Is Fraud Contagious? Career Networks and Fraud by Financial Advisors☆

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Abstract

We show that the propensity to commit fraud is transmitted through career networks. We use a novel dataset of U.S. financial advisors, which includes individuals' employment histories and records of fraudulent behavior. To identify the effect of career networks on fraud we use changes in co-workers caused by mergers of financial advisory firms; the tests include merger-firm fixed effects to exploit the variation in changes to career networks across different branches of the same firm. The probability an advisor commits fraud increases if his new co-workers, encountered in the merger, have a history of fraud. Further, this effect is stronger between demographically similar employees.

Keywords: Financial advisors, Financial misconduct, Fraud, Social networks, Peer effects, Career networks

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Prior to its expulsion from the industry, the investment advisory firm Stratton Oakmont earned a reputation for fraudulent behavior. After its expulsion, many financial advisors[1] from Stratton Oakmont moved to other firms, where they encountered new co-workers. Shortly thereafter, these new co-workers began to commit frauds similar to those perpetrated at Stratton Oakmont. Although only a small fraction of financial advisors ever commit fraud, many of those who do are linked to each other through their employment histories. Indeed, recognizing the relation between career networks and fraud, the Financial Industry Regulatory Authority (FINRA) has additional regulatory requirements for any advisory firm that employs a significant number of alumni from disciplined firms.[2]

Although there is anecdotal evidence that fraud is correlated within career networks, empirically identifying whether career networks influence fraudulent behavior is difficult. Career networks are endogenous; similar people choose to associate with each other. For example, dishonest financial advisors may select an employer that encourages dishonest behavior. As a result, it is difficult for observational studies to disentangle whether behavioral similarity within a network is caused by: (1) contagion, or the transmission of behavior through interpersonal networks; (2) selection, or the formation of ties due to matching on individual characteristics; (3) common response to a shared environment (Manski, 1993, 2000).

In this paper, we test whether fraud is transmitted through career networks. We define an advisor's career network as the co-workers employed at the same branch of a firm at the same time. To avoid the problem of endogenous network formation, we use changes to career networks caused by mergers of financial advisory firms (i.e., the change in co-workers

[1]Throughout the paper we use "advisor" and "financial advisor" to refer to "registered representatives" - individuals who register as advisors with FINRA. This includes individuals who are commonly referred to as brokers and financial planners.

[2]https://www.finra.org/web/groups/industry/@ip/@reg/@notice/documents/notices/p014653.pdf

that occurs following a merger). Of course, merger decisions are themselves endogenous; however, we exploit a unique feature of our data; we can look within the firm and identify the specific individual who commits fraud. We also observe information about the financial advisory firm, the branches within the firm, and the individual financial advisors within a branch. In our empirical tests, we concentrate on the within-firm variation by including merger-firm fixed effects. The key to our identification is that mergers occur at the *firm* level, but changes in co-worker networks occur within firms at the *branch* level. Our empirical tests exploit across-branch variation and the impact of combining branches during a merger - while removing all effects at the firm level - which addresses the most obvious endogeneity concerns.

For illustration, consider a merger between two hypothetical firms: Acquirer Firm has branches in Atlanta, Boston, and Chicago. Target Firm has branches in Boston, Chicago, and Detroit. When the firms merge, the branches in Boston and Chicago are combined, and the branches in Atlanta and Detroit remain unchanged. Suppose that the financial advisors at the Boston branch of Acquirer Firm have a history of fraudulent behavior, and the advisors at all other branches of both firms have clean histories. Thus, following the merger there are changes to the career networks of the advisors at the Boston and Chicago branches (of both Acquirer Firm and Target Firm). However, only the career networks of the advisors from the Boston branch of Target Firm have changed to now include individuals with a history of fraud (the advisors from the Boston branch of Acquirer Firm). The empirical question, then, is whether the advisors from the Boston branch of Target Firm are now more likely to commit fraud *relative to advisors from the Chicago branch of Target Firm.* The comparison between the two branches removes any variation common to all branches of the pre-merger firm and any common time-series changes in the propensity to commit fraud.

We find evidence that fraudulent behavior is transmitted through career networks. Controlling for merger-firm fixed effects, and using changes to a financial advisor's network due to a merger, we show that an advisor is more likely to commit fraud if his new co-workers have a history of fraud. These results hold even after conditioning on the history and characteristics of the advisor, as well as the history and characteristics of the advisor's pre-merger co-workers.

We conduct multiple robustness tests to rule out alternative explanations. First, we estimate a placebo test using a bootstrap procedure. In this test, we randomly "assign" each financial advisor to a branch within the merged firm, and then estimate the relation between the (counterfactual) Introduced Branch and fraud. We repeat this procedure 5,000 times. The results confirm that the career network effects documented in our main tests are unlikely to be spurious. Second, we show the results are not driven by across-branch variation in supervision. Third, we show the results are similar for both target firm and acquirer firm advisors. Fourth, we show the results are robust to including merger firm-county fixed effects, effectively reducing the comparison to different branches of the same firm within the same county. Finally, we show that the relative size of the merged branches matters; advisors from the larger branch have more influence on the behavior of advisors from the smaller branch than vice versa.

Next, we build on prior studies that show network effects are stronger between similar individuals (e.g., Pool, Stoffman, and Yonker, 2014), and test how similarity amplifies the transmission of fraudulent behavior within career networks. Although we find evidence of network effects across all advisors, the effects are stronger among advisors who are of similar ages or of the same ethnicity.

Our paper contributes to the literature on peer effects in financial markets,[3] specifically, the literature about peer effects on financial misconduct. Chiu, Teoh, and Tian (2013) show that interlocking boards are associated with the spread of earnings management. Chidambaran,

[3]Prior studies show peer effects in portfolio choice (Hong, Jeffrey D, and Stein, 2004; Brown, Ivković, Smith, and Weisbenner, 2008; Ivković and Weisbenner, 2007; Kaustia and Knüpfer, 2012), governance practices (Bouwman, 2011), firm policies (Shue, 2013), and retirement savings (Duflo and Saez, 2002, 2003).

Kedia, and Prabhala (2012) show that CEO-board connections are associated with financial statement misreporting. Parsons, Sulaeman, and Titman (2014) find peer effects in financial statement misreporting among geographically proximate firms. Unlike these studies, which measure wrongdoing at the firm level, we observe fraud at the level of individual employees located within distinct branches of the firm. This allows our identification strategy, which is based entirely on within-firm variation across individual employees.

Our paper also contributes to the literature on financial advisors. The U.S. financial advisory industry is economically significant, advising trillions of dollars in assets and generating billions in revenues (more than $98 billion in 2013 according to the Securities Industry and Financial Markets Association). The industry is also a major employer (635,837 financial advisors[4] in 2013), and advisors are important for the financial well-being of many households; Hung, Clancy, Dominitz, Talley, Berribi, and Suvankulov (2008) report that 73% of individual investors use an advisor for investment decisions.

