

Death of a Salesman's Manager: Conflicted Supervision and the Dark Side of Soft Information *

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Abstract

Branch managers in financial advisory firms are responsible for advisor compliance but are compensated based on advisors' revenues, creating conflicting incentives. Using unexpected manager deaths as exogenous shocks to supervisory relationships, we find that advisor misconduct declines sharply after a manager's death and then fades over time. The decline is greatest for closer manager-advisor relationships and where soft information matters most. It is driven by misconduct that generates branch revenue, rather than violations benefiting advisors alone, and is weaker under stronger regulatory oversight. When supervisors face conflicting incentives, soft information can facilitate misconduct rather than prevent it.

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Misconduct against customers can be extraordinarily profitable in markets for expert advice, where the same lack of sophistication that creates the need for advice also leaves customers vulnerable to exploitation.¹ Because such conduct is often difficult to distinguish from legitimate practice, effective oversight requires contextual judgment that distant monitors typically cannot provide. Firms and regulators therefore frequently delegate front-line oversight to local supervisors who, through day-to-day interactions, accumulate soft information about their subordinates' behavior and practices. Prior studies show that local monitoring can reduce misconduct.² Yet this delegation can place discretion in the hands of supervisors who are rewarded for their teams' revenues. When supervisors face conflicted incentives, theory predicts that soft information may not merely fail to improve monitoring but can instead actively enable misconduct (Tirole, 1986, 1992; Faure-Grimaud et al., 2003). Whether informed local supervision deters misconduct or enables it is an open empirical question.

We examine this issue in the financial advisory industry, where misconduct is widespread and consequential.³ Most households that invest use a financial advisor (Egan et al., 2024), but typically lack the ability to monitor them. Within firms, branch managers serve as the primary local monitors. Regulators have encouraged this structure on the premise that managers' interactions with advisors allow them to accumulate knowledge about each advisor's tendencies, client relationships, and sales practices (Fanto, 2015). Branch managers' compensation, however, is closely tied to their advisors' revenues, creating a conflict between their supervisory and revenue-generation roles.⁴

¹See Dulleck and Kerschbamer (2006) and Balafoutas and Kerschbamer (2020) for reviews of self-serving advice in credence goods markets.

²See Kedia and Rajgopal (2011) for regulatory enforcement, Heese and Pérez-Cavazos (2020); Heese et al. (2021) for corporate misconduct, and Chhaochharia et al. (2012) for accounting fraud. Liberti and Petersen (2019) provide a general review of soft information and monitoring in finance.

³Egan, Matvos, and Seru (2019) document that the financial advisory industry plays an important role in household finance, yet ranks among the least trusted sectors in the U.S. economy. Approximately 6.6% of U.S. advisors have a record of regulatory violations, fraud, or serious customer disputes.

⁴Advisors can increase their own compensation and firm revenues through practices such as churning and recommending unsuitable products. Hamdi et al. (2023) show that finance-sector employees who engage in misconduct have higher incomes. For examples of how branch managers' compensation is related to

Over time, branch managers learn which advisors can generate revenue aggressively without attracting regulatory scrutiny, and advisors learn how far they can push ethical boundaries and how much protection to expect if detected. This mutual learning can produce outcomes ranging from active collusion, where managers explicitly encourage misconduct and help advisors avoid detection, to tacit complicity, where managers simply overlook violations or delay sanctions. In this paper, we test whether the soft information generated by supervisory relationships serves to protect investors or instead to accommodate financial advisor misconduct.

Identifying the causal effect of these relationships is challenging because supervisory assignments are endogenous. Managers may choose to hire compliant advisors while advisors seek lenient oversight, and turnover events such as retirements, transfers, and terminations are correlated with branch performance and misconduct. To overcome this challenge, we exploit unexpected deaths of branch managers as exogenous shocks that sever established supervisory relationships. When a branch manager dies, years of accumulated soft information about individual advisors vanish instantly while formal oversight structures remain intact.

Using a matched difference-in-differences design, we find that advisor misconduct declines sharply following manager deaths. This reduction persists for several years but reverts as new relationships form, consistent with the gradual rebuilding of supervisory relationships. Placebo tests confirm the effect is specific to supervisor deaths: deaths of non-branch-manager coworkers have no effect on misconduct, ruling out general bereavement or peer effects. The results persist when restricted to sudden, unexpected deaths. We also rule out the possibility that the decline in misconduct reflects business disruption rather than changes in behavior: advisors' credit outcomes and employment patterns are unaffected by the death of their branch manager.

their subordinates' sales, see Sullivan (2005) and FINRA's 2013 Report on Conflicts of Interest (<https://www.finra.org/rules-guidance/guidance/reports/conflicts-of-interest>).

We next examine the mechanisms through which supervisory relationships affect misconduct. First, we show that the treatment effect is greater for stronger relationships. The reduction in misconduct is larger for advisors who had longer shared tenures with the deceased manager and for advisors who share the manager’s race. These results are consistent with the importance of soft information, but also with alternative mechanisms such as personal ties that compromise managers’ willingness to discipline familiar advisors.

Second, we examine whether the effect operates through soft information. If so, the treatment effect should be stronger when contextual knowledge is more valuable for supervision and when oversight relies more on local managerial discretion. Consistent with this prediction, the effect is significantly larger for advisors with complex businesses spanning multiple products and services, where evaluating conduct is particularly context-dependent. The effect is also larger in firms with weaker compliance technology, where oversight relies less on centralized systems. Together, these patterns support soft information as an important mechanism linking supervisory relationships to misconduct.

Third, we test whether managers are complicit in advisor misconduct. We classify misconduct by whether it generates revenue for the branch (and advisor) or benefits only the advisor. If the post-death decline reflected advisor-side caution under unfamiliar supervisors, or reduced favoritism because the new manager lacks personal ties to the advisors, we would expect similar declines across both categories. Instead, only shared-benefit misconduct declines significantly following manager deaths; advisor-only-benefit misconduct is unchanged. This selective decline in misconduct is difficult to reconcile with advisor-side caution or the elimination of leniency due to personal ties, but is consistent with managers selectively enabling profitable misconduct.

