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 their employment histories and records of fraudulent behavior. We identify the effect of career networks on fraud using changes in these networks caused by mergers of financial advisory firms; the tests include merger fixed effects to exploit the variation in changes to career networks across different branches of the same firm. We show that interacting with co-workers who have a history of fraud increases the propensity to commit fraud. Further, this effect is stronger for less experienced employees, when co-workers are demographically similar, or when a fraudulent co-worker is a supervisor.

JEL Classifications: G20, G24, G28, K22

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"If you look at the family tree, you will find a lot of people who learned the trade at Stratton Oakmont" - Barry Goldsmith (NASD chief enforcement officer)

Stratton Oakmont, founded by Jordan Belfort and Kenneth Greene in 1989, quickly earned a reputation as one of the worst boiler rooms in the financial advisory industry. Within a year of the firm's expulsion from the industry, financial advisors[1] at several firms founded by Stratton Oakmont alumni, including employees who had never worked at Stratton Oakmont, were caught engaging in similar activity. Although only a small fraction of financial advisors ever commit fraud, many of the advisors who do are linked through their employment histories. Indeed, recognizing that career linkages are related to 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 the propensity to engage in fraud is difficult. Career networks are endogenous; people usually associate with others that possess similar characteristics. For example, dishonest financial advisors may select an employer that encourages dishonest behavior. As a result, it is very difficult for observational studies to disentangle whether behavioral similarity within a network is the result of: (1) contagion, or influence through interpersonal networks; (2) homophily, or the formation of ties due to matching on individual characteristics (Shalizi and Thomas, 2011).

In this paper, we test whether fraud is transmitted through career networks. We define an advisor's career network as the advisor's co-workers employed at the same branch of a firm at

[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

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 that occurs following a merger). Of course, merger decisions are themselves endogenous; however, we are able to exploit a unique feature of our financial advisor 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 following the merger the advisors from the Boston branch of Target Firm are more likely to commit fraud all else equal. All tests include controls for individual advisors' characteristics and fixed effects for the pre-merger branch. The comparison between the two branches removes any common time-series changes in the propensity to commit fraud and any effects common to all branches within the merged firm.

Our results support the idea that fraudulent behavior can be 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 the probability an advisor commits fraud increases if his merger branch includes people who have previously committed fraud. These results hold even after conditioning on the advisor's own history and the history of the advisor's pre-merger co-workers.

We conduct multiple robustness tests to help 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 firms, and then estimate the relation between the (counterfactual) merger branch and fraud. We repeat this procedure 300 times. The results confirm that the career network effects documented in our main tests are unlikely to be spurious. Second, we separate the sample into financial advisors employed at acquirer firms and at target firms. In both samples, an advisor is significantly more likely to commit fraud in the next three years if his merger branch includes co-workers with a history of fraud. Thus the results are not driven by one group of advisors. Third, we show that advisor departure (e.g., firing or quitting) cannot explain our results. Post-merger turnover is not related to the pre-merger fraud of the advisor, of his pre-merger branch, or of his merger branch.

Next, we test how various factors amplify the effect of networks on financial advisors' propensity to commit fraud. Prior studies show that network effects are stronger between similar individuals (e.g., see Pool, Stoffman, and Yonkers, 2014 in the context of mutual fund managers). Similarly, although we find evidence of network effects across all financial advisors, the effects are stronger among advisors who are of a similar age or ethnicity. We also find that a position of authority in the network matters; the effect is greater when the fraudulent co-worker merged in to advisor's career network is a supervisor. Finally, we find that network effects are stronger for less experienced advisors.

Our paper 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[3] in 2013). Financial advisors are important for the financial well-being of many households; Hung et al. (2008) report that 73% of individual investors use a financial advisor for investment decisions. Despite the economic importance of the financial advisor industry, there are relatively few academic studies. Many of the studies that do exist focus on agency problems. Financial advice is a credence good, and is especially difficult for households to evaluate given the low financial literacy of many households (van Rooij, Lusardi, and Alessie, 2011; Lusardi and Mitchell, 2011). The difficulty of evaluating financial advice, coupled with commission-based compensation, creates a significant agency problem. Prior studies generally find that financial advisors steer clients towards high fee investments[4] and fail to find measurable benefits of advisors (Bergstresser, Chalmers, and Tufano, 2010; Bhattacharya et al. 2012; Chalmers and Reuter, 2011; Hoechle, Ruenzi, Schaub, and Schmid, 2013; Mullainathan, Noeth, and Schoar, 2012). In contrast, we focus on how the career networks of financial advisors affect fraud.

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

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

The evidence suggests that fraud by financial advisors is common. FINRA reports thousands of incidents each year, and during our sample (1990-2011) the average annual value of fines, settlements, and arbitration awards due to fraud by financial advisors is $519 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). 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) reports 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.

We also add to a recent but growing literature on contagion in financial misconduct. Chiu, Teoh, and Tian (2013) and Chidambaran, Kedia, and Prabhala (2013) examine financial statement misreporting in networks of corporate directors. Parsons, Sulaeman, and Titman (2014) examine peer effects in financial statement misreporting among geographically related firms. A key advantage of our focus on fraud by financial advisors, instead of financial statement misreporting, is that we observe wrongdoing at the level of individual employees rather than at the company level. This allows our identification strategy, which is based entirely on within-firm variation across individual employees.