Despite the economic importance of the financial advisor industry, there are relatively few academic studies. Of the studies that do exist, many focus on agency problems. Financial advice is a credence good and its quality is difficult for households to evaluate, particularly given the low financial literacy of many households (Lusardi and Mitchell, 2011; van Rooij, Lusardi, and Alessie, 2011). The difficulty of evaluating financial advice, coupled with commission-based compensation, creates significant agency problems. Prior studies generally find that financial advisors steer clients towards high fee investments[5] and fail to produce any measurable benefits (Bergstresser, Chalmers, and Tufano, 2009; Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012; Chalmers and Reuter, 2011; Hoechle, Ruenzi, Schaub, and Schmid, 2013; Mullainathan, Noeth, and Schoar, 2012). In our study, we focus on how the

[4]See `http://www.finra.org/Newsroom/Statistics/`.

[5]Anagol, Cole, and Sarkar (2013) and Brown and Minor (2013) find similar results in the insurance industry.

career networks of financial advisors affect fraud.

The evidence suggests that fraud by financial advisors is common. FINRA reports thousands of incidents each year, and during our sample (1999-2011) the average annual value of fines, settlements, and arbitration awards due to fraud by financial advisors is $717.6 million. To put this in perspective, the average annual value of settlements due to financial statement misreporting is $527 million (Karpoff, Lee, and Martin, 2008) over a similar period. Thus, although settlements for financial statement misreporting are generally much larger per event, financial advisor fraud is much more frequent, and the overall magnitudes are comparable. Despite these similar magnitudes, there is vastly more research on financial statement misreporting: Karpoff, Koester, Lee, and Martin (2012) report that over 150 academic studies examine the approximately 1,000 cases of financial statement misreporting in the U.S. during the past three decades; in contrast, we are the first academic study to examine the approximately 50,000 cases of financial advisor fraud over the past two decades.

This paper has policy implications regarding the appropriate punishment for fraud by financial advisors. Our finding of contagion through career networks suggests that the optimal penalty should reflect not only the harm of the event itself, but also the negative externality created by influencing the behavior of others (Becker, 1968); an advisor's fraud harms not only his clients, but also the clients of the other advisors he influences. More generally, our results provide evidence that the social transmission of crime, modeled by Glaeser, Sacerdote, and Scheinkman (1996) and Sah (1991) in the context of street crime, occurs even within a professional setting.

1. Data

We obtain data on financial advisors' characteristics, employment histories, and fraud from the Registered Representative database produced by Meridian-IQ. All registered representatives (the formal legal term for what we call "financial advisors") in the U.S. are registered with FINRA when their employer files a Uniform Application for Securities Industry Registration or Transfer (Form U4). The information disclosed in Form U4 is collected in the Central Registration Depository (CRD), which assigns each advisor a unique identification number that remains constant even if the advisor switches employers. Information about individual advisors is disclosed to the public through FINRA's BrokerCheck system and through state regulatory agencies.

Our primary source of historical U4 filings is Meridian-IQ's Registered Representative Database. Meridian-IQ obtains these filings from state regulators. Because not all state regulators supply the full set of variables we require, our universe of financial advisors consists of those registered in 32 states. Many firms register all of their employees in all states,[6] and so we have data for many advisors even in the states that do not supply information. The only advisors we do not observe are those who never register in a reporting state and who only accept clients living in the non-reporting states (approximately 28% of advisors in 2012). From Meridian-IQ we obtain a survival-bias free set of U4 filings for the period 1999-2014, but our sample includes only mergers occurring from 1999 through 2011 because we require at least three years post-merger to measure fraud (see Section 1.3.). During the sample period, we have data for 522,363 unique individuals. The Meridian-IQ dataset is missing information for many of the advisors' personal characteristics (such as age and gender), and so we obtain additional data directly from cooperating state securities regulators.[7] To our knowledge, the data set summarized in Table 1, is the most comprehensive sample of financial advisors used in an academic study.

[6]This is because an advisor must be registered in every state from which he accepts customers.

[7]We thank the state securities regulators of Alabama, Arkansas, California, Connecticut, Florida, Kentucky, Maryland, Michigan, Minnesota, Nevada, Pennsylvania, New York, Texas, Vermont, and Washington for providing data on advisors registered in their states.

1.1. Financial Advisory Firms, Branches, and Financial Advisors

The full sample includes 34,579 unique firms. Because our identification strategy is based on mergers, our analyses focus only on the firms that are involved in the 483 mergers occurring during the sample period. Figure 1 shows the distribution of the mergers over time. As Table 1 shows, the firms in the merger sample are substantially larger than average. In the full sample, the median number of financial advisors per firm is two; there are many very small firms with only one or two advisors.

A financial advisory firm can have one or more branches (a "branch office" is defined by FINRA as any distinct business address where one or more associated persons of a member regularly conduct the business of effecting any transactions in, or inducing or attempting to induce the purchase or sale of, any security, or that is held out as such). Using the branch identifier from Form U4, we identify an advisor's co-workers as those advisors working at the same branch of the firm at the same time. The majority of the firms in the full sample have only a single branch. To enter our merger sample, however, we require that both the target and the acquirer firms have multiple branches, because our identification strategy uses variation across the branches of a single firm. Following the merger, an average of 31.0% (38.7%) of the target (acquirer) advisors work at a branch with at least one acquirer (target) advisor. The remaining advisors either continue to work at the same branch without meeting anyone from the merger-partner or leave the firm (12.5% of target advisors and 0.5% of acquirer advisors leave the firm).[8] In our study, we focus on the set of target and acquirer advisors that are introduced due to the merger. For an average merger, this set consists of 128 (median 20) target advisors and 184 (median 32) acquirer advisors mixed across an average of 12 (median 3) unique branches.

The demographic characteristics of the financial advisors in the merger sample are similar

[8] See Internet Appendix 2 for evidence that advisor exit does not bias the results.

to those in the full sample. As Table 1 shows, in the merger sample the average advisor is about 40 years old and has over 10 years of experience in the financial advisory industry. Target advisors are slightly older, more experienced, and have higher levels of assets under management.[9] We define supervisors as advisors that have passed the necessary tests (Series 9 or 10) to be a General Securities Sales Supervisor, which allows an advisor to manage or supervise a firm's sales and securities operations. Approximately 6% of advisors in our sample are supervisors. We map last names to ethnic categories using the classification algorithm developed by Ambekar, Ward, Mohammed, Male, and Skiena (2009). Pool, Stoffman, and Yonker (2014) show this algorithm works well at classifying a sample of mutual fund managers. Approximately 90% of the advisors in our sample are classified as white, and most of the remainder are classified as either Asian or Hispanic.[10]

1.2. Mergers of Financial Advisory Firms

We identify mergers between financial advisory firms using advisors' employment histories in the Meridian data. Each financial advisor must disclose his employment history, including the reason for leaving each prior job. If the advisor left because his firm (the target firm) was acquired in a merger, the reason for leaving is given as "Mass Transfer."[11] We use mass transfers to identify mergers, and classify firms as targets or acquirers. We cross-check the mergers in our sample with news stories and with the mergers listed in the appendix of Hong

[9]Meridian provides the assets under management (AUM) for 57.2% of the financial advisors in the sample, but this variable is only available as a cross-section observed at the end of the sample period.

[10]We cannot associate an ethnicity with every advisor for several reasons. First, some last names are indeterminate (e.g., 48.52% and 46.72% with the name Williams identify as white and African American, respectively). Second, we do not have last names for all of the advisors in the Meridian-IQ database. Finally, because of the commonality between white and African American last names, we have difficulty clearly identifying African American advisors.

