(0.0125)	
Post ×				
Instrumented Madoff victim exposure		-1.8592^a		0.0479^a
		(0.3594)		(0.0135)
Adviser FE	N	Y	N	N
Filing period FE	N	Y	N	N
Zip code FE	N	N	N	Y
Additional controls	N	Y	N	Y
R^2	0.3403	0.9596	0.3294	0.9888
N	4,390	17,184	19,240	76,565

Online Appendix to

Trust Busting: The Effect of Fraud on Investor Behavior

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Table A.1: Confidence and Madoff victims

Displayed are the estimates and robust standard errors clustered by zip code of $\beta_{M,T}$, which estimates the difference in the change in confidence in Madoff exposed and non-Madoff exposed areas from the pre-Madoff time period (2007 and 2008) to the post Madoff event period (2009 and 2010), in the regression:

$$Confidence_{i,t} = \alpha + \beta_{M,0} + \beta_{M,T}\text{Post}_t \times \text{Madoff Exposure}_{i,t}$$

$$+ \sum_k (\beta_{C,k,0}\text{Control}_{i,k,t} + \beta_{C,k,T}\text{Post} \times \text{Control}_{i,k,t}) + \epsilon_{i,t},$$

where $Confidence_{i,t}$ is the level of confidence reported by respondent i in year t, to the Gallup survey question, "Please tell me how much confidence you, yourself, have in each one – a great deal, quite a lot, some, or very little?" Confidence is coded as integers from 4 through 0, with four being high confidence. The response getting a score of zero is "none," which was a voluntary response provided by many respondents. $MadoffExposure$ is measured as a dummy variable that is one if at least one Madoff victim is located in the respondent's zip code. Control variables include respondent's education level (College or no college), log of income (coded as the average income in the range of income respondended), and age. Responses to confidence in the criminal justice system, banks, and big business are displayed in columns 1 through 3. Rows 1 through 5 show coefficient estimates within different subsamples of respondents. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	How much confidence to you have in			
	The criminal justice system?	banks?	big business?	N
Full sample	-0.1855*	-0.0670	-0.0291	2474
	(0.1093)	(0.1095)	(0.1106)	
College	-0.3730***	-0.0494	-0.0294	1590
	(0.1196)	(0.1188)	(0.1145)	
No college	0.3783	-0.0876	-0.0192	884
	(0.2410)	(0.2363)	(0.2547)	
Income > \$60K	-0.3404***	-0.0125	-0.0924	1371
	(0.1307)	(0.1290)	(0.1293)	
Income < \$60K	0.1290	-0.1517	0.0177	1103
	(0.1949)	(0.2028)	(0.1832)	

Table A.2: RIA flow robustness

The table displays regression results of the log of investment adviser AUM on exposure to Madoff victims following the Madoff fraud in December of 2008. Victim exposure is measured as the log of the average number of Madoff victims in the zip codes as each of the advisers' offices. The table serves as a supplement to Table 4 of the main text. Specifically, the model in column 2 of Table 3 is estimated with additional controls to account for zip-code specific economic conditions and using an alternative measure of local high end wealth. The regression in column 1 includes the interaction of the post period with the average zip code level top tier house price change in the zip codes where the RIA has offices. These data come from Zillow.com and are the average house price changes in the top third of home prices in the zip from the peak of the housing market in February 2007 until December 2008 (just prior to the post period). The model in column 2 restricts the sample to only RIAs for which zip code level house price changes are available and reports the results without the control. The models in columns 3 and 4 include the average percentage of households making over $200 thousand in the counties where the RIA has offices. These data are from the 2000 U.S. Census. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Post ×				
Log(Num. victims)	-0.0541^a	-0.0550^a	-0.0389^a	-0.0338^a
	(0.0087)	(0.0087)	(0.0070)	(0.0067)
Log(Beg. AUM)	-0.0624^a	-0.0624^a	-0.0474^a	-0.0424^a
	(0.0055)	(0.0055)	(0.0044)	(0.0040)
Log(Num. of offices)	0.0985^a	0.0992^a	0.1085^a	0.1077^a
	(0.0152)	(0.0152)	(0.0126)	(0.0126)
Avg. age in office zips	-0.0034^a	-0.0034^a	-0.0016^b	-0.0019^b
	(0.0010)	(0.0010)	(0.0008)	(0.0008)
Log(Avg. income in office zips)	0.0340	0.0376	0.0212	0.0216
	(0.0245)	(0.0244)	(0.0187)	(0.0187)
Log(RIA AUM in main office zip)	0.0165^a	0.0151^a	0.0086^a	
	(0.0040)	(0.0039)	(0.0032)	
Avg. Pct. affinity group in office counties	-0.0004	0.0001	-0.0036	-0.0024
	(0.0029)	(0.0028)	(0.0025)	(0.0025)
Zip code top tier house price chg. in main office zip	-0.2699^c			
	(0.1417)			
Avg. pct. of county households with income > $200K			-0.0004	-0.0003
			(0.0038)	(0.0038)
Adviser FE	Y	Y	Y	Y
Main office state-year FE	Y	Y	Y	Y
R^2	0.9560	0.9560	0.9584	0.9584
N	12,160	12,160	18,147	18,155