This paper has implications for policy issues 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). Beginning in 1981, the information disclosed in Form U4 has been collected in the Central Registration Depository (CRD), which assigns each financial advisor a unique identification number that remains constant even if the financial advisor switches employers. Information about individual advisors is disclosed to the public through FINRA's BrokerCheck system and through state regulatory agencies.

Meridian-IQ collects this information from state regulators. Because not all state regulators supply the full set of variables needed for our study, our universe of financial advisors consists of those registered in 32 states. Many financial advisors are registered in multiple states, because an advisor dealing with customers in any state must register with that state's securities regulator.[5] Furthermore, regulators keep historical records for ten years following deregistration. As such, although we only have 32 of 50 states, we have data for the vast majority of financial

[5] Many financial advisory firms register all of their employees in all states, and so we have data for many financial advisors even in the states that do not supply information. Only advisors that only have clients in one of the 18 non-reporting states and never register in a reporting state during their career are not observed.

advisors (~72% in 2012); we have data for 522,363 unique individuals over the full sample period. We supplement the Meridian data with data from state securities regulators, which includes some variables that are not available in the Meridian data.[6] To our knowledge, no prior academic study has used these data, and our data set, summarized in Table 1, is the most comprehensive sample of financial advisors studied.

A. Financial Advisory Firms, Branches, and Financial Advisors

The full sample includes 34,579 unique firms. Because our identification strategy is based on mergers between firms, our analyses focus on the 1,042 firms that are involved in the 521 mergers that occur during the sample period. 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 that employ only one or two financial advisors.

A financial advisory firm can have one or more branches (i.e., distinct business addresses). Using the branch identifier from Form U4, we identify an advisor's co-workers as those advisors working at the same branch (within the same firm) at the same time. The majority of the firms in the full sample have only a single branch. However, in the merger sample, both target and acquirer firms typically have multiple branches. This is important, as our identification strategy uses the variation across the branches of a single advisory firm. On average, about 27% (19%) of the target (acquirer) financial advisors end up working at a branch with at least one acquirer (target) financial advisor after the merger. The remainder of the financial advisors either continue to work at the same branch without meeting any advisors from the merger-partner or leave the firm (~14%). In our study, we focus on the set of target and acquirer advisors that are

[6] 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 additional data on advisors registered in their states.

introduced due to the merger. For an average merger, this set consists of 124 target advisors and 177 acquirer advisors mixed in 11 unique branches.

The demographic characteristics of the financial advisors in the merger sample are similar to those in the full sample. As Table 1 shows, in the merger sample the average advisor is about 40 years old and has 10 to 11 years of experience in the financial advisory industry. Target advisors are slightly older, more experienced, and have higher levels of assets under management.[7] We use the Census Bureau's genealogy data to create a mapping between last names and the ethnicity categories defined by the Office of Management and Budget. If more than 50% of respondents with a specific last name report the same ethnicity, we classify the advisor into that ethnic category. For example, 85.8% of people with the last name Miller self-report as white, so we associate the last name Miller with identifying as white. Similarly, because 93.8% of people with the last name Hernandez identify as Hispanic, we associate the last name Hernandez with identifying as Hispanic. Approximately 90% of the advisors in our sample are identified as white, and most of the remainder are identified as either Asian or Hispanic.[8] Finally, we define supervisors as advisors that have passed the necessary tests (Series 9 or 10) to be a General Securities Sales Supervisor. This designation allows an advisor to manage or supervise a firm's sales and securities operations. Approximately 6% of advisors in our sample are supervisors.

[7] 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.

[8] Because the Census Bureau does not report data for all last names and some last names are indeterminate (e.g., 48.52% and 46.72% with the name Williams identify as white and black, respectively), we cannot associate an ethnicity with every advisor. Additionally, because of variation within our data sources, we do not have a name for every advisor. Because of the commonality between white and black last names in the US, we have difficulty clearly identifying black advisors.

B. Mergers of Financial Advisory Firms

We identify mergers between financial advisory firms using advisors' past employment history in the Meridian data. Each financial advisor must disclose his past employment history, including the reason for leaving each prior job. If the advisor left a job because his firm (the target firm) was acquired in a merger, the reason for leaving is given as "Mass Transfer."[9] 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 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 can 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, January 5, and January 16. Because the transfer dates the advisors report

[9] The mass transfer program is intended for the bulk transfer of registration data in the event of a merger, consolidation, or reorganization. During our sample period, the mass transfer program allowed firms to avoid paying some additional registration fees and reduced the number of required filings, making usage of the mass transfer code advantageous. A mass transfer must involve at least 50 individuals to qualify.

vary, 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 ensure that we observe true post-merger employment, 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 January 1, 2004 to December 31, 2006 and the three year post-merger period is from January 2, 2007 to January 1, 2010; we do not include the initial transfer date in either the pre- or post-merger period.

C. 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 complaints from customers 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 a broker or planner advises a client to invest in 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.[10] FINRA arbitration decisions or customer withdrawals generally occur within two years of the complaint.[11] Although the Meridian data includes complaints filed through 2014 we include only complaints filed before 2012; thus our sample includes only substantiated complaints against the financial advisor.