[11]The mass transfer program is intended to simplify the bulk transfer of registration data in the event of a merger, consolidation, or reorganization. A mass transfer must involve at least 50 individuals to qualify, and allows the firm to avoid paying some additional registration fees and reduces the number of required filings. Note that this implies our merger sample implicitly conditions on the target firm having at least 50 employees.

and Kacperczyk (2010), and find this method reliably identifies and classifies merging firms.

We define the merger date as the date of the earliest mass transfer between a target-acquirer pair (many mergers involve several mass transfers at slightly different dates). The pre-merger period is defined as the three years prior to the merger date, and the post-merger period is defined as the three years after the merger date. To avoid biases due to variation in filing and reporting dates (many target advisors appear to be employed at both the target and the acquirer for several weeks), we observe pre-merger employment 30 days before the merger date. Because we use the earliest mass transfer date and some advisors are not reported as transferred until several months later, we observe post-merger employment 100 days after the merger. For example, in 2006 Advanced Equities Financial Corp. acquired First Financial Planners Inc. (FFP). The first mass transfer took place on January 1, 2007. We observe employment for advisors at Advanced Equities and FFP as of December 2, 2006, thirty days prior, because some FFP advisors began work at Advanced Equities in December. There were three additional mass transfers, on January 3, 5, and 16. Because there are multiple transfer dates, observing employment of FFP advisors in January 2007 could give the appearance that many advisors remained at FFP, when in fact they all moved to Advanced Equities. To avoid this problem, we observe where advisors for both firms were registered as of April 11, 2007, one hundred days after the first transfer date. The three year pre-merger period is from December 2, 2003 to December 2, 2006 and the three year post-merger period is from April 11, 2007 to April 11, 2010; we do not include the initial transfer date in either the pre- or post-merger period.

1.3. Fraud

We identify cases of fraud by financial advisors based on mandatory disclosures collected by Meridian-IQ. FINRA Rule 3070 requires firms to report all written customer complaints to the appropriate regulator through the CRD system. Nearly all customer complaints are based on the legal concepts of fraud or negligence. The most common customer complaints include one or more of: unsuitability, unauthorized trading, churning, and misrepresentation or omission. Unsuitability occurs when an advisor recommends assets that are outside the client's risk tolerance or are not suited for the client's financial goals. Unauthorized trading occurs when an advisor fails to obtain permission before trading securities, or acts against a client's express instructions. Churning is the excessive trading of securities to generate commissions. Misrepresentation or omission occurs when an advisor knowingly misstates or omits material information about an investment. Financial advisors, however, are not responsible if their investment advice simply turns out to be unprofitable ex post (i.e., if an advisor recommends an investment, in good faith and with full disclosure, but the investment loses money).

A complaint remains on an advisor's record unless it is dismissed by the FINRA arbitration panel or the customer withdraws the complaint.[12] Nearly all FINRA arbitration decisions or customer withdrawals occur within two years of the complaint.[13] Although the Meridian data includes complaints filed through 2014, we include only complaints filed before 2012; thus our sample includes only substantiated complaints.

Table 2 shows summary statistics of fraud by the financial advisors in the sample of merged firms. Pre-Merger Individual Fraud is an indicator variable equal to one if the advisor committed fraud in the three years prior to the merger. Post-Merger Individual Fraud is an indicator variable equal to one if the advisor commits fraud in the three years following the merger. Panel A shows that 1.14% of advisors committed fraud in the pre-merger period and 1.80% committed fraud during the post-merger period.[14] Unsurprisingly, individuals who

[12]The advisor must continue to disclose withdrawn complaints if the customer receives a settlement of $10,000 or more in relation to the complaint (this amount was increased to $15,000 towards the end of our sample period).

[13]The median complaint is resolved in less than six months, with over 90% resolved within two years. We thank the Attorney General's Office of Florida for providing the data used to calculate resolution times.

[14]These rates are quite similar to the full sample. In the full sample, 1.80% of advisors commit fraud in

committed fraud in the pre-merger period are more likely to commit fraud in the post-merger period: 15.19% vs. 1.65%.

For each advisor, we identify two networks: Pre-Merger Co-Workers are the advisor's co-workers at the Original Branch just before the merger. New Co-Workers are the advisor's new colleagues who worked at the merger partner, and are then merged into the same branch as the advisor. For each network, we measure fraud in three ways: (1) Fraud Dummy is an indicator variable equal to one if any of the other individuals in the advisor's network committed fraud during the pre-merger period; (2) Fraud Rate is the percentage of other individuals in the advisor's network who committed fraud during the pre-merger period; (3) High Fraud Rate is an indicator variable equal to one if the Fraud Rate for the advisor's network is greater than the sample individual advisor average of 1.14% (i.e., a very large branch would not be classified as High Fraud Rate if only 1 of 100 advisors had committed fraud during the pre-merger period). Note that for all three measures of fraud, we do not include the advisor's own history of fraud when calculating the network fraud variables. Further, all three measures include only information from the pre-merger period.

Panel A of Table 2 shows there is a positive relation between fraud by an advisor and fraud by his Pre-Merger Co-Workers. An advisor whose Pre-Merger Co-Workers committed fraud in the pre-merger period is 1.33 percentage points more likely to have committed fraud in the pre-merger period, and 1.10 percentage points more likely to commit fraud in the post-merger period.

Panel B of Table 2 shows cross-tabulations of the merged branches based on the branches Pre-Merger fraud status. "Clean" ("Dirty") indicates a branch at which none (at least one) of the financial advisors have committed a prior fraud. A significant fraction (33.5%) of observations are in the off-diagonal cells, suggesting that mergers often change an advisor's

any three-year window.

exposure to co-workers who have committed fraud (i.e., clean and dirty branches are frequently mixed together).

Panel C summarizes post-merger fraud for the sample of advisors who did not commit fraud during the pre-merger period. The panel reports a two-by-two cross tabulation: the top (bottom) row reports results for advisors whose Pre-Merger Co-Worker Fraud Rate was below (above) the sample average of 1.14%. Similarly, the columns divide the sample based on the New Co-Worker Fraud Rate. The clearest pattern is that an advisor is substantially more likely to commit fraud during the post-merger period if he encounters new co-workers with a high fraud rate.

2. Career Networks and Fraud

The primary empirical problem in network studies is distinguishing influence (contagion) from self-selection (the tendency for individuals to associate with similar individuals). For example, unethical individuals may actively seek employment at a firm with a reputation for unethical behavior. Thus, identifying contagion requires an exogenous change to a financial advisor's network. We use changes in networks caused by mergers of financial advisory firms. Of course, it is possible that firms choose to merge for reasons related to fraud. For example, a firm with a poor reputation might actively solicit acquisition by a firm with a good reputation, and firms with good reputations may avoid acquiring firms with poor reputations. Such endogenous reasons for a merger, however, operate at the firm-level, and not the branch- or individual-level. In our tests, we include merger-firm fixed effects (i.e., for each merger all advisors from the acquirer receive one fixed effect and all advisors from the target receive a separate fixed effect). By including these fixed effects, we effectively eliminate any variation at the firm-level, including the (potentially) endogenous reasons for the merger. Our analyses use only the residual variation that remains at the branch- or individual-level. This allows our tests to measure contagion and not self-selection, subject to the assumption that firms do not systematically make merger decisions based on within-firm, branch-specific characteristics that are correlated with fraud.