Finally, we examine whether regulatory oversight can constrain this behavior. Exploiting variation in failure-to-supervise enforcement across FINRA districts, we find that the treatment effect of manager death is smaller in districts where regulators more aggressively penalize

supervisors for their subordinates’ misconduct. This attenuation is driven by enforcement targeting supervisors rather than advisors, suggesting that regulatory incentives can partially offset the financial incentives that otherwise lead managers to accommodate misconduct.

We contribute to the literature on financial advisor misconduct by examining internal supervision, which has received less attention than external regulatory oversight.⁵ We also add to the growing literature on the determinants of financial advisor misconduct, including peer effects (Dimmock et al., 2018), regulator quality (Charoenwong et al., 2019), local demographics (Egan et al., 2019), ethics training (Kowaleski et al., 2020), property rights to client relationships (Clifford and Gerken, 2021; Gurun et al., 2021), real estate shocks (Dimmock et al., 2021), economic conditions (Law and Zuo, 2021), childhood exposure to misconduct (Clifford et al., 2024), and corporate control transactions (Tookes and Yimfor, 2024). Most closely related to our study is Kowaleski, Sutherland, and Vetter (2024), who demonstrate that supervisors significantly influence misconduct beyond firm-level effects, as evidenced by the explanatory power of supervisor fixed effects. Our study complements theirs by taking a different approach. While Kowaleski et al. (2024) analyze the determinants and implications of endogenous matching between supervisors and branches, we identify the causal effect of supervisor turnover by exploiting the exogenous shock of branch manager deaths. This approach allows us to identify the *directional* effect of supervisor turnover on misconduct, and also to highlight the mechanism, namely the loss of accumulated soft information, that drives the observed reduction in advisor misconduct.

We also contribute to the literature on the role of soft information in monitoring.⁶ In numerous settings, where the monitor has no direct conflict of interest, studies find that soft information improves monitoring.⁷ In contrast, we document the dark side of soft

⁵See Charoenwong, Kwan, and Umar (2019), Egan, Matvos, and Seru (2019), Kowaleski, Sutherland, and Vetter (2020), Honigsberg, Hu, and Jackson Jr (2022), and Bhattacharya, Illanes, and Padi (2025).

⁶In addition to the literature on monitoring, there is a large literature on soft information and screening in lending markets (see Stein, 2002 and the review by Liberti and Petersen, 2019). These studies generally find that soft information is useful but can be exploited by agents (Hertzberg et al., 2010; Campbell et al., 2019).

⁷See Kedia and Rajgopal (2011) and Gopalan et al. (2019) for monitoring by regulators; Giroud (2013) and

information in monitoring. Consistent with the theoretical models of [Tirole \(1986, 1992\)](#) and [Faure-Grimaud et al. \(2003\)](#), we show that when the monitor has conflicting incentives, soft information can be exploited to enable misconduct rather than prevent it, a finding that has important implications for regulatory policy.

Finally, although our evidence is drawn from the financial advisory industry, the issue we examine is broadly applicable to settings in which supervisors and agents can jointly benefit from misconduct that requires some degree of trust and coordination, either explicit or tacit. For example, law partners responsible for preventing overbilling by associates, bank managers tasked with preventing money laundering, or hospital administrators overseeing physicians with incentives to perform unnecessary procedures. In all of these settings, soft information can facilitate misconduct through mutual learning between supervisors and agents. Supervisors learn which subordinates can push boundaries while managing regulatory risk, while agents learn what actions will be tolerated and what protection to expect if detected. As both parties acquire relationship-specific knowledge, the trust needed to co-offend develops and the uncertainty associated with misconduct decreases, making misconduct more attractive. This produces a surprising outcome: a more informed supervisory relationship can increase misconduct.

[Heese and Pérez-Cavazos \(2020\)](#) for monitoring of plants by corporate headquarters; [Lerner \(1995\)](#), [Bernstein et al. \(2016\)](#), and [Ewens and Sosyura \(2023\)](#) for monitoring by venture capital funds; [Chhaochharia et al. \(2012\)](#) for monitoring by institutional investors; and [Choi et al. \(2012\)](#) for monitoring by auditors. Note that while [Heese and Pérez-Cavazos \(2020\)](#) find on average improved headquarters access reduces facility-level workplace safety violations, this relation can reverse at firms under performance pressure, consistent with misaligned monitoring incentives.

1 Institutional Setting and Data

1.1 Institutional Setting

FINRA Rule 3110 requires firms to supervise the conduct of their advisors.⁸ Firms must “establish and maintain a system to supervise the activities of each associated person that is reasonably designed to achieve compliance with applicable securities laws and regulations.” Rule 3110 also requires firms to register all branch office locations⁹ and designate one or more supervisors with formal responsibility for the conduct of the advisors at that branch. FINRA can sanction supervisors on charges of “failure-to-supervise” for the misconduct of their subordinates with penalties ranging from fines to expulsion from the industry.

Although FINRA does not explicitly define a “branch manager,” firms typically rely on this position for day-to-day branch supervision. Indeed, an SEC study on investor protection in the brokerage industry refers to branch managers as the “first line of defense.”¹⁰ The branch manager’s supervisory responsibilities typically include conducting background checks on new hires, reviewing advisor correspondence with clients (e-mail, text messages, etc.), reviewing transactions, and approving new clients.¹¹ These responsibilities provide a clear mechanism through which branch managers accumulate information about their advisors.

In addition to compliance, branch managers are typically also responsible for generating revenues, hiring and retaining advisors, and branch operations (Sullivan, 2005). The responsibility to generate revenues can conflict with oversight responsibilities. This con-

⁸Section 15(a)(1) of the Securities Exchange Act of 1934 requires all advisors to be associated with a member firm, and FINRA Rule 3110(a) obliges member firms to supervise all associated persons. See Fanto (2015) for discussion.