Table 2 shows summary statistics of the fraud variable for the financial advisors in the sample of merged firms. Pre-Merger Individual Rate is the number of frauds committed by the advisor during the pre-merger period. Panel A shows that, at the time of the merger, financial advisors averaged 0.011 frauds in the previous three years (slightly less than 1% of advisors have any frauds as the same advisor can have multiple frauds during the period). The second and third columns divide the financial advisors based on whether they commit fraud in the three-year period following the merger. Individuals who committed fraud in the pre-merger period are more likely to commit fraud in the post-merger period.

Based on the advisors' employment histories, we construct two measures of their career networks. The first is the advisor's Pre-Merger Branch; this includes the advisor's co-workers during the three-year pre-merger period (with whom the advisor potentially chose to work). Pre-Merger Branch Fraud Rate is the number of frauds committed by the advisor's branch during the pre-merger period (Pre-Merger Branch Frauds) divided by the number of co-workers in the branch (Pre-Merger Branch Size).

The second measure of the advisors' career networks is Merger Branch; this includes the new co-workers that the advisor encounters due to the merger (and thus, excludes co-workers

[10] 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).
[11] 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.

from the Pre-Merger Branch). Merger Branch Fraud Rate is the number of frauds committed during the pre-merger by the new colleagues that an advisor encounters due to the merger (Merger Branch Frauds) divided by the number of new colleagues (Merger Branch Size).

Not surprisingly, advisors that commit fraud in the post-merger period have higher rates of fraud in their Pre-Merger branch (the co-workers they potentially chose). Interestingly, individuals that commit fraud in the post-period also have higher rates of fraud in their Merger Branch (the new co-workers encountered due to the merger). These effects are not due to differences in branch size. Fraudulent advisors have smaller Pre-Merger and Merger branch size.

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 of observations are in the off-diagonal cells, suggesting that mergers often change an advisor's exposure to co-workers who have committed fraud; clean acquirer branches merge with dirty target branches and vice versa.

2. Career Networks and Fraud

The primary empirical problem in network studies is distinguishing influence due to network effects (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 network effects requires an exogenous change to a financial advisor's network. We use changes in networks caused by mergers of financial advisory firms. Of course, firms could 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. By including merger-firm fixed effects in our analyses, 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 network influence effects and not homophily, subject to the assumption that firms do not systematically make merger decisions based on within-firm, branch-specific characteristics that are correlated with fraud.

A. 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 financial advisor-merger, and we estimate the following specification:

$$Pr\left(y_{i,m} = 1 | x_{i,m}\right) = F\left(\beta \cdot Merger\ Branch\ Fraud_{i,m} + \boldsymbol{X}_{i,m} \cdot \boldsymbol{\delta} + \alpha_{m,f}\right) \qquad (1)$$

Where $y_{i,m}$ is an indicator equal to one if financial advisor i is caught for fraud in the three-year period following merger m; $F(\cdot)$ indicates the logit function; Merger Branch $\text{Fraud}_{\text{i,m}}$ is an indicator variable equal to one if at least one of the financial advisor's new colleagues at the merged branch was caught for fraud in the pre-merger period; $\boldsymbol{X}_{i,m}$ is a vector of control variables; and $\alpha_{m,f}$ indicates a separate fixed effect for each merger-firm combination (this fixed effect is not included in column (1)). For the purposes of comparison, column (1) does not include the merger-firm fixed effects. All specifications include the following controls: (1) Pre-Merger Individual Fraud Dummy, which is set to one if the financial advisor was caught for fraud in the pre-merger period; (2) Pre-Merger Branch Fraud Dummy, which is set to one if anyone in the financial advisor's pre-merger branch was caught for fraud in the pre-merger period; (3) ln(Pre-Merger Branch Size), which is the natural logarithm of the number of advisors in the financial advisor's branch prior to the merger; and (4) ln(Merger Branch Size), which is the natural logarithm of the number of new co-workers encountered at the branch into which financial advisor *i* is merged. The z-scores reported in Table 3 are based on standard errors clustered by merger.

Column (1) of Table 3 shows results for a logit regression that does not include merger-firm fixed effects, and is included to provide a baseline for comparison. Column (2) includes merger-firm fixed effects (separate fixed effects for the target and acquirer in each merger) and additional control variables: advisory firm type,[12] advisor age, gender, advisor experience, and assets-under-management.[13]

In both columns, the coefficient on Merger Branch Fraud is significant and positive: When a financial advisor's network changes due to a merger, he is more likely to commit fraud in the next three years if his merger branch includes people who have previously committed fraud. The coefficient in column (2) is slightly smaller than in column (1), suggesting that even after including the fixed effects, however, the implied economic magnitude is large: the results in column (2) imply a financial advisor is 60% more likely to commit fraud if his merger branch includes an individual who has committed fraud. Given the merger-firm fixed effects, the results in column (2) imply the following. Suppose there are two identical financial advisors, who work at different branches of the same firm. When the firm merges, one of the advisors is merged into a new branch at which at least one of the advisors has committed fraud (dirty branch). The other advisor is merged into a branch at which no advisor has committed fraud (clean branch). The

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

[13] 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.