Another important point is that the dependent variable, Post-Merger Individual Fraud, is measured during the post-merger period. All of the independent variables are measured during the pre-merger period. By measuring the dependent variable over a separate time-period from the independent variables, we avoid some of the mechanical biases that can occur in network studies (e.g., see Angrist, 2014).

2.1. Networks and Fraud: Changes in Career Networks and Changes in Fraud

Table 3 reports the results from logit regressions that relate fraud by financial advisors to the advisor's network. There is one observation per advisor-merger, and we estimate the following specification:

$$Pr(y_{i,m} = 1|x_{i,m}) = F(\beta \cdot New\,Co\text{-}Worker\,Fraud_{i,m} + \mathbf{X_{i,m}} \cdot \sigma + \alpha_{\mathbf{m,f}}) \tag{1}$$

Where $y_{i,m}$ is an indicator equal to one if financial advisor i commits fraud in the three-year period following merger m; $F(\cdot)$indicates the logit function; $New\,Co\text{-}Worker\,Fraud_{i,m}$ measures fraud during the pre-merger period committed by the advisor's new colleagues at the merged branch; $\mathbf{X_{i,m}}$ is a vector of control variables; and $\alpha_{m,f}$ indicates a separate fixed effect for each merger-firm combination (separate fixed effects for the target and acquirer in each merger). All specifications reported in Table 3 include controls for: (1) *Pre-Merger Co-Worker Fraud*, which measures fraud during the pre-merger period by individuals in the advisor's Original Branch; (2) *Pre-Merger Individual Fraud Dummy*, which is set to one if the advisor was caught for fraud in the pre-merger period; (3) *ln(# of Pre-Merger Co-Workers)*, which is the natural logarithm of the number of people in the advisor's branch prior to the merger; and (4) *ln(# of New Co-Workers)*, which is the natural logarithm of the number of new co-workers at the branch into which the advisor is merged. The models also include controls for advisory firm type,[15] advisor age, gender, advisor experience, and assets-under-management.[16] The Z scores reported in Table 3 are based on standard errors clustered by merger. Internet Appendix Table 1 shows the results are similar with alternative specifications (no fixed-effects panel logit, linear fixed effects model, or a count model of the number of frauds).

Table 3 reports three specifications, each using a different variable to measure fraud in an advisor's network. In column (1), the variable is a dummy equal to one if any of the co-workers in the network committed fraud during the pre-merger period. In column (2), the variable is the percentage of co-workers that committed fraud. In column (3), the variable is set equal to one if the percentage of co-workers that committed fraud is above the individual advisor sample average. The indicator variable in column (1) has the advantage of simplicity, but the disadvantage of a mechanical positive relation with the number of advisors in the branch. All three variables give similar results, and so for the remainder of the paper we focus on the high percentage variable in column (3) as it combines simplicity while avoiding a mechanical relation with branch size.

The results show that an advisor is significantly more likely to commit fraud if he is merged into a branch whose employees have a history of fraud. The coefficient reported in column (3) of Table 3 implies that an advisor is 38% more likely to commit fraud in the three years following a merger if his Introduced Branch co-workers have an above average rate of individuals who have committed fraud. Given the merger-firm fixed effects, the results can be interpreted as follows. Suppose there are two identical advisors who work at different branches of the same firm. When the firm merges, one of the advisors is merged into a new

[15]We include indicator variables for the advisory firm types reported by Meridian-IQ: wirehouse, bank, independent, institutional, regional, discounter, product distributor, insurance, and other.

[16]Data for for age, assets under management, and gender are missing for some financial advisors. We insert a value of zero for missing data and include dummy variables equal to one if the variable is missing. The results are very similar if we instead drop these observations.

branch with a high fraud rate (dirty branch). The other advisor is merged into a clean branch. The advisor merged into the dirty branch is significantly more likely to commit fraud in the next three years *relative to the advisor at the clean branch*.

The results for the control variables reported in Table 3 are intuitively reasonable and consistent across specifications. The coefficients on the Original Branch Fraud variables are all positive and significant, indicating advisors who worked at a dirty branch prior to the merger are more likely to commit fraud after the merger. The coefficients on Pre-Merger Individual Fraud Dummy are also positive and significant, indicating that advisors who committed fraud before the merger are also more likely to commit fraud after the merger.

Overall, the results are consistent with the transmission of fraudulent behavior through career networks. The inclusion of merger-firm fixed effects removes the variation common to all advisors in a pre-merger firm, and shows that the post-merger propensity to commit fraud varies depending on the characteristics of the new co-workers encountered due to the merger.

2.2. Placebo Test

As robustness test, we use a bootstrap procedure to impose the null of no career network effects by randomizing assignment to post-Introduced Branches. Specifically, within each merger-firm, we counterfactually assign each advisor to a random post-Introduced Branch to create a pseudo post-Introduced Branch. This allows us to randomize the advisors with respect to their post-Introduced Branch connections, but leave all other characteristics unchanged. Using these counterfactual branch assignments, we recalculate Introduced Branch High Fraud Rate (and Introduced Branch Size). We then estimate the regression in column (3) of Table 3. We repeat this procedure 5,000 times.

Figure 2 plots the distribution of the coefficients estimated using the counterfactual Introduced Branch High Fraud Rate variable. The figure clearly shows that the actual estimate from column (3) of Table 3 lies well to the right of the entire mass of the distribution of estimates from the placebo test. The actual estimated coefficient of 0.330 is over seven standard deviations above the mean of the simulations (-0.006). The key takeaway is that actual branch assignments, and thus the actual connections with new co-workers from the Introduced Branch, are crucial for generating the observed effect of career networks, ruling out a host of potential alternative explanations.

3. Robustness and Alternative Explanations

Given the placebo test results, any alternative explanation of Table 3 must satisfy two criteria. First, the alternative mechanism must be based on across-branch variation within a firm. Second, this across-branch variation must be spuriously correlated with fraud. In this section, we identify and test potential alternative explanations meeting these criteria.

3.1. Within-Firm Across-Branch Variation in Supervision

One potential alternative explanation is that, even within an advisory firm, the degree of oversight and supervision varies across branches. In this case, branches with lax supervisors could have higher (pre-merger) fraud rates than branches with strict supervisors. Advisors merged into a new branch with a lax supervisor would be relatively more likely to commit fraud. This alternative explanation is similar to the career-networks explanation; it implies that an individual's propensity to commit fraud is affected by the characteristics of the new co-workers encountered due to a merger, but in this case the new co-worker is also a supervisor. Although supervisors could affect fraud via the same informal, peer-to-peer channels as other co-workers, supervisors also have a more formal, hierarchical relation with the advisors in their branch. Thus, if fraudulent supervisors drive the results, this would complicate the interpretation, as contagion via supervisors blurs together two conceptually distinct mechanisms.