⁹FINRA defines a branch office as any location at which “one or more associated persons of a member regularly conducts the business of effecting any transactions in, or inducing or attempting to induce the purchase or sale of, any security, or is held out as such.” See section (f)(2) of FINRA Rule 3110.

¹⁰See page 292 of the 1963 Report of Special Study of Securities Markets of the Securities and Exchange Commission.

¹¹See FINRA’s Supervisory Procedures Checklist: <https://www.finra.org/compliance-tools/wsp-broker-dealers-checklist>.

flict is exacerbated by a compensation structure that rewards branch managers for revenue production but “they do not get a bonus for compliance” (Sullivan, 2005).¹²

1.2 Identification of Branch Relationships

Our empirical tests require data that precisely identify branch–manager–advisor relationships and advisor misconduct. We construct such a dataset by combining records from two sources. First, Discovery Data identifies branch managers and the specific advisors they supervise, providing precision beyond that which can be imputed from licenses and firm–county combinations. Second, FINRA’s BrokerCheck supplies comprehensive misconduct records covering advisors’ entire careers.

Our primary data source is Discovery Data, which covers 975,352 advisors at 4,692 firms from 2015–2023. Discovery Data compiles information from federal and state regulators, firm websites, and other commercial sources to record advisors’ branch affiliations and designated branch managers. A key advantage of using Discovery Data is that it allows us to precisely identify branches and branch manager–subordinate relationships using branch CRD numbers¹³ and street addresses. Prior studies often use firm–county combinations to proxy for branches, which can conflate multiple distinct locations. This issue is particularly severe in high-population counties. For example, Figure 1 shows more than 100 J.P. Morgan branches operating in Los Angeles County in a typical year. Discovery Data, in contrast, provides a precise mapping from advisors to specific branches.

Discovery Data also identifies branch managers. The “branch manager” position is not formally defined by regulators, so we rely on Discovery Data’s definition as “a registered representative responsible for managing an office and handling local functions such as hiring,

¹²For further discussion of the link between branch manager compensation and revenue production, see Sullivan (2005), Fanto (2015), and pages 31–32 of FINRA’s 2013 Report on Conflicts of Interest: <https://www.finra.org/rules-guidance/guidance/reports/conflicts-of-interest>.

¹³FINRA Central Registration Depository (CRD) numbers are unique identifiers issued by FINRA for securities professionals, firms, and branches.

supervision, training, and community relations,” which follows the legacy NYSE Rule 9 definition of a Branch Office Manager. Discovery Data identifies these individuals using web scraping of firm websites and résumé platforms such as LinkedIn, and may fail to identify branch managers in some cases. FINRA’s regulatory definition of a branch is broad, encompassing any location where an advisor regularly conducts business including, for example, an advisor’s home office. We focus on the subset of branches where local supervisory relationships are most meaningful: 16,730 branches with at least two advisors and an identified branch manager, yielding 65,492 branch–manager–year observations. Branches in our sample are relatively small office units: the median branch has 8 advisors. Internet Appendix Table 2 compares these managers to non-manager advisors at the same branches: managers are older, more experienced, more likely to be registered investment advisors, and have higher rates of misconduct. They also more frequently hold sales-related licenses (e.g., Series 6/7 and Series 63), consistent with career paths that begin in client-facing sales roles.

Our use of Discovery Data to identify branch managers provides more precise identification of supervisory roles than has been possible in prior studies. Previous studies have relied upon supervisory licenses, especially Series 24, as indicators of supervisor status. However, we find that supervisory licenses do not map cleanly to the branch manager role. Among our identified branch managers, 90% hold at least one supervisory license, most commonly Series 24 (41%), followed by Series 9/10 (35%), Series 8 (17%), and Series 26 (10%).¹⁴ Yet the majority of individuals with supervisory licenses are not branch managers, and some branch managers hold specialized credentials not captured by standard supervisory licenses. By identifying managers based on their organizational role rather than license status alone, we more precisely capture those with genuine branch-level managerial authority.

We combine Discovery Data with FINRA’s BrokerCheck,¹⁵ which is based on FINRA Form

¹⁴Series 24 authorizes general securities supervision; Series 9/10 covers sales supervision of corporate, municipal, and options products; Series 8 was the former branch office manager exam; and Series 26 covers supervision of investment company and variable contracts sales.

¹⁵The data were retrieved annually and last retrieved in May 2024 from <https://brokercheck.finra.org/>.

U4 filings and provides comprehensive, survivorship-free information on advisor misconduct. BrokerCheck allows us to track misconduct over each advisor’s entire career, including the years before the first branch manager death in 2015. It also provides precise dates for employment and licenses, so we can build detailed career histories. From the merged dataset, we obtain career and demographic variables such as advisor age, industry experience, dual registration with the SEC, and indicators for various FINRA licenses.

We define misconduct following Charoenwong et al. (2019), Clifford and Gerken (2021), and Law and Zuo (2022), as all complaints initiated by customers. This approach captures instances of wrongdoing specifically from the client’s perspective and avoids potential biases introduced by firm or branch manager interventions.¹⁶ This distinction is important for accurately measuring the effectiveness of local supervision, as client complaints are less likely to be influenced by internal firm dynamics.

1.3 Branch Manager Deaths

We identify exogenous disruptions to branch–manager–advisor relationships using Form U5 death records obtained through state FOIA requests. Branch manager deaths provide plausibly exogenous shocks to the accumulated familiarity between managers and advisors, allowing us to identify the causal effect of relationship loss on advisor misconduct.¹⁷ Endogenous branch manager turnovers, such as retirements, transfers, and terminations, are confounded by factors correlated with branch performance and misconduct, which would complicate identification. Indeed, in the full sample the probability that a branch manager departs (for

Complete terms of use are available at <https://brokercheck.finra.org/terms>.

¹⁶We choose this measure as the most appropriate given that our study focuses on within-firm changes in misconduct. This measure excludes firm-initiated items, such as “Employment Separation After Allegations” used in Egan et al. (2019), which are a function of firm and branch managers’ decisions, and are thus potentially affected by changes in branch management. Similarly, using only settled or arbitrated customer complaints, instead of all customer complaints, is potentially influenced by the firm or branch manager’s approach to handling customer complaints.