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*.

In both columns, the coefficient on Pre-Merger Branch Fraud Dummy is positive and significant; financial advisors whose Pre-Merger branch includes individuals who had committed fraud are more likely to commit fraud after the merger. The size of the coefficient decreases by nearly half when the merger-firm fixed effects are included in column (2); this suggests that a sizeable portion of the relation between pre-merger branch and fraud is driven by endogenous matching between employees and firms. The continued significance of the coefficient in column (2), suggests that even after removing the firm-level endogeneity, career-networks affect fraud. In the remainder of the paper, we focus on the Merger branch rather than the Pre-Merger branch, as the merger-firm fixed effects cannot remove within-firm endogenous matching between employees and *branches*, which could bias this coefficient.

The coefficients on the control variables are similar across specifications and the results are intuitively reasonable. Financial advisors with a past history of fraud before the merger are more likely to commit fraud after the merger. Both of the controls for the size of the networks show a negative relation with future fraud. This may reflect our choice of variable construction, in that the influence of any single fraudulent co-worker becomes relatively smaller as the branch gets larger. The additional tests reported in subsections C and D, however, show that the main results are robust to alternative specifications and variable definitions.

Overall the results support the idea that the propensity to commit fraud can be transmitted through career networks. Even after including merger-firm fixed effects to remove the effect of homophily, the effects of career networks are statistically and economically significant.

B. Career Networks and Fraud: Target and Acquirer Advisors

Table 4 reports the results of logit models that relate fraud by financial advisors to the advisor's career network. In column (1) the sample includes only financial advisors from target firms. In column (2) the sample includes only financial advisors from acquirer firms. Aside from splitting the sample, the specifications are the same as in column (2) of Table 3; merger-firm fixed effects are included and the standard errors are clustered by merger-firm.

Because the analyses include merger-firm fixed effects, any alternative explanation of the results must be based on within-firm branch-level variation that is correlated with fraud. One potential alternative explanation is that, even within a financial advisory firm, the degree of oversight and supervision varies across branches. In this case, branches with lax supervision could have higher rates of fraud than branches with strict supervision. Financial advisors merged into a new branch with lax supervision would be more likely to commit fraud relative to advisors merged into branches with strict supervision. This could create a spurious correlation between career 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, would persist 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.

The coefficient estimates on Merger Branch Fraud, reported in Table 4, are similar for both subsamples. The point estimate in the acquirer subsample is larger than in the target subsample, but we cannot reject that the coefficients are equal. This is inconsistent with the alternative explanation. We also note that additional results, presented in Section 3, are also inconsistent with this alternative explanation.

C. Count Model Results

Table 5 presents results from several robustness checks, which test whether the results presented in Table 3 are robust to reasonable changes in methodology or variable definitions. As in column (2) of Table 3, all specifications presented in Table 5 include merger-firm fixed effects and the full set of additional branch and individual control variables. All significance tests are based on standard errors clustered by merger-firm.

Column (1) of Table 5 shows results estimated with a negative binomial count model. In this specification, the dependent variable is the number of post-merger frauds, instead of an indicator variable. Although it is relatively rare to be caught for multiple frauds during the three year post-merger period (84.4% of individuals caught for fraud during this period are caught for only a single case), arguably the count model has more information than the logit, as it places greater weight on the financial advisors caught for more frauds. The count model results are generally similar to those from the logit, but are statistically somewhat stronger.

D. Alternative Definitions of the Career Network Fraud Variable

In columns (2) and (3) of Table 5, we return to a logit specification in which the dependent variable equals one if the advisor commits fraud in the post-merger period. In column (2) of Table 5 the key independent variable is the rate of fraud rather than a dummy (i.e., the proportion of advisors who have committed at least one fraud). Very large branches are mechanically more likely to have at least one advisor that has committed fraud, potentially exaggerating the "dirtiness" of a branch and thus the dirtiness of an advisor's pre- and post-merger branches. The results are generally similar to the results from the dummy variable specifications. Column (3) shows estimates in which the key independent variable is a simple count of the number of frauds; again, the results are similar to the dummy variable specifications.

E. Placebo Test

As an alternative approach to establish robustness of the network influence effect, we use a bootstrap procedure to impose the null of no network effect by randomizing assignment to post-merger branches. Specifically, within each merger firm, we counterfactually assign each advisor to a random post-merger branch to create a counterfactual Merger Branch. This allows us to randomize the financial advisors with respect to their Merger Branch connections, but leave all other characteristics unchanged. We then estimate the regression in column (2) of Table 3. We repeat this procedure 300 times.

Figure 1 plots the distribution of the odds ratios derived from our estimates of the counterfactual Merger Branch Fraud Dummy coefficient. The figure clearly shows that the actual estimate from column (2) of Table 3 lies well to the right of the entire mass of the distribution under the null. The actual estimated value (odds ratio of 1.60) is over seven standard deviations above the mean of the simulations (odds ratio of 1.11). The mean odds ratio of the simulations is slightly above one, as some financial advisors are randomly assigned to their actual post-merger branch simply by chance. The key takeaway is that actual branch assignment, and thus the new merger branch connections generated, are crucial in creating the observed network effect ruling out a host of potential alternative explanations.