The specifications reported in Table 4 test whether fraud by supervisors drives the results. The specifications in all three columns are based on that reported in column (3) of Table 3, and include merger-firm fixed effects. Columns (1) and (2) of Table 4 also include a control for whether the advisor is a sales supervisor. Column (2) also includes Introduced Branch Dirty Supervisor, an indicator variable equal to one if a sales supervisor at the merger-branch committed fraud during the three years prior to the merger. Column (2) also includes Original Branch Dirty Supervisor, an indicator variable equal to one if the sales supervisor at the advisor's Original Branch has a history of fraud. Column (3) excludes all sales supervisors from the sample.

In all three specifications reported in Table 4, the coefficient on Introduced Branch High Fraud Rate is essentially identical to that in Table 3. In columns (2) and (3), the coefficient on Introduced Branch Dirty Supervisor is not significant. The results show that fraud by supervisors does not drive the results, and fail to support the notion that across-branch variation in supervision causes the observed relation between Introduced Branch Fraud and post-merger fraud.

3.2. Variation in Branch-Level Policies or Internal Controls

A closely related alternative explanation is that there is within-firm, but across-branch, variation in policies or internal controls. In this case, branches with poor internal controls could have more fraud before the merger, and because of changed incentives advisors merged into these branches could commit more fraud post-merger; this would result in a spurious correlation between carer networks and fraud. This alternative explanation, however, implies asymmetric effects for advisors from target and from acquirer branches. Target advisors are generally merged into the acquirer's branches; it seems reasonable to assume that the oversight and supervision of the acquiring branch, and not the target branch, persists following the merger. Thus, this alternative explanation implies a strong effect for advisors from the target branch, but no effect (or a much weaker effect) for advisors from the acquirer branch.

Column (1) of Table 5 reports a specification that includes an interaction term between

Introduced Branch High Fraud Rate and Acquirer Branch; the specification is otherwise identical to that in column (3) of Table 3. The alternative explanation predicts that the coefficient on the interaction term would be negative. The estimated coefficient, however, is positive and insignificant. Thus this test fails to support the alternative explanation that branch-specific policies or internal controls drive the results.

3.3. Relative Sizes of the Merging Branches

When two branches merge, all else equal, we expect that the culture and social norms of the larger branch will have a greater effect on behavior in the merged branch. Column (2) of Table 5 includes an indicator variable, Relative Branch Size, equal to one if the Introduced Branch is larger than the advisor's Original Branch. We also interact this indicator variable with Introduced Branch High Fraud Rate. The coefficient on the interaction term is positive and significant at the 10% level, suggesting that the effect of fraud by new co-workers from the Introduced Branch is stronger when the advisor moves from a smaller branch to a larger branch.

3.4. Geographical Variation

Our identification strategy assumes that, after conditioning on Original Branch and individual characteristics, advisors at different branches of the same firm would have similar rates of fraud if the merger had not occurred. Arguably, fraud could vary across different branches of the same firm due to different local demographic or financial conditions, state-level regulatory environments, or other variation across geographical regions. If this geographical variation is correlated with fraud at the merger-branch partner, it could bias the results. It is not obvious why this geographic variation would be correlated with merger-branch fraud. Nevertheless, to guard against this possibility we estimate additional specifications that include geographic fixed effects.

The specifications reported in Table 6 extend the baseline specification by including geographic fixed effects. The specification in column (1) includes 5-digit zip code fixed effects, effectively removing all time-invariant characteristics of a narrow geographic area. The specification in column (2) includes state-year fixed effects, effectively removing all variation in a state during a given year. The strongest specification, in column (3), includes merger firm-county fixed effect. This last specification effectively compares different branches of the same firm and in the same county; thus controlling for all common variation across different branches of the same firm in a given area at a given point in time. For all three specifications, the coefficient on Introduced Branch Fraud High Rate remains positive and statistically significant.

4. Similarity and Contagion

Prior studies show that the transmission of behavior through social networks is stronger between individuals who are more similar. For example, Pool, Stoffman, and Yonker (2014) find that mutual fund managers in the same community hold similar portfolios, and this effect is stronger when both managers are similar in age or of the same ethnic background. (McPherson, Smith-Lovin, and Cook, 2001, rank age and ethnicity as the two most important factors in social network formation.) Based on the financial advisors' ages and ethnicities, we create several additional variables: (1) *Same Age Fraud Dummy*: an indicator equal to one if an individual whose age is within 5 years (i.e., the other advisor's age is +/- 5 years or less) at the Introduced Branch has previously been caught for fraud; (2) *ln(1 + Merger Same Age Network Size)*: the natural logarithm of the number of people at the other branch whose age is within +/- 5 years of the advisor; (3) *Same Ethnicity Fraud Dummy*: an indicator equal to one if an individual of the same ethnicity at the Introduced Branch has previously been caught for fraud; (4) *ln(1 + Merger Same Ethnicity Network Size)*: the natural logarithm of the number of people at the Introduced Branch with the same ethnicity as the financial advisor.

Column (1) of Table 7 shows the results for similar age. The coefficient estimate for *Introduced Branch High Fraud Rate*, reported in the first row, remains positive and significant. Thus, the effect of career networks is not driven entirely by advisors with similar age. The coefficient estimate for *Introduced Branch High Fraud Rate* × *Same Age Fraud Dummy* is positive and significant at the 10% level. This result is consistent with a stronger contagion effect between individuals whose ages are similar.

Column (2) of Table 7 shows the results for same ethnicity. Once again, the coefficient estimate for Introduced Branch High Fraud Rate remains positive and significant, implying that the effect of career networks is not driven entirely by advisors with the same ethnicity. The coefficient estimate for Introduced Branch High Fraud Rate Same Ethnicity Fraud Dummy is positive and significant at the 10% level. This result is consistent with a stronger contagion effect between individuals of the same ethnicity.

Both results are consistent with prior studies that find the effects of social networks on behavior are stronger for similar people. These results also imply that any alternative explanation of the results, must explain why age and ethnicity would affect the relation between career networks and fraud *within a branch*.

5. Conclusion

Despite the large size and economic importance of the financial advisory industry, and the large losses suffered due to fraud occurring within this industry, there has been little academic study of financial advisors. We conduct the first large scale academic study of fraud by financial advisors.

We show that the propensity to commit fraud is transmitted through career networks. We identify the effects of career networks using changes in co-workers due to mergers; we include merger-firm fixed effects in our analyses and thus use the variation across different advisors and different branches within the same firm. The results show that fraudulent co-workers affect the propensity to commit fraud. After a merger, an advisor is 38% more likely to commit fraud if he is merged into a new branch that includes individuals with a history of fraud (relative to an advisor from the same firm who is merged into a branch with no history of fraud). This result holds even controlling for the advisor's own history of fraud, the fraudulent behavior of his pre-merger co-workers, individual characteristics such as age, experience, and assets under management, and firm-level effects. The effect of career networks is stronger when the co-workers have similar age or the same ethnicity. Our results suggest that the optimal penalties for fraud by financial advisors should reflect not only the harm of the event itself, but also the negative spillover created by encouraging such behavior in others.