Table A.3: Characteristics of wealth managers and private fund advisers

The table displays means of various RIA characteristics for the sample of wealth managers and private fund advisers and also for Bernard L. Madoff Investment Securities (BLMIS). Private fund advisers are those RIAs that disclosed in 2007 that they advise a private fund. Wealth managers are RIAs that did not make this disclosure. Characteristics included are the percentage of clients that are individuals, but not high net worth, the percentage of clients that are high net worth individuals, a dummy variable indicating whether the RIA provides financial planning services, a dummy variable indicating whether the RIA advises a private fund, a dummy variable that indicates whether the RIA is compensated by a performance-based fee, and a dummy variable that indicates whether the firm has custody of cash or securities. All characteristics are disclosures made in form ADV during fiscal year 2007.

	Wealth mgrs.	Prvt. fund advisers	BLMIS
Pct. clients individuals (not high net worth)	33.99	15.69	0
Pct. clients high net worth individuals	42.03	27.14	18
Provide financial planning services	0.54	0.22	0
Compensated by performance-based fee	0.08	0.59	0
Custody of cash or securities	0.13	0.48	1

Table A.4: RIA characteristics and flows—Adviser-based exposure

The table displays regression results of the log of investment adviser AUM on adviser location-based exposure to Madoff victims following the Madoff fraud in December of 2008. Regressions follow those in column 4 of Table 4, but also include the listed RIA characteristic interacted with the post period and the interaction of the post period, the RIA characteristic, and the measure of Madoff victim exposure. Coefficient estimates and their standard errors clustered by RIA and filing period are reported for these three terms for three different samples; the full sample, the sample of wealth managers, and the sample of private fund advisers. Private fund advisers are those RIAs that disclosed in 2007 that they advise a private fund. Wealth managers are RIAs that did not make this disclosure. Characteristics included are the percentage of clients that are individuals, but not high net worth, the percentage of clients that are high net worth individuals, a dummy variable indicating whether the RIA provides financial planning services, a dummy variable indicating whether the RIA advises a private fund, a dummy variable that indicates whether the RIA is compensated by a performance-based fee, and a dummy variable that indicates whether the firm has custody of cash or securities. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively

	Full sample			Wealth managers			Private fund advisers		
	Post×			Post×			Post×		
RIA characteristic	Victim exposure	RIA char.	Interact. term.	Victim exposure	RIA char.	Interact. term.	Victim exposure	RIA char.	Interact. term.
Pct. clients individuals (not high net worth)	-0.0489^{a}	0.0006^{b}	0.0004^{b}	-0.0396^{a}	-0.0002	0.0002	-0.0417^{a}	0.0023^{a}	0.0002
	(0.0057)	(0.0003)	(0.0002)	(0.0078)	(0.0003)	(0.0002)	(0.0094)	(0.0007)	(0.0004)
Pct. clients high net worth individuals	-0.0646^{a}	0.0000	0.0007^{a}	-0.0518^{a}	-0.0010^{a}	0.0004^{b}	-0.0475^{a}	0.0021^{a}	0.0004
	(0.0065)	(0.0003)	(0.0001)	(0.0101)	(0.0003)	(0.0002)	(0.0104)	(0.0006)	(0.0002)
Financial planning services	-0.0484^{a}	0.1049^{a}	0.0298^{a}	-0.0457^{a}	0.0557^{a}	0.0290^{a}	-0.0408^{a}	0.2183^{a}	0.0047
	(0.0056)	(0.0172)	(0.0100)	(0.0077)	(0.0165)	(0.0112)	(0.0093)	(0.0431)	(0.0212)
Compensated by performance-based fee	-0.0308^{a}	-0.1121^{a}	-0.0159^{c}	-0.0304^{a}	0.0216	-0.0436^{b}	-0.0335^{b}	-0.1538^{a}	-0.0067
	(0.0067)	(0.0210)	(0.0087)	(0.0066)	(0.0321)	(0.0178)	(0.0144)	(0.0375)	(0.0157)
Custody of cash or securities	-0.0312^{a}	-0.0005	-0.0329^{a}	-0.0360^{a}	0.0379	0.0026	-0.0230^{c}	-0.0015	-0.0364^{b}
	(0.0062)	(0.0198)	(0.0086)	(0.0066)	(0.0245)	(0.0159	(0.0119)	(0.0371)	(0.0143)
Advise a private fund	-0.0359^{a}	-0.0647^{a}	-0.0098						
	(0.0075)	(0.0186)	(0.0088)						

Table A.5: RIA closures and client proximity to Madoff victims—probit regressions

The table displays probit regression results predicting the probability of RIAs going out of business following the Madoff event in either 2009 or 2010. The full sample (column 1) is composed of all U.S.-based RIAs in existence in 2007, subject to the filters discussed in the main text with one exception: RIAs are not required to exist in 2009 (we are trying to predict whether they go out of business in 2009 or 2010). The regresssions in columns 2 and 3 include only RIAs that are categorized as "wealth managers" and "private fund advisers," respectively. Private fund advisers are those RIAs that disclosed in 2007 that they advised a private fund. If they did not make this disclosure, the RIA is categorized as a wealth manager. Data on RIA closures come from Form ADV-W, which is the registration withdrawal statement. In this statement, firms list the reason for their withdrawal from SEC registration. The dependent variable is an indicator variable that is one if the RIA withdraw from SEC registration due to business closure. Marginal effects and heteroscedastic robust standard errors are reported as well as the probability of the RIA going out of business. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

Sample:	Full	Wealth mgrs.	Prvt. fund advisers
	(1)	(2)	(3)
Avg. victims per 1000 pop. in client states	0.1583^a	0.0580	0.2168^a
	(0.0338)	(0.0457)	(0.0597)
Log(Beg. AUM)	-0.0024	-0.0020	-0.0061^b
	(0.0015)	(0.0024)	(0.0024)
Log(Num. client states)	-0.0034	0.0003	-0.0053
	(0.0027)	(0.0030)	(0.0047)
Avg. age in client states	-0.0019	-0.0005	-0.0029
	(0.0015)	(0.0017)	(0.0028)
Log(Avg. income in client states)	-0.0017	0.0017	0.0111
	(0.0264)	(0.0293)	(0.0497)
Log(RIA AUM in main office zip)	0.0013^c	-0.0009	0.0021
	(0.0008)	(0.0010)	(0.0014)
Prob. of RIA closure	0.0237	0.0167	0.0345
Pseudo R^2	0.0323	0.0069	0.0633
N	4,726	2,872	1,854