3. What Factors Affect the Relation Between Career Networks and Fraud?

The previous section shows that a financial advisor is more likely to commit fraud if he is exposed to other financial advisors who have committed fraud. In the previous section, we treat all network contagion as equivalent. It is plausible, however, that the strength of network effects could vary with other factors. In this section, we test how various factors alter the relation between career networks and financial advisors' propensity to commit fraud. The specifications discussed in this section are extensions of those in column (2) of Table 3, and include merger-firm fixed effects as well as the full set of control variables.

The first two factors are based on the similarity between financial advisors. Prior studies suggest 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 from the same racial background. (McPherson, Smith-Lovin, and Cook, 2001 rank age and ethnicity as the two most important factors in general social network formation.) Based on the financial advisors' age and ethnicities, we create several additional variables: (1) Merger Same Age Network 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 other 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 with the same age-decade as the financial advisor; (3) Merger Same Ethnicity Fraud Dummy: an indicator equal to one if an individual of the same ethnicity at the other 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 other branch with the same ethnicity as the financial advisor.

Column (1) of Table 6 shows the results of the same age tests. The coefficient on Merger Same Age Fraud Dummy is positive and significant. The coefficient on Merger Branch Fraud Dummy remains significant but is smaller in magnitude than in Table 3. The earlier results show that a financial advisor is significantly more likely to commit fraud after a merger if his new colleagues have committed fraud; the results in column (1) show this effect is especially strong when a new colleague of similar age has committed fraud. Column (2) of Table 6 shows analogous results for the same-ethnicity tests. The coefficient on Merger Same Ethnicity Fraud Dummy is positive and significant, while Merger Branch Fraud Dummy retains its significance. This is consistent with prior studies that find the effects of social networks on behavior are significantly stronger for people with similar backgrounds. 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*.

Within a network, some individuals will be more influential than others. Within a financial advisory firm, we expect individuals in leadership positions will be particularly influential. Using data from the U4 filings, we create the variable Sales Supervisor, an indicator variable equal to one for those financial advisors who have passed the Series 9 and 10 exams. Passing these exams qualifies an individual to supervise sales of other financial advisors (i.e., passing these exams is a requirement for managerial positions). The variable Move from Clean to Fraud Supervisor is equal to one if an advisor who previously worked under a “clean” supervisor now works under a supervisor who has been caught for fraud. We also include Supervisor Fraud, a dummy equal to one if the advisor now works under a supervisor who has been caught for fraud.

The results, reported in column (3) of Table 6, show that Move from Clean to Fraud Supervisor has a significant positive relation with fraud. The coefficient on Supervisor Fraud is positive but insignificant. When a sales supervisor with a prior fraud is added to a financial advisor’s network due to a merger, the financial advisor is 45% more likely to be caught for fraud in the next three years (relative to a financial advisor whose network changes as a result of a merger, but does not change to a sales supervisor with a prior fraud).

Within a network, some individuals will be more susceptible to social network effects than others. In financial advisory firms, we would expect less experienced advisors to be more susceptible to network effects. Advisors with less experience are still learning the social norms of the profession, and are likely more open to change. The variable Inexperienced is equal to one if the advisor has below median experience working in the industry. We interact Inexperienced with the Merger Branch Fraud Dummy to test whether the effect of fraud in an advisor's career network is stronger for the less experienced advisors. Note that we control for advisor experience in all tables, but suppress the output for brevity.

The results, reported in column (4) of Table 6, show that the interaction between Inexperienced and Merger Branch Fraud Dummy is positive and significant. When a co-worker with a history of fraud is added to an advisor's network, the increase in the probability of committing fraud is much larger for less experienced advisors (relative to more experienced advisors from the same pre-merger branch). This result is consistent with network effects, and implies that any alternative explanation of the results must explain why the effect of career networks differs with experience (for two advisors from the same branch).

4. Survivorship

One potential concern that is not addressed by the preceding robustness tests is survivorship. Although an advisor likely cannot control the choice of new co-workers encountered due to the merger, the advisor has the option to leave the firm following the merger. If the advisor's decision to leave the firm depends on the types of new co-workers encountered due to the merger, then survivorship could affect our inferences.

To address this concern, Table 7 examines how long advisors remain at the merged firm following the merger. This table reports coefficients from Tobit models, in which the dependent variable is the length of employment in days after merger (up to 3 years, i.e., 1,095 days). In column (1), we include our main variable of interest, Merger Branch Fraud Dummy, as well as the other controls. None of the coefficients are significant; we do not find any evidence that encountering fraudulent co-workers increases the probability that an advisor leaves the merged firm. In column (2), we regress the length of employment after the merger on post-merger fraud. The results show that that engaging in fraud during the post-period increase the probability that the advisor leaves the firm (either voluntarily or through termination). This suggests that we have sufficient power to identify factors that affect the length of employment, and thus the insignificance in column (1) is not due to low power. In untabulated results, we find that the target advisors that go directly to non-acquirer firms (i.e., that never join the merged branch) have fewer frauds in the pre-merger period but no significant difference in the post-merger period. In sum, we do not find any evidence that our results could be driven by advisors choosing not to participate in the merger.