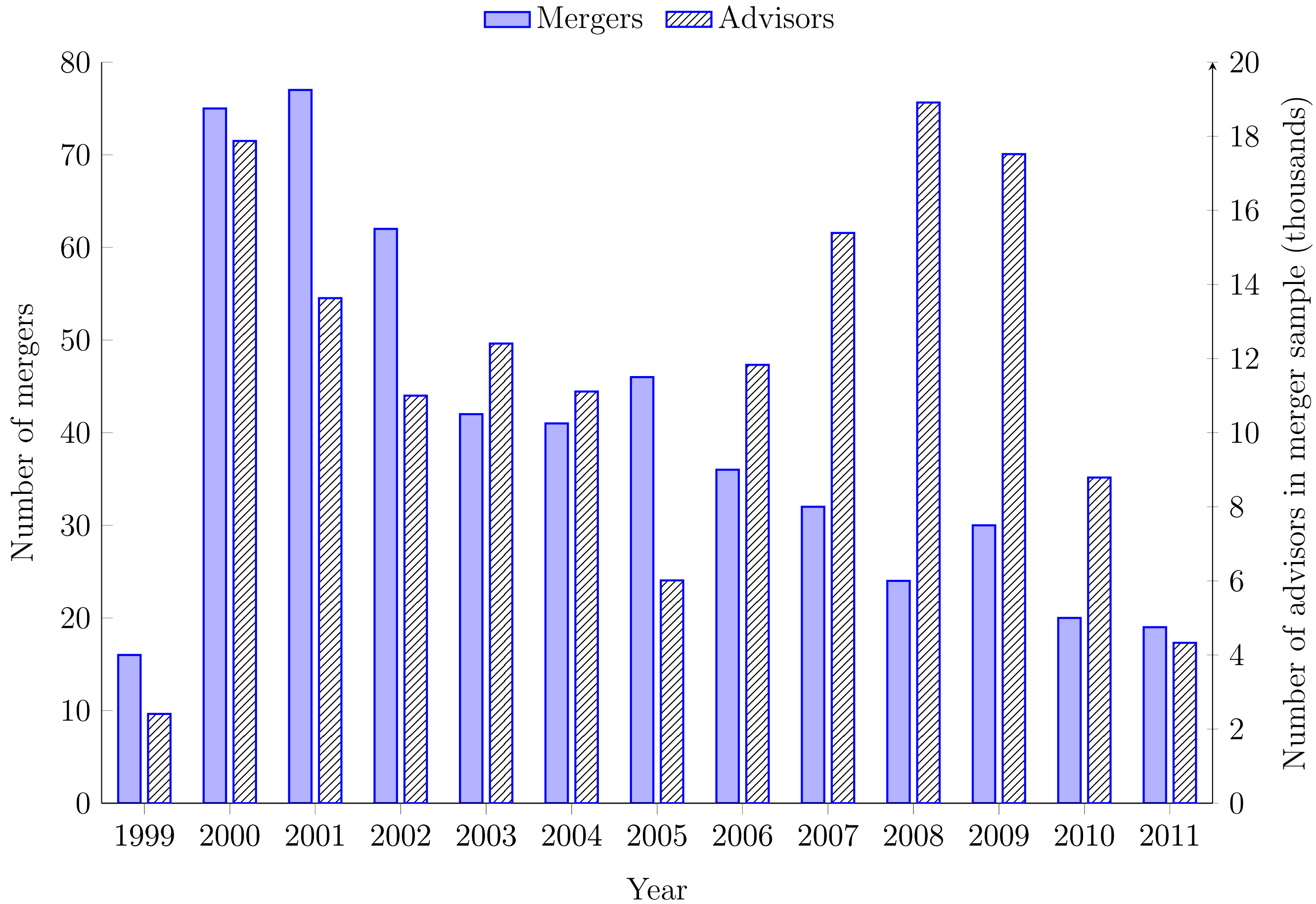

Figure 1
Advisor Mergers by Year

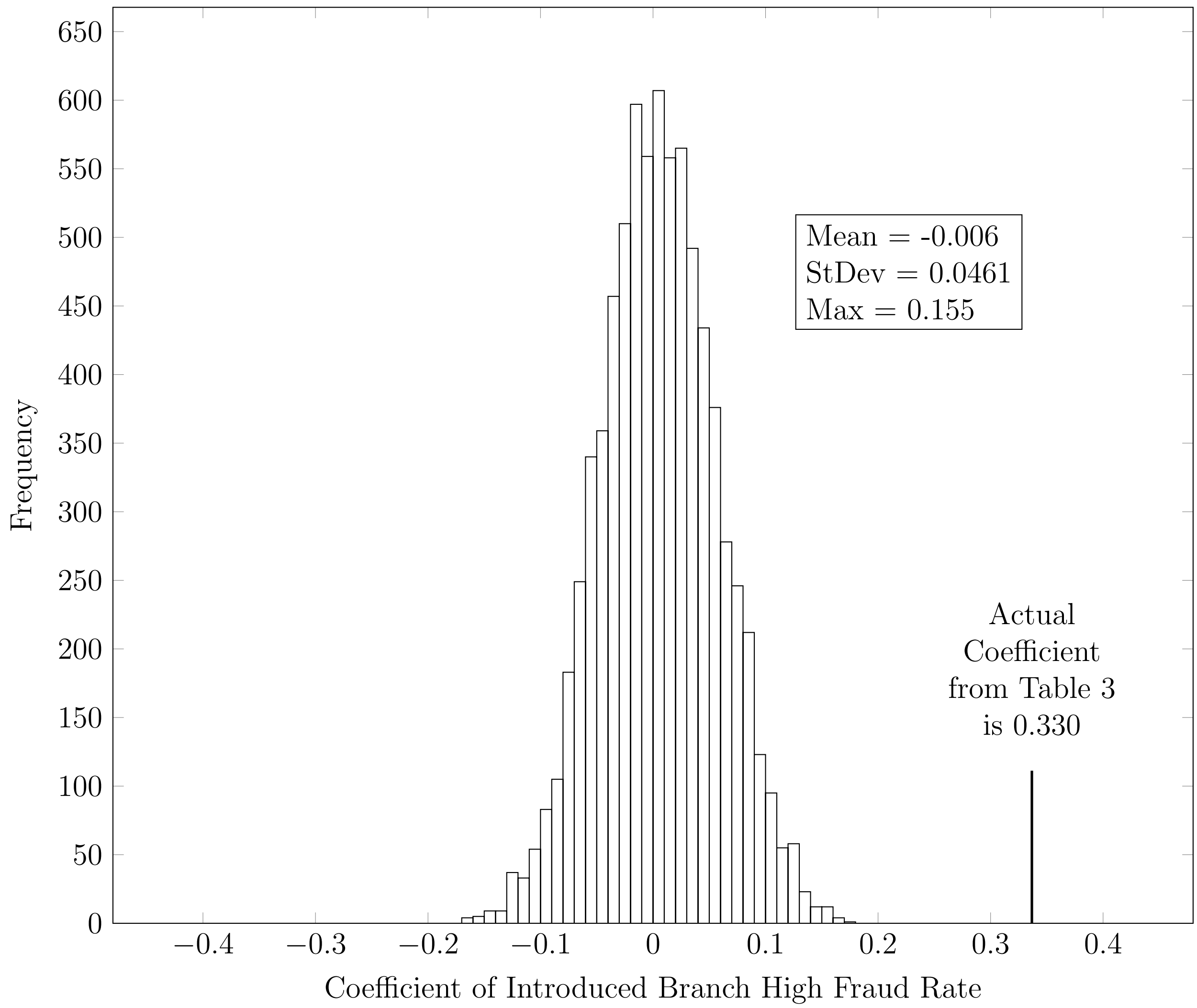

Figure 2
Coefficient Estimates in Placebo Samples

The figure shows a histogram of Introduced Branch High Fraud Rate coefficients from 5,000 bootstrap simulations of the model in Table 3, column (3). For each iteration, each advisor is randomly assigned to a branch within the same merger-firm (creating new counterfactual values for Introduced Branch High Fraud Rate and Introduced Branch Size). The model is re-estimated using the counterfactual Introduced Branch values.