¹⁷Many prior studies in finance use death as an exogenous shock. See for example, Andersen and Nielsen (2011), Becker and Hvide (2022), Ewens and Sosyura (2023), and Bernstein et al. (2025), among others.

reasons other than death) rises by 20.1% when the branch’s misconduct rate is one standard deviation above the mean.

We identify deaths of registered representatives using FINRA’s Form U5 (Uniform Termination Notice for Securities Industry Registration). Firms must file Form U5 within 30 days of an advisor leaving the firm, and categorize the reason as: “Voluntary,” “Deceased,” “Permitted to Resign,” “Discharged,” or “Other.” We focus on the “Deceased” category and use the separation date as the date of death. To collect comprehensive U5 data, we filed FOIA requests with all state regulators. Although some states did not provide the requested U5 data,¹⁸ our dataset is still highly representative. This is because advisors must register in every state in which they conduct business, and many choose to register nationwide, giving us information on advisors operating in all 50 states.

Form U5 is filed only for current employees—meaning our sample of deceased advisors was actively employed at the time of their death, and had not retired or left the firm due to poor health. This suggests that their passing was not anticipated by their colleagues. Thus, when a branch manager dies, years of accumulated familiarity between the manager and advisors are suddenly lost while formal firm structures remain intact. This creates an ideal setting to measure how the loss of accumulated familiarity affects advisor behavior, separate from other organizational changes.

1.4 Sample Construction and Matching

We begin with 64,757 branch-year observations in the intersection of the Discovery Data and BrokerCheck samples that have an identified branch manager.¹⁹ We then construct a

¹⁸We have U5 data for advisors registered in Arkansas, Arizona, Colorado, Connecticut, Florida, Idaho, Illinois, Iowa, Maine, Michigan, Minnesota, Mississippi, Montana, Nebraska, Nevada, New Hampshire, New York, Pennsylvania, Rhode Island, South Dakota, Texas, Vermont, Washington, and Wyoming.

¹⁹The majority of branches in the data do not have an identified branch manager. The vast majority of these branches are small and supervised remotely by a principal at an Office of Supervisory Jurisdiction. Of branch-years without an identified manager, 60.3% have only a single advisor and 17.4% have two. In some cases, Discovery Data may fail to identify the local branch manager during the data collection process.

sample of branches that experience a branch manager death (treated) and matched control observations as follows. First, because we are interested in the effect of branch managers on other advisors, we eliminate all branch-years that do not have at least one non-manager advisor (removes 8,989 branch-year observations). Second, we retain only the year during which a branch manager dies for branches that are ever treated, to ensure treated branches are never used as controls (removes 378 branch-years). Third, we retain only branch-years with a single treated branch manager or a single control manager, because in multi-manager branches we cannot match specific advisors to their supervisor (removes 6,553 branch-years). Fourth, we eliminate all branches with more than 100 advisors, because in large branches the branch manager is unlikely to have much familiarity with individual advisors (removes 1,168 branch-years). This results in a sample of 47,669 branch-years, including 97 branch-years with a deceased branch manager.

Because deceased managers tend to be older than managers at never-treated branches (mean 61.9 vs. 54.5), we use matching to identify control branches with similar branch manager and branch subordinate characteristics. Although using death as an exogenous shock mitigates the most obvious endogeneity problems, matching addresses additional potential concerns. For example, if older branch managers are both more likely to die and are less vigilant (e.g., due to reduced career concerns or diminished capacity), matching on branch manager age controls for this concern. Similarly, we match on the number of advisors in the branch to control for the depth of familiarity: in larger branches interactions are divided across more relationships.

Following [Jaravel et al. \(2018\)](#) and [Bernstein et al. \(2025\)](#) we construct a control sample of matched “placebo deceased” branch managers. We require that the control managers are identified by Discovery Data as a branch manager, and that no other advisor at the branch is identified as a branch manager. We then match the deceased managers, without replacement,

using exact matching on year and on ventiles of age and number of advisors.²⁰ We retain up to five matches. If there are more than five exact matches, we select the five nearest neighbors based on propensity score matching using the branch manager’s years of work experience, as well as averages across all advisors at the branch of age, experience, investment advisor, and licenses (series 6, 7, 24, 63, 65, and 66). We do not match on past misconduct to avoid potential biases from mean reversion (Roth et al., 2023). We keep weights from the matching procedure: when there are n matching control branches, each control branch receives a weight of $1/n$ in the regressions. Our resulting sample contains 97 treated branches and 481 control branches.

We keep all advisors who were at a treated or matched control branch at the start of the event year ($k = 0$). We term the branch where the advisor was located in the event year as the event-branch. We keep the observations for these advisors for all years they are in the sample. For example, we retain the complete career history of all advisors who were present at the time of the manager’s death, regardless of their previous or subsequent branch changes. Retaining advisors in the treated and control samples, even if they leave the event-branch, is important to avoid selection bias (e.g., if firms’ decisions to transfer advisors across branches after branch managers die are correlated with misconduct). We drop the deceased and pseudo-deceased branch managers, as our focus is on how branch managers’ relationships affect their subordinates’ behavior. Following Jaravel et al. (2018), we also drop advisors who are connected to more than one event-branch.²¹ Table 1 compares the mean characteristics of treated and matched control advisors at the match date ($k = 0$). The values are generally similar between the two groups, indicating that the matching procedure

²⁰Following Jaravel et al. (2018), we match sequentially by year to ensure each control is matched to only one deceased branch manager. We begin in 2015 and match the deceased managers in that year. The pseudo-deceased branches that are matched in 2015, are then removed from the sample of potential matches for future years. We then repeat this procedure in 2016, 2017, etc.