5. Conclusion

We conduct the first large scale academic study of fraud by financial advisors. Although many studies have analyzed related behaviors such as financial misstatement fraud, financial advisors are not well studied in the financial literature, nor are their crimes, despite the size of both the industry and the costs of fraud by advisors.

We show that the propensity to commit fraud is transmitted through social networks. We identify the effects of career networks using changes in career networks 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 60% 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 advisors' own history of fraud, the fraudulent behavior of their 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 ethnicity, when the fraudulent co-workers are in a supervisory role, and for less experienced advisors. Our results suggest that FINRA's penalties for fraud should reflect not only the harm of the event itself, but also the negative spillover created by encouraging such behavior in others.

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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	521	521
Average Advisors per Firm	50.9	177.4	124.2
Branches			
Number of Branches	156,297	6,198	9,002
Average Branches per Firm	9.8	11.9	17.3
Average Financial advisors per Branch	2.4	14.9	7.2
Individual Financial advisors			
Number of Financial advisors	522,363	92,404	64,683
Age	42.3	38.9	41.5
Experience	9.7	10.3	11.8
AUM	73.8	77.7	86.5
Male	76.2%	70.9%	70.2%
Ethnicity – White	89.7%	89.3%	90.2%
Ethnicity – Asian	4.4%	5.3%	4.3%
Ethnicity - Hispanic	4.9%	4.4%	4.5%
Ethnicity – Other	1.1%	1.9%	1.9%
Supervisor	4.1%	6.0%	6.9%

Table 2
Fraud by Financial Advisors

This table provides summary statistics of fraud by financial advisors in the merger sample. Panel A tabulates averages of fraud measures based on post-merger fraud status (i.e., whether the advisor commits fraud in the 3 years after the merger). Pre-Merger Individual Rate is the number of frauds committed by the advisor during the pre-merger period (3 years prior to merger). Pre-Merger Branch Fraud Rate is the number of frauds committed by the advisor's branch during the pre-merger period divided by the number of co-workers in the branch. Merger Branch Fraud Rate is the number of frauds committed during the pre-merger by the new colleagues that an advisor encounters due to the merger divided by the number of new colleagues. Panel B of Table 2 shows cross-tabulations of the merged branches based on whether the branch had any frauds in the pre-merger period. The terms "Clean" and "Dirty" indicates a branch at which none (at least one) of the financial advisors have committed a prior fraud.

Panel A: Fraud Summary Statistics

	All	No Post-Merger Fraud	Post-Merger Fraud	Difference
Observations	157,087	154,350	2,737	
Pre-Merger Individual Fraud Rate	0.011	0.010	0.097	0.088***
Pre-Merger Branch Fraud Rate	0.014	0.013	0.046	0.033***
Merger Branch Fraud Rate	0.013	0.012	0.027	0.014***

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

		Target	
		Clean	Dirty
Acquirer	Clean	55.2%	12.1%
	Dirty	22.6%	10.1%

Table 3
Mergers, New Networks, and Fraud

This table reports coefficients from logit models of post-merger fraud (3-year window). *Merger Branch Fraud Dummy* equals 1 if the advisor's new colleagues from the other firm in the merger committed fraud before the merger (3-year window). *Pre-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud before the merger (3-year window). *Pre-Merger Branch Fraud Dummy* equals 1 if any of the advisors at the advisor's pre-merger branch committed fraud before the merger (3-year window). *ln(Pre-Merger Branch Size)* is the natural logarithm of 1 plus the number of advisors at the branch the advisor worked at before the merger. *ln(Merger Branch Size)* is the number of advisors from the other firm in the merger the advisor works with after the merger. Z-scores clustered by merger-firm are in brackets.

	(1)	(2)
Merger Branch Fraud Dummy	0.530 ***	0.473 ***
	[5.26]	[7.62]
Pre-Merger Individual Fraud Dummy	1.417 ***	1.355 ***
	[15.37]	[13.81]
Pre-Merger Branch Fraud Dummy	0.882 ***	0.449 ***
	[8.07]	[6.59]
ln(Pre-Merger Branch Size)	-0.251 ***	-0.422 ***
	[9.03]	[17.88]
ln(Merger Branch Size)	-0.318 ***	-0.303 ***
	[8.00]	[12.32]
Advisor and Advisory Firm Controls	No	Yes
Year Fixed Effects	Yes	Subsumed
Merger-Firm Fixed Effects	No	Yes
Number of Obs.	151,204	151,204

Table 4

Mergers, New Networks, and Fraud – Targets and Acquirers

This table reports coefficients from logit models of post-merger fraud (3-year window). *Merger Branch Fraud Dummy* equals 1 if the advisor's new colleagues from the other firm in the merger committed fraud before the merger (3-year window) estimated separately on target and acquirer advisors. *Pre-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud before the merger (3-year window). *Pre-Merger Branch Fraud Dummy* equals 1 if any of the advisors at the advisor's pre-merger branch committed fraud before the merger (3-year window). *ln(Pre-Merger Branch Size)* is the natural logarithm of 1 plus the number of advisors at the branch the advisor worked at before the merger. *ln(Merger Branch Size)* is the number of advisors from the other firm in the merger the advisor works with after the merger. Z-scores clustered by merger-firm are in brackets.