Table 1
Summary Statistics: Financial Advisory Firms, Branches, and Financial Advisors

Full Sample reports pooled averages for the entire sample of financial advisors (except for branch averages which are calculated based on a cross-section at the midpoint of our sample period). Acquirer and Target are based on the merger sample only. Assets under management (AUM) and ethnicity are summarized using only those observations for which we have data. Supervisors are advisors that have passed the necessary tests (Series 9 or 10) to be a General Securities Sales Supervisor.

	Full Sample	Acquirer	Target
Financial Advisory Firms			
Number of Firms	34,579	483	483
Average Advisors per Firm	50.9	291.0	145.5
Branches			
Number of Branches	156,297	5,959	8,396
Average Branches per Firm	9.8	19.5	19.7
Average Financial advisors per Branch	2.4	14.9	7.4
Individual Financial Advisors			
Number of Financial Advisors	522,363	89,055	62,149
Experience	9.7	10.2	11.7
Assets Under Managment (AUM)	73.8	78.6	87.3
Supervisor	4.1%	6.1%	7.0%
Male	76.2%	71.1%	70.9%
Age	42.3	38.8	41.4
Ethnicity - White	89.7%	89.4%	90.6%
Ethnicity - Asian	4.4%	5.2%	4.3%
Ethnicity - Hispanic	4.9%	4.3%	4.2%
Ethnicity - Other	1.1%	1.0%	1.0%

Table 2
Fraud by Financial Advisors

This table provides summary statistics of fraud by financial advisors in the merger sample. Panel A tabulates various unconditional and conditional percentages of advisors that commit fraud. Pre-Merger period is the 3 years prior to the merger. Post-Merger period is the 3 years after the merger. Pre-Merger Co-Worker Fraud equals "Yes" if any other advisor in the advisor's Original Branch committed fraud. Panel B of Table 2 reports the percentage of advisors in post-Introduced Branches split by the number of frauds in their respective Original Branch. The term Clean (Dirty) indicates a branch at which none (at least one) of the advisors committed fraud during the 3 years prior to the merger. Panel C of Table 2 reports the percentage of advisors that commit fraud in the post-merger period for those advisors with no frauds in the pre-period. The target (acquirer) branches in are split in columns (rows) by above/below average fraud rate for the advisor's Original Branch and the branch with which it merges.

Panel A: Fraud Summary Statistics	
Pre-Merger Individual Fraud	1.14%
Post-Merger Individual Fraud	1.80%
Post-Merger Individual Fraud| Pre-Merger Individual Fraud = "Yes"	15.19%
Post-Merger Individual Fraud| Pre-Merger Individual Fraud = "No"	1.65%
Pre-Merger Individual Fraud | Pre-Merger Co-Worker Fraud = "Yes"	2.04%
Pre-Merger Individual Fraud | Pre-Merger Co-Worker Fraud = "No"	0.71%
Post-Merger Individual Fraud| Pre-Merger Co-Worker Fraud = "Yes"	2.54%
Post-Merger Individual Fraud| Pre-Merger Co-Worker Fraud = "No"	1.44%

Panel B: Target-Acquirer Branch Pairs by Pre-Merger Fraud Status: % of Advisors

		Target Branch	
		Clean Branch No Fraud in Pre-Period	Dirty Branch At Least One Fraud in Pre-Period
Acquirer Branch	Clean Branch	60.1%	18.9%
	Dirty Branch	14.6%	6.4%

Panel C: Post-Merger Fraud Rate for Advisors with No Frauds in Pre-Merger Period

		New Co-Workers	
		Low Pre-Merger Rate	High Pre-Merger Rate
Pre-Merger	Low Pre-Merger Rate	1.51%	2.42%
Co-Workers	High Pre-Merger Rate	1.99%	2.41%

Table 3
Mergers, New Networks, and Fraud

This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch Fraud Dummy equals 1 if the advisor's new co-workers from the other firm in the merger committed fraud before the merger (3-year window). Original Branch Fraud Dummy equals 1 if anyone at the advisor's Original Branch committed fraud before the merger (3-year window). Introduced Branch Fraud Rate equals the percentage of the advisor's new co-workers from the other firm in the merger who committed fraud before the merger (3-year window). Original Branch Fraud Rate equals the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new co-workers from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). ln(Original Branch Size) is the natural logarithm of the number of co-workers at the advisor's Original Branch. ln(Introduced Branch Size) is the number of advisors from the other firm in the merger the advisor works with after the merger. The models also include controls for advisory firm type, advisor age, gender, experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
Introduced Branch Fraud Dummy	0.281***		
	[4.11]		
Original Branch Fraud Dummy	0.303***		
	[3.85]		
Introduced Branch Fraud Rate		0.817***	
		[3.93]	
Original Branch Fraud Rate		0.731***	
		[3.31]	
Introduced Branch High Fraud Rate			0.330***
			[4.72]
Original Branch High Fraud Rate			0.370***
			[4.42]
Pre-Merger Individual Fraud Dummy	1.455***	1.443***	1.436***
	[13.53]	[13.65]	[13.45]
ln(Original Branch Size)	-0.093***	-0.132***	-0.114***
	[4.22]	[5.36]	[5.13]
ln(Introduced Branch Size)	-0.231***	-0.277***	-0.25***
	[7.54]	[8.42]	[7.82]
Advisor and Advisory Firm Controls	Yes	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes	Yes
Number of Observations	122,284	122,284	122,284

Table 4
Mergers, New Networks, and Fraud: Supervisor Effects

This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). Introduced Branch Dirty Supervisor equals 1 if the supervisor from the other firm in the merger committed fraud before the merger (3-year window). Original Branch Dirty Supervisor equals 1 if the supervisor from the advisor's Original Branch committed fraud before the merger (3-year window). Supervisor Dummy equals 1 if the advisor is a supervisor. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Introduced Branch High Fraud Rate	0.329***	0.318***	0.317***
	[4.72]	[4.25]	[3.87]
Introduced Branch Dirty Supervisor		0.115	0.094
		[0.91]	[0.68]
Original Branch Dirty Supervisor		-0.287**	-0.236**
		[2.53]	[2.06]
Supervisor Dummy	-0.122	-0.111	
	[1.49]	[1.36]	
Original Branch High Fraud Rate	0.368***	0.388***	0.393***
	[4.39]	[4.47]	[4.26]
Pre-Merger Individual Fraud Dummy	1.434***	1.445***	1.462***
	[13.48]	[13.32]	[13.22]
Exclude Sales Supervisors	No	No	No
Advisor and Advisory Firm Controls	Yes	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes	Yes
Number of Observations	113,602	113,602	104,723