²¹For example, suppose an advisor is at a treated branch in 2016, and then moves to a new branch in 2017, and in 2020 that branch is matched as a control branch to a different event. We drop 84 advisors who are connected to multiple branches: 10 treated advisors and 74 control advisors.

achieves good overall covariate balance.²²

2 Branch Manager Death and Advisor Misconduct

This section presents our main empirical results. We begin by describing the research design and establishing the baseline treatment effect of branch manager death on advisor misconduct. Subsequent sections examine the mechanisms underlying this effect.

2.1 Research Design

Using the matched sample of treated and control branches described above, we estimate the causal effect of branch manager death on advisor misconduct. The regression specification follows [Jaravel et al. \(2018\)](#) and [Bernstein et al. \(2025\)](#), who also estimate spillover effects from death using matched difference-in-differences. We use the following subscripts: i for individual advisors, t for calendar years, k for event years (e.g., $k = 0$ indicates the year when the branch manager dies or pseudo dies, $k = 1$ the year after, etc.), b for the event-branch (advisor’s branch at $k = 0$), and m for the matched group of treated and control branches. Our main sample estimates results using the window from $k = -4$ to $k = +4$; Internet Appendix Table 3 shows the results are robust for alternative windows.

We estimate the following specification:

$$Misc_{i,t} = \sum_{k=-4}^4 \beta_k^{treat} \cdot \mathbb{1}_{b_{i,k}^{treat}} + \gamma \cdot \mathbf{X}_{i,t} + \lambda_i + \lambda_{m \times k} + \epsilon_{i,t} \quad (2.1)$$

where $Misc_{i,t}$ is an indicator equal to 100 if advisor i has a customer complaint in calendar year t , $\mathbb{1}_{b_{i,k}^{treat}}$ are indicators for the treated advisors in event-year k , $\mathbf{X}_{i,t}$ is a set of control

²²The average levels of past misconduct for both the treated and control samples are large relative to the rate in the overall sample (7.7% during our sample period). Relative to the full population, the advisors in our sample are older, more experienced, and work in smaller branches, all of which are associated with higher rates of past misconduct.

variables, λ_i is an advisor fixed effect, and $\lambda_{m \times k}$ is a fixed effect for each matched group-event year. The $\lambda_{m \times k}$ fixed effect subsumes time effects and allows for arbitrary time trends within each matched group of treated and control branches. Our interest is in the coefficients β_k^{treat} , which show the causal effects of branch manager death on misconduct k years from the death.

For many of our tests, we follow [Jaravel et al. \(2018\)](#) and report results from a simpler specification that provides more easily interpretable magnitudes. This specification replaces the year-by-year treatment indicators with a single indicator variable for the post-event-years:

$$Misc_{i,t} = \beta^{treat} \times Treated_i \times Post_k + \gamma \cdot \mathbf{X}_{i,t} + \lambda_i + \lambda_{m \times k} + \epsilon_{i,t} \quad (2.2)$$

where $Treated_i \times Post_k$ is equal to 1 for treated firms after the branch manager dies (i.e., $k = 1, 2, 3, 4$).²³

The control variables include indicators for advisor licenses (Series 6, 7, 24, 63, and 65/66) and whether the advisor is registered with the SEC as an investment advisor, as prior studies show these relate to misconduct (e.g., [Egan et al., 2019](#)).²⁴ The standard errors are clustered by event-branch.²⁵ Although our sample includes 97 treated branches, which exceeds conventional thresholds for reliable cluster-robust inference ([Cameron and Miller, 2015](#)), Internet Appendix Table 5 shows the results are robust to using the wild cluster bootstrap.

As discussed in [Bernstein et al. \(2025\)](#), by using a matched control group that is never treated and allowing for arbitrary time trends for each matched group of treated and control branches (by including $\lambda_{m \times k}$), we avoid the issues discussed in the recent staggered difference-in-differences literature ([Baker et al., 2022](#); [Roth et al., 2023](#)). We confirm this in robustness

²³Internet Appendix Table 4 shows the results are similar if we define treatment starting from $k = 0$.

²⁴Although prior studies in the financial advisory industry show that past misconduct is a strong predictor of future misconduct (e.g., [Dimmock and Gerken, 2012](#); [Egan et al., 2019](#); [Dimmock et al., 2020](#)), we do not include it to avoid the [Nickell \(1981\)](#) bias that would occur due to the advisor fixed effects.

²⁵Clustering at the branch-level follows the recommendations of [Roth et al. \(2023\)](#) to cluster at the level at which treatment is assigned.

tests following [de Chaisemartin and D’Haultfoeuille \(2020\)](#) and [Jakiela \(2021\)](#), by showing that none of the implicit weights in our fixed effects regressions are negative.

For some tests examining the mechanism, we extend our baseline specification and estimate triple-differences models:

$$\begin{aligned} Misc_{i,t} = & \beta^{treat} \times Treated_i \times Post_k + \beta^{char} \times Treated_i \times Post_k \times Char_i \\ & + \beta^{post} \times Post_k \times Char_i + \gamma \cdot \mathbf{X}_{i,t} + \lambda_i + \lambda_{m \times k} + \epsilon_{i,t} \end{aligned} \quad (2.3)$$

where $Treated_i \times Post_k$ is equal to 1 for treated branches after the branch manager dies, $Char_i$ is a characteristic of advisor i , and $Post_k$ is an indicator equal to 1 for both treated and control observations in the post period. The coefficient of interest is β^{char} , which captures how the treatment effect varies with advisor characteristics. The advisor fixed effects λ_i absorb the main effect of $Char_i$, while the match-group-event-year fixed effects $\lambda_{m \times k}$ absorb the main effect of $Post_k$. The interaction term $Post_k \times Char_i$ controls for any common time-trend in how the characteristic affects both treated and control advisors. We measure $Char_i$ at the beginning of year $k = 0$, prior to the branch manager’s death, because post-death characteristics may reflect endogenous responses to the treatment. For example, post-death employment decisions such as branch transfers or the characteristics of the newly appointed branch managers could be correlated with both advisor characteristics and misconduct risk, introducing post-treatment bias. Measuring $Char_i$ prior to the death avoids this concern.