	Target	Acquirer
Merger Branch Fraud Dummy	0.398 ***	0.573 ***
	[4.48]	[6.67]
Pre-Merger Individual Fraud Dummy	1.344 ***	1.357 ***
	[10.38]	[9.19]
Pre-Merger Branch Fraud Dummy	0.423 ***	0.482 ***
	[4.54]	[5.04]
ln(Pre-Merger Branch Size)	-0.414 ***	-0.391 ***
	[12.95]	[12.05]
ln(Merger Branch Size)	-0.250 ***	-0.401 ***
	[9.08]	[11.01]
Advisor and Advisory Firm Controls	Yes	Yes
Year Fixed Effects	Subsumed	Subsumed
Merger-Firm Fixed Effects	Yes	Yes
Number of Obs.	62,149	89,055

Table 5

Mergers, New Networks, and Fraud – Alternate Models

This table reports coefficients from a negative binomial model (column 1) and logit models (columns 2 and 3) of post-merger fraud (3-year window). The dependent variable for the negative binomial model is the number substantiated fraud cases against an advisor after the merger (3-year window). The dependent variable for the logit models is equal to 1 if the advisor committed fraud before the merger (3-year window). *Merger Branch Fraud Dummy* equals 1 if the advisor's new colleagues from the other firm in the merger committed fraud before the merger (3-year window). *Pre-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud before the merger (3-year window). *Pre-Merger Branch Fraud Dummy* equals 1 if any of the advisors at the advisor's pre-merger branch committed fraud before the merger. *ln(Pre-Merger Branch Size)* is the natural logarithm of 1 plus the number of advisors at the branch the advisor worked at before the merger. *ln(Merger Branch Size)* is the number of advisors from the other firm in the merger the advisor works with after the merger. *Rate* variables divide complaints by the number of advisors in the *Pre-Merger Branch* and the *Merger Branch*, and the number of years of experience the advisor has for *Pre-Merger Fraud*. *Count* variables are the number of fraud cases. Z-scores clustered by merger-firm are in brackets.

	(1)	(2)	(3)
Merger Branch Fraud Dummy	0.514 ***		
	[6.51]		
Pre-Merger Individual Fraud Dummy	1.470 ***		
	[11.13]		
Pre-Merger Branch Fraud Dummy	0.474 ***		
	[6.49]		
Merger Branch Fraud Rate		0.466 ***	
		[3.35]	
Pre-Merger Individual Fraud Rate		7.744 ***	
		[5.85]	
Pre-Merger Branch Fraud Rate		1.520 ***	
		[5.00]	
Merger Branch Fraud Count			0.035 ***
			[4.84]
Pre-Merger Individual Fraud Count			0.870 ***
			[6.68]
Pre-Merger Branch Fraud Count			0.058 ***
			[3.43]
ln(Pre-Merger Branch Size)	-0.310 ***		-0.399 ***
	[11.84]		[14.68]
ln(Merger Branch Size)	-0.434 ***		-0.297 ***
	[17.42]		[12.64]
Advisor and Advisory Firm Controls	Yes	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes	Yes
Number of Obs.	151,204	151,204	151,204

Table 6

Factors That Modulate Fraud

This table reports coefficients from logit models of post-merger fraud (3-year window). *Merger Branch Fraud Dummy* equals 1 if the advisor's new colleagues from the other firm in the merger committed fraud before the merger (3-year window). *Pre-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud before the merger (3-year window). *Pre-Merger Branch Fraud Dummy* equals 1 if any of the advisors at the advisor's pre-merger committed fraud before the merger (3-year window). *ln(Pre-Merger Branch Size)* is the natural logarithm of 1 plus the number of advisors at the branch the advisor worked at before the merger. *ln(Merger Branch Size)* is the number of advisors from the other firm in the merger the advisor works with after the merger. *Merger Same Age Network Fraud Dummy* equals 1 if the advisors in the New Network with +/- 5 years of age of the advisor had any complaints before the merger. *Merger Same Ethnicity Network Fraud Dummy* equals 1 if the advisors in the New Network that have the same Census-defined ethnicity had any complaints before the merger. *Move from Clean to Fraud Supervisor* equals 1 if the advisor's supervisor before the merger had not committed fraud and the advisor's supervisor after the merger had committed fraud. *Supervisor Fraud* equals 1 if the advisor's post-merger supervisor has committed fraud. *Inexperienced* equals 1 if the advisor has below median experience. Z-scores clustered by merger-firm are in brackets.