Table A.6: Bank deposit robustness

The table displays the results of difference-in-difference regressions of the natural logarithm of zip code-level total bank deposits on the "treatment" and various control variables for all U.S. zip codes within the 50 states that are included in the FDIC Summary of Deposits data for the years 2007 to 2010. The table serves as a supplement to Table 6 of the main text. Specifically, the model in column 3 of Table 6 is estimated with additional controls to account for zip-code specific economic conditions and using an alternative measure of local high end wealth. The regression in column 1 includes the interaction of the post period with the average zip code level top tier house price change in the zip codes where the RIA has offices. These data come from Zillow.com and are the average house price changes in the top third of home prices in the zip from the peak of the housing market in February 2007 until December 2008 (just prior to the post period). The model in column 2 restricts the sample to only RIAs for which zip code level house price changes are available and reports the results without the control. The models in columns 3 and 4 include the average percentage of households making over $200 thousand in the counties where the RIA has offices. These data are from the 2000 U.S. Census. Significance levels are denoted by *c*, *b*, and *a*, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Post ×				
At least one victim in zip	0.0322^{a}	0.0322^{a}	0.0399^{a}	0.0602^{a}
	(0.0073)	(0.0073)	(0.0062)	(0.0061)
Avg. age in zip	0.0004	0.0004	0.0006^{b}	0.0005^{c}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Log(Avg. income in zip)	0.1286^{a}	0.1285^{a}	0.0832^{a}	0.0921^{a}
	(0.0072)	(0.0073)	(0.0046)	(0.0046)
Log(RIA AUM in zip)	0.0041^{a}	0.0041^{a}	0.0041^{a}	
	(0.0003)	(0.0003)	(0.0002)	
Log(zip population)	0.0823^{a}	0.0823^{a}	0.0455^{a}	0.0428^{a}
	(0.0036)	(0.0036)	(0.0017)	(0.0017)
Log(Beg. deposits)	-0.0703^{a}	-0.0702^{a}	-0.0454^{a}	-0.0375^{a}
	(0.0022)	(0.0022)	(0.0014)	(0.0013)
Pct. affinity group in county	0.0029^{a}	0.0029^{a}	0.0008	0.0004
	(0.0008)	(0.0008)	(0.0007)	(0.0007)
Zip code top tier house price chg.		-0.0064		
		(0.0338)		
Pct. of county households with income > $200K			0.0030^{b}	0.0062^{a}
			(0.0012)	(0.0012)
Zip code FE	Y	Y	Y	Y
State-year FE	Y	Y	Y	Y
R^2	0.9846	0.9846	0.9892	0.9891
N	33,717	33,717	76,564	76,564

Table A.7: Bank deposits and Madoff victims—Matched sample

The table displays the results of difference-in-difference regressions of the natural logarithm of zip code-level total bank deposits on the "treatment" and various control variables for a matched sample of U.S. zip codes for the years 2007 to 2010. The first column displays the results of a probit regression predicting whether at least one Madoff victim resides in the zip code using data from 2009. Difference in difference estimates for the Madoff treatment variables are displayed in columns 2 through 4 for a nearest neighbor without replacement matched sample based on propensity scores from the model estimated in column 1. The treatment and control variables follow those outlined in Table **??**. Where indicated, regressions include additional controls (following those in Table **??**), zip code, and county-year fixed effects. Also reported are the number of observations used in the estimation as well as the R^2 (pseudo-R^2 for the probit regression). The table reports standard errors clustered by zip code in models 1 and 2 and by zip code and county-year in models 3 and 4. Significance levels are denoted by c, b, and a, which correspond to 10%, 5%, and 1% levels, respectively.

Dependent Variable:	At least one Madoff victim	Log (bank deposits)		
	(1)	(2)	(3)	(4)
Avg. age in zip	0.0344^a			
	(0.0031)			
Log(Avg. income in zip)	0.6090^a			
	(0.0479)			
Log(RIA AUM in zip)	0.0268^a			
	(0.0019)			
Log(zip population)	0.1586^a			
	(0.0228)			
Log(Beg. deposits)	0.2161^a			
	(0.0173)			
Pct. affinity group in county	0.1398^a			
	(0.0047)			
Post ×				
At least one victim in zip		0.0353^a	0.0440^a	
		(0.0134)	(0.0101)	
Log(Num. victims)				0.0257^a
				(0.0061)
Additional controls	N	N	Y	Y
Zip code FE	N	Y	Y	Y
County-year FE	N	N	Y	Y
R^2	0.4000	0.9754	0.9803	0.9803
N	19,404	11,245	11,245	11,245