2.2 Treatment Effects

Table 2 shows the regression results for equation (2.1) and the coefficients β_k^{treat} from column (2) are graphically displayed in Figure 2. The dots represent the coefficient estimates, while the vertical bars indicate the 95% confidence intervals based on standard errors clustered by event-branch. The point estimate for the event-year preceding the death is normalized to zero.

As a robustness check, Figure 3 displays the results for alternative difference-in-differences estimation methods (Cengiz et al., 2019; Callaway and Sant’Anna, 2021; Sun and Abraham, 2021); all methods produce similar results.

The results for the pre-event periods are consistent with the parallel trends assumption. All coefficients in the pre-event periods are close to zero and there is not a discernible pre-trend. We do not include past misconduct in the matching procedure, and so the similarity of misconduct during the pre-event period provides reassurance that our matching procedure selects appropriate control observations.

Misconduct by treated advisors falls significantly in the event-year ($k = 0$), with a coefficient of -0.525 (p -value = 0.04). Misconduct falls even more in the first full year after the branch manager’s death ($k = +1$), with a coefficient of -1.164 (p -value = 0.001), likely because the branch manager’s death during the event-year leaves only a half year on average for misconduct to change, compared to a full year in $k = +1$.²⁶ The effect on misconduct remains negative in subsequent years, and is statistically significant in year 2 (p -value = 0.04) and year 3 (p -value = 0.06). These results are directionally inconsistent with the hypothesis that supervisory relationships and accumulated soft information are used primarily to improve monitoring. Instead, the results are consistent with theoretical predictions that when monitors face conflicting incentives, supervisory relationships can facilitate rather than prevent misconduct (Tirole, 1986, 1992; Faure-Grimaud et al., 2003).

If the decline in misconduct reflects the loss of relationship-specific knowledge, it should attenuate as new relationships form. Figure 2 shows suggestive evidence of this pattern, as the coefficient for treated advisors becomes closer to zero and is statistically insignificant in $k = +4$, although it is not significantly different from the coefficients in $k = +1$ through

²⁶We observe the date a customer files a complaint, not when the underlying action occurred, meaning some misconduct during the event-year may be reported in the following year. Using FINRA data that are not publicly available, Qureshi and Sokobin (2015) find that the lag between misconduct and the complaint is usually less than a year.

$k = +3$. Column (3) of Internet Appendix Table 3 shows that the treatment effect becomes positive but statistically insignificant in $k = +5$, and is significantly different from the treatment effects in $k = +1$ through $k = +4$. Overall, this evidence suggests the effect of manager death on misconduct dissipates over time, consistent with new supervisory relationships gradually forming.

Table 3 reports the static treatment effect specification in equation (2.2). Column (1) does not include the control variables and column (2) does. The results in both columns are nearly identical. Relative to matched control observations, there is a significant drop in misconduct by advisors following the death of a branch manager.²⁷ This implies one fewer misconduct case during the four-year post-period per 35 treated advisors.

The remainder of the paper uses the regression in column (2) as the baseline specification. The following sections examine the mechanism and the effects of regulatory oversight, before Section 6 presents a battery of robustness tests of the main result shown in this section.

3 Supervisory Relationships and Soft Information

The baseline results show that advisor misconduct declines following branch manager death. This section examines *why* the loss of a specific manager-advisor relationship produces this effect. We argue that repeated interactions between branch managers and advisors build relationships that generate both soft information and personal ties, expanding the scope for discretionary supervision. When a branch manager dies, these accumulated relationships disappear abruptly.

This framework yields two testable implications. First, the treatment effect should be larger for manager-advisor pairs with stronger relationships. Second, if relationships operate through soft information, the effect should be larger in settings where supervision relies more

²⁷This result is robust to wild cluster bootstrap inference ($p < 0.01$).

heavily on judgment rather than mechanical rules. We test these implications in turn.

3.1 Relationship Strength

Supervisory relationships deepen through repeated interactions. Over time, advisors learn which forms of misconduct their manager will tolerate, while managers learn which advisors can push boundaries without taking excessive regulatory risks (Ayers and Braithwaite, 1992, p. 56). Repeated interactions may also generate personal ties that make it difficult for managers to discipline advisors they have come to know and favor. If the post-death decline in misconduct reflects the loss of these relationship-specific factors, the effect should be larger for manager-advisor pairs with stronger relationships. We test this prediction using two proxies for relationship strength: shared tenure and shared race.

Our first proxy for relationship strength is the duration of shared employment. For each manager-advisor pair, *Shared Tenure* is the number of years the pair were concurrently employed at the event firm, measured at the beginning of the event-year.²⁸ Column (1) of Table 4 shows that the post-death decrease in misconduct is significantly larger for advisors with longer *Shared Tenure*.²⁹

Our second proxy for relationship strength is whether the branch manager and advisor share the same race. We posit that relationship strength depends not only on shared tenure but also on the intensity of interactions during that tenure. Although we cannot directly

²⁸Discovery Data identifies branch–manager–advisor relationships beginning in 2015, which defines the start of our sample. BrokerCheck provides reliable firm-level employment start dates but does not consistently identify branch-level assignments. Accordingly, we measure shared tenure at the firm-level, which captures the maximum potential duration that the pair could have worked together. Any imprecision from using firm-level, instead of branch-level, shared tenure will bias our estimates towards zero.

²⁹Because the decline in misconduct is larger for manager-advisor pairs with longer *Shared Tenure*, the results might seem to suggest a policy of mandatory rotation of branch managers (mandatory rotation is common in settings such as diplomacy (Malis, 2021), auditing (Reid and Carcello, 2017; Gipper et al., 2021), and commercial lending (Hertzberg et al., 2010)). We caution against this simple interpretation, because we do not observe the offsetting benefits of longer branch manager tenure, such as improved mentoring. Consequently, our results do not address the net benefits of such a policy, and we defer further discussion of policy implications to Section 5.

observe these interactions, a large literature documents that race and ethnicity strongly affect social connections.³⁰ Accordingly, we expect stronger relationships between manager-advisor pairs who share the same race, implying that the sudden death of the branch manager is a greater shock for same-race pairs.