Table 5
Mergers, New Networks, and Fraud: Targets, Acquirers, and Relative Branch Size

This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). Acquirer Dummy equals one if the advisor worked for the acquirer before the merger; working for the target firm is the base group. Relative Size Dummy equals one if Introduced Branch is larger than advisor's Original Branch. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Acquirer (1)	Relative Size (2)
Introduced Branch High Fraud Rate	0.295***	0.383***
	[2.59]	[3.40]
Introduced Branch High Fraud Rate × Acquirer Dummy	0.088	
	[0.49]	
Relative Branch Size Dummy		-0.032
		[0.30]
Introduced Branch High Fraud Rate × Relative Size Dummy		0.224*
		[1.73]
Original Branch High Fraud Rate	0.372***	0.372***
	[4.43]	[4.42]
Pre-Merger Individual Fraud Dummy	1.437***	1.435***
	[13.33]	[13.48]
Advisor and Advisory Firm Controls	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes
Number of Observations	113,602	113,602

Table 6
Mergers, New Networks, and Fraud: Geographic Effects

This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). Column (1) includes zip-code fixed effects in addition to merger-firm fixed effects. Column (2) includes state-year fixed effects in addition to merger-firm fixed effects. Column (3) includes merger-firm-county fixed effects. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Introduced Branch High Fraud Rate	0.281***	0.374***	0.399***
	[3.03]	[4.86]	[2.65]
Original Branch High Fraud Rate	0.356***	0.360***	0.414***
	[4.04]	[3.93]	[3.65]
Pre-Merger Individual Fraud Dummy	1.435***	1.424***	1.475***
	[13.26]	[11.47]	[10.60]
Zip Fixed Effects	Yes	No	No
State-Year Fixed Effects	No	Yes	No
Merger Firm-County Fixed Effects	No	No	Yes
Advisor and Advisory Firm Controls	Yes	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes	Subsumed
Number of Observations	113,602	85,474	70,719

Table 7
Similarity and Contagion: Age and Ethnicity

This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). Same Age Fraud Dummy equals 1 if an advisor's new colleagues of similar age (+/- 5 years) committed fraud before the merger (3-year window). ln(Merger Same Age Network Size) is the number of advisors of similar age from the other firm in the merger the advisor works with after the merger. Same Ethnicity Fraud Dummy equals 1 if an advisor's new colleagues of similar ethnicity (classified using the approach from Ambekar, Ward, Mohammed, Male, and Skiena, 2009) committed fraud before the merger (3-year window). ln(Merger Same Ethnicity Network Size) is the number of advisors of similar ethnicity from the other firm in the merger the advisor works with after the merger. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Introduced Branch High Fraud Rate	0.250***	0.190*
	[3.12]	[1.66]
Introduced Branch High Fraud Rate × Same Age Fraud Dummy	0.168*	
	[1.67]	
Introduced Branch High Fraud Rate × Same Ethnicity Fraud		0.225*
		[1.75]
ln(Merger Same Age Network Size)	-0.053	
	[1.20]	
ln(Merger Same Ethnicity Network Size)		-0.056
		[1.04]
Original Branch Fraud Dummy	0.307	0.347
	[3.73]	[4.26]
Pre-Merger Individual Fraud Dummy	1.306	1.372
	[13.15]	[10.78]
Advisor and Advisory Firm Controls	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes
Number of Observations	71,021	86,026
Net Effect: Introduced Branch High Fraud Rate + Interaction	*0.419****	*0.415****
χ^2	*15.72*	*26.14*

Internet Appendix Table 1
Robustness Tests

The dependent variable is post-merger fraud (3-year window). Column one reports estimates from a logit model without merger-firm fixed effects. Column two reports estimates from a logit model without merger-firm fixed effects. Column three reports estimates from a negative binomial model with merger-firm fixed effects. Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). ln(Original Branch Size) is the natural logarithm of the number of advisors at the branch the advisor worked at before the merger. ln(Introduced Branch Size) is the number of advisors from the other firm in the merger the advisor works with after the merger. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets in columns one and two. Z-scores without clustering are reported in column three. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Logit	Linear F.E.	Count Model
	(1)	(2)	(3)
Introduced Branch High Fraud Rate	0.310***	0.006**	0.299***
	[3.06]	[2.17]	[5.11]
Original Branch Fraud Rate	0.472***	0.009***	0.380***
	[4.58]	[4.48]	[8.06]
Pre-Merger Individual Fraud Dummy	1.322***	0.111***	1.326***
	[12.18]	[14.21]	[19.87]
Advisor and Advisory Firm Controls	Yes	Yes	Yes
Merger-Firm Fixed Effects	No	Yes	Yes
Number of Observations	151,204	151,204	113,602

Internet Appendix Table 2
Survival, Mergers, New Networks, and Frauds: Counterfactual with All Target Advisors

In this table, we report analysis in which we counterfactually assign any target advisor that departs to another firm (not the acquirer) to the post-merger acquirer branch that the plurality of the advisor's Original Branch work. We then recalculate all network variables based on these counterfactual assignments. This table reports coefficients from logit models of post-merger fraud (3-year window). Introduced Branch High Fraud Rate equals 1 if the percentage of the advisor's new colleagues from the other firm in the merger who committed fraud before the merger (3-year window) is above the mean rate. Original Branch Fraud Rate equals 1 if the percentage of the advisors at the advisor's Original Branch who committed fraud before the merger (3-year window) is above the mean rate. Pre-Merger Individual Fraud Dummy equals 1 if the advisor committed fraud before the merger (3-year window). Target Advisor Leaves Merged Firm equals 1 if the advisor departs to another firm in the real data. The models also include controls for size of the Original Branch and Introduced Branch, advisory firm type, advisor age, gender, advisor experience, and assets-under-management. Z-scores clustered by merger are in brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Introduced Branch High Fraud Rate	0.289***
	[3.91]
Introduced Branch High Fraud Rate × Target Advisor Leaves Merged Firm	-0.290
	[1.19]
Target Advisor Leaves Merged Firm	0.237
	[0.95]
Original Branch High Fraud Rate	0.411***
	[5.88]
Pre-Merger Individual Fraud Dummy	1.414***
	[16.12]
Advisor and Advisory Firm Controls	Yes
Merger-Firm Fixed Effects	Yes
Number of Observations	152,806

Internet Appendix Table 3
Alternate Windows

This table reports the Introduced Branch Fraud Dummy coefficient from models of post-merger fraud using alternate pre-merger and post-merger windows. The models are based on the specification in Table 3 column 3. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Coefficient of Introduced Branch High Fraud Rate

	Post-Merger Window Length		
	1-year	3-year	5-year
1-year Pre-Merger Window	0.423***	0.395***	0.408***
	[3.41]	[4.87]	[4.73]
3-year Pre-Merger Window	0.442***	0.330***	0.348***
	[3.94]	[4.72]	[5.06]
5-year Pre-Merger Window	0.367***	0.304***	0.347***
	[3.81]	[4.63]	[4.93]
10-year Pre-Merger Window	0.280**	0.175**	0.173**
	[2.64]	[2.41]	[2.23]
Full Pre-Merger Window	0.250**	0.191***	0.196***
	[2.54]	[2.93]	[2.77]

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