	(1)	(2)	(3)	(4)
Merger Branch Fraud Dummy	0.338 ***	0.204 *	0.418 ***	0.409 ***
	[4.75]	[1.82]	[6.60]	[5.46]
Pre-Merger Individual Fraud Dummy	1.245 ***	1.299 ***	1.355 ***	1.342 ***
	[12.72]	[12.05]	[13.61]	[13.68]
Pre-Merger Branch Fraud Dummy	0.396 ***	0.375 ***	0.435 ***	0.441 ***
	[5.53]	[5.65]	[7.00]	[6.40]
Merger Same Age Network Fraud Dummy	0.329 ***			
	[4.75]			
Merger Same Ethnicity Network Fraud Dummy		0.269 **		
		[2.15]		
Move from Clean to Fraud Supervisor			0.375 ***	
			[2.68]	
ln(Merger Same Age Network Size)	-0.024			
	[0.53]			
ln(Merger Same Ethnicity Network Size)		0.107 **		
		[2.03]		
Supervisor Fraud			0.049	
			[0.55]	
Inexperienced × Merger Branch Fraud Dummy				0.364 **
				[2.19]
ln(Pre-Merger Branch Size)	-0.420 ***	-0.412 ***	-0.419 ***	-0.417 ***
	[17.66]	[15.62]	[18.41]	[17.99]
ln(Merger Branch Size)	-0.308 ***	-0.400 ***	-0.315 ***	-0.292 ***
	[7.60]	[6.87]	[14.06]	[12.38]
Advisor and Advisory Firm Controls	Yes	Yes	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of Obs.	91,495	104,166	151,204	151,204

Table 7
Survival, Mergers, New Networks, and Fraud

This table reports coefficients from Tobit model of length of employment in days after merger (up to 3 years, i.e., 1095 days). *Merger Branch Fraud Dummy* equals 1 if the advisor's new colleagues from the other firm in the merger committed fraud before the merger (3-year window). *Pre-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud before the merger (3-year window). *Pre-Merger Branch Fraud Dummy* equals 1 if any of the advisors at the advisor's pre-merger branch committed fraud before the merger (3-year window). *Post-Merger Individual Fraud Dummy* equals 1 if the advisor committed fraud after the merger (3-year window). Z-scores clustered by merger-firm are in brackets.

	(1)	(2)
Merger Branch Fraud Dummy	20.1	
	[0.30]	
Pre-Merger Individual Fraud Dummy	-20.0	
	[0.32]	
Pre-Merger Branch Fraud Dummy	37.2	
	[0.73]	
Post-Merger Individual Fraud Dummy		-106.0 *
		[1.95]
Advisor and Advisory Firm Controls	Yes	Yes
Merger-Firm Fixed Effects	Yes	Yes
Number of Obs.	151,204	151,204

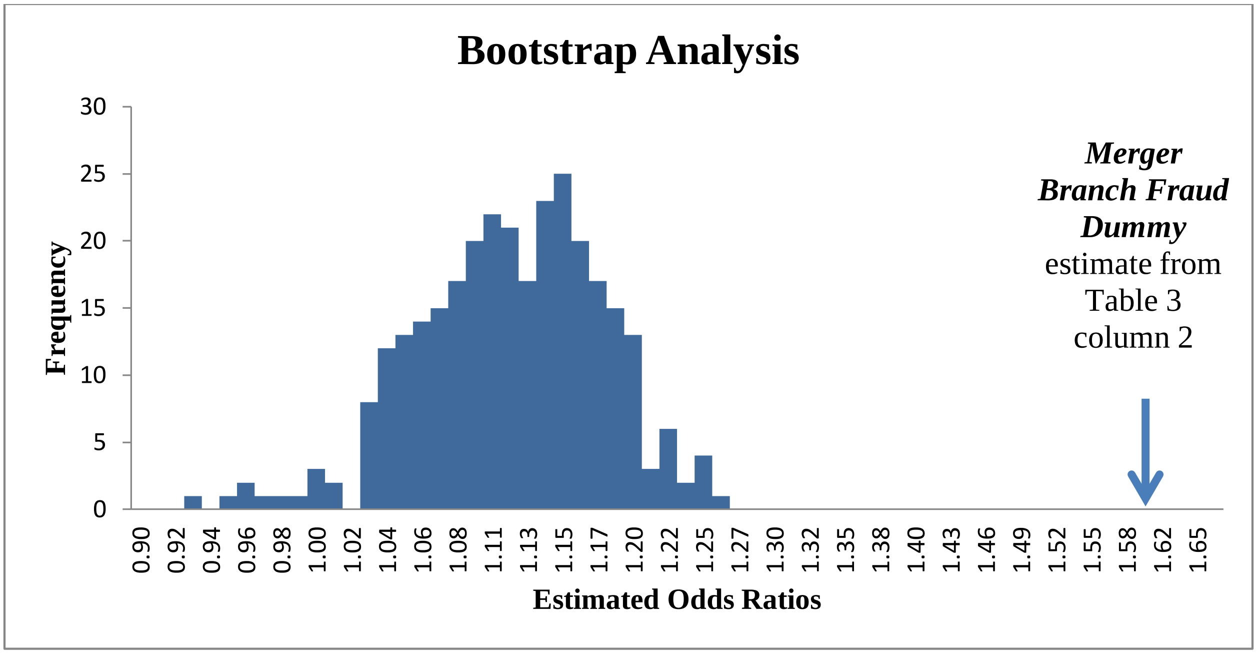

Figure 1: Bootstrap Analysis of New Network Dummy

The figure shows a histogram from 300 bootstrap simulations of *Merger Branch Fraud Dummy* coefficient (converted to an odds ratio) using the model in Table 3, column (2). For each iteration, each advisor is randomly assigned to a branch within the same merger (creating new counterfactual values for *Merger Branch Fraud Dummy* and *Merger Branch Size*) and the model is re-estimated.