To test this hypothesis, we impute race using the Bayesian Improved First Name Surname Geocoding (BIFSG) algorithm developed by Voicu (2018).³¹ This method predicts race using first names, surnames, and the racial composition of the advisor’s geographic location. Clifford et al. (2023) apply this method to a sample of financial advisors and show that the classifications closely match the known demographics of the industry. Using this method, we classify each branch manager–advisor pair as either same or different race.

Column (2) of Table 4 shows that the post-death decline in misconduct is stronger for advisors who shared the same race as the deceased branch manager. Similar to the finding for *Shared Tenure*, the effect is larger for pairs where we expect the strongest relationships.

Columns (3) and (4) show that the triple-difference results are robust to replacing the match-group $\times$ year fixed effects with event-branch $\times$ year fixed effects, which limit comparisons to advisors within the same branch and year. Instead of relying on matched control branches to difference out time trends, this specification directly absorbs any time-varying shocks specific to each branch-year, such as administrative delays, temporary disorganization, or shifts in workload. Under this design, the post-death decline in misconduct remains significantly greater for advisors with higher *Shared Tenure* or with *Shared Race*.³² This

³⁰McPherson et al. (2001) review the literature on homophily and social connections and find that “Race and ethnicity are clearly the biggest divide in social networks today in the United States” (p. 420). Dimmock et al. (2018) and Clifford et al. (2023) show that shared race and ethnicity affect interactions in the financial advisory industry. Egan et al. (2022) show that African American and Hispanic advisors are punished more harshly for misconduct, but this effect is reduced when there are more same-race managers at the firm.

³¹Derby et al. (2024) and Greenwald et al. (2024) examine the accuracy of racial classification algorithms and find a systematic bias: minorities are more likely to be misclassified as white, and that misclassification is non-random (higher-income minorities are more likely to be misclassified). In our regressions, which include advisor fixed effects, such misclassification would bias against finding a significant coefficient on the triple-differences term.

³²Because treatment is assigned at the branch-level, $Treated \times Post$ does not vary within event-branch $\times$ year

finding reinforces our interpretation that the effect is driven by manager-advisor relationships rather than by branch-wide disruptions or artifacts of the matching procedure.

These results establish that the treatment effect concentrates in stronger relationships, but they do not identify why relationship strength matters. Stronger relationships may facilitate misconduct because they generate soft information that managers can exploit, or because they create personal ties that make discipline uncomfortable. The next set of tests helps distinguish these explanations by focusing on settings where soft information is especially important for supervision.

3.2 Soft Information and Managerial Discretion

Soft information refers to relationship-specific, context-dependent knowledge that becomes valuable when supervision requires judgment rather than mechanical rule-following. As [Liberti and Petersen \(2019\)](#) note, because soft information is difficult to codify and transmit, reliance on it necessarily requires delegating decision-making discretion to local managers. If the treatment effect operates through soft information, it should be largest in settings where such information is most valuable: where advisor activities are complex enough to require contextual understanding, and where firms rely on local managerial judgment rather than centralized compliance systems.

3.2.1 Complexity of Advisors' Activities

We first test whether the effect of branch manager death varies with the informational demands of advisors' business activities. Advisors vary widely in the complexity of their activities. Some focus on narrow product offerings and standardized services, while others provide customized portfolios that span multiple products, compensation structures, and client objectives. As this complexity increases, effective supervision increasingly requires

fixed effects and is absorbed, and only the triple-difference term is identified.

contextual understanding of how products, fees, and client needs interact over time. This type of understanding is difficult to codify and is instead accumulated through repeated exposure to an advisor’s business practices.

The loss of this relationship-specific soft information after a branch manager’s death creates significant uncertainty, especially in more complex settings, where the new manager is less able to evaluate borderline conduct using standardized rules alone. This greater uncertainty increases the supervisor’s career risk from leniency or extending an advisor the benefit of the doubt on borderline conduct. Advisors also face greater uncertainty about the new branch manager’s tolerance for misconduct and how they will respond to client complaints. Because there is greater uncertainty and career risk for both sides in more complex businesses, the post-death decrease in misconduct should be larger. In contrast, simpler advisory businesses rely less on soft information to reduce interpretive uncertainty. Thus, we predict the post-death decline in misconduct will be stronger for advisors engaged in more complex activities.

We capture advisory complexity using two complementary measures. First, following [Kowaleski et al. \(2024\)](#), we construct *High Product Complexity*, an indicator equal to one if the advisor’s firm offers an above-average number of distinct investment products, including debt, derivatives, mutual funds, private placements, and variable life insurance. This measure reflects the breadth of products an advisor may combine in serving clients, increasing the informational demands placed on supervision.

Second, we construct a *Complexity Index* using information from brokerage firms’ mandatory Form CRS filings.³³ These disclosures summarize services offered, fees, conflicts of interest, compensation arrangements, and related practices. As detailed in Internet Ap-

³³Form CRS was introduced in mid-2020 and downloaded in October 2021. Accordingly, we construct the *Complexity Index* from a 2021 cross-section of Form CRS filings and treat it as a time-invariant firm characteristic, which we apply to all years in our 2015-2023 sample. This approach assumes that firms’ advisory-service offerings and product complexity are stable over this period.

pendix [IA-1.1](#), we use ChatGPT³⁴ to score firms along three dimensions associated with how difficult it is for managers to evaluate advisor behavior using standardized criteria: service scope, product diversity, and account customization. We aggregate these components to create *Complexity Index*, which is standardized to have mean zero and a standard deviation of one.³⁵

Table 5 shows that, for both measures, the decline in misconduct following a branch manager’s death is significantly larger for advisors with more complex business activities. The results are consistent with the importance of soft information. As advisory business activities become more complex, the branch manager’s soft information is increasingly important, and so the loss of a branch manager has a correspondingly larger effect on advisor behavior.

3.2.2 Compliance Technology and Managerial Discretion

We next examine whether the effect of branch manager death depends on how much firms rely on standardized compliance systems rather than local managerial judgment. Although all firms combine formal rules with human oversight, the balance varies considerably. Firms that invest heavily in regulatory compliance technology (RegTech) embed monitoring rules directly into software and centralized systems. These systems generate standardized information that headquarters can evaluate, which reduces the incremental value of the local branch manager’s relationship-specific soft information and constrains managers’ discretion in supervision. Accordingly, if our earlier findings operate through soft information, we expect stronger results at firms with lower investments in RegTech.

To test this implication, we exploit cross-firm variation in compliance technology using the RegTech index developed by [Charoenwong et al. \(2024\)](#).³⁶ The index captures firm-level investments in compliance-related technology, including enterprise resource planning software,

³⁴[Hansen and Kazinnik \(2023\)](#) show that ChatGPT performs well at classifying financial text.

³⁵Results for each sub-index are reported in Internet Appendix Table 8.

³⁶We thank Ben Charoenwong and Zach Kowaleski for suggesting this test and providing the data.

IT infrastructure, and customer relationship management systems. We classify firms as *Low RegTech* if their index value falls below the sample median.

Table 6 reports the results. The decline in misconduct following branch manager death is significant for both high and low RegTech firms, but the decline is significantly larger for *Low RegTech* firms (at the 10% level). This pattern is consistent with standardized monitoring systems partially substituting for local managerial judgment. In firms with weaker compliance technology, advisor misconduct depends more on the presence of a specific branch manager, consistent with greater reliance on soft information and managerial discretion.

Taken together, the evidence in this section indicates that supervisory relationships facilitate misconduct through soft information. The treatment effect concentrates in stronger relationships, and within those relationships, the effect is largest in settings where soft information is most valuable: complex advisory businesses and firms with weaker compliance technology. Soft information facilitates misconduct by reducing uncertainty on both sides of the relationship. Branch managers with soft information better understand which advisors can push boundaries without attracting regulatory scrutiny and what the likely consequences of leniency will be. Advisors, in turn, learn their manager’s tolerance for misconduct and what protection to expect if complaints arise. This mutual understanding lowers the perceived risk of misconduct for both parties.

4 Branch Manager Motives and Complicity

In this section, we test whether the decline in misconduct following branch manager death depends on whether the misconduct generates financial benefits for the branch manager. Our identification relies on variation across types of misconduct in whether financial gains are shared between advisors and their managers. This test addresses two issues. First, the evidence in the previous section indicates that soft information matters, but does not

distinguish whether it is used primarily to accommodate misconduct for financial gain or for interpersonal benefits, such as avoiding conflict or favoring longstanding colleagues (e.g., [Prendergast and Topel, 1996](#)). Second, it addresses an alternative advisor-side explanation in which branch managers are not complicit in misconduct and advisors simply become more cautious under unfamiliar supervision after a death, which would predict similar reductions across all forms of misconduct.

We classify misconduct into two categories based on whether the allegation text indicates revenue generation through the firm’s commission and fee channels. *Advisor-only-benefit* misconduct encompasses violations where the firm’s revenue channels are bypassed or uninvolved, such as misappropriation of client assets, forgery, undisclosed outside business activities (e.g., selling away), commingling of client funds, and Ponzi schemes. These actions impose reputational and regulatory risk on the branch without providing compensating financial benefits for the branch or the manager.

In contrast, *Shared-benefit* misconduct encompasses violations that explicitly reference commission- or fee-generating activity, including churning/excessive trading, unsuitable high-fee recommendations, unnecessary account switches or replacements, and misrepresentation in connection with product sales. Although harmful to clients, these practices increase branch revenues and, in turn, branch manager compensation, which is typically tied directly to branch revenue production.³⁷ This creates incentives for branch managers to exercise discretion in ways that accommodate such behavior. Internet Appendix [IA-2](#) provides additional details on the classification procedure. Among advisor-years with misconduct in our sample, 9.1% are classified as advisor-only, 72.0% as shared-only, 1.7% involve both categories in the same year (reflecting multiple complaints), and 17.2% are unclassified.

³⁷[FINRA’s 2013 Report on Conflicts of Interest](#) (see pg. 32) notes that most branch managers are compensated based on branch revenue and this creates a conflict of interest. For another example, brokerage firm [LPL’s conflicts of interest disclosure document](#) states that it pays branch managers based on sales at their branch, and that this can affect their ability to provide objective supervision.

Table 7 presents the results. Column (1) shows that the effect of branch manager death on advisor-only-benefit misconduct is small and statistically insignificant. Column (2) shows a large and statistically significant decline in shared-benefit misconduct. The difference between the coefficients in the two regression models is significant (p -value = 0.02). This difference is not driven mechanically by the lower base rate of advisor-only misconduct. Scaling each coefficient by the mean of its dependent variable, the ratio for shared-benefit misconduct is nearly five times larger than that for advisor-only misconduct. Thus, the post-death reduction in misconduct is concentrated in activities that generate financial benefits shared between advisors and the branch.

These results provide evidence that financial incentives shape how branch managers exercise their discretion in supervising. If branch managers were simply more lenient toward familiar advisors regardless of financial considerations, we would expect similar post-death declines in both categories. In contrast, our finding of no decline for *Advisor-only-benefit* misconduct and a significant decline for *Shared-benefit* misconduct is consistent with managers selectively tolerating or failing to discipline revenue-generating misconduct from which they stand to gain. We stress, however, that financial incentives and personal ties are not mutually exclusive, and evidence consistent with financially motivated leniency is not evidence against a complementary role for interpersonal motivations.

These findings also rule out explanations based purely on advisor behavior. If the decline reflected only advisors becoming more cautious or adjusting their behavior under unfamiliar supervision, we would expect similar reductions across both categories of misconduct. The concentration of the effect in *Shared-benefit* misconduct indicates that managerial behavior and incentives play an important role in driving the result.

Overall, the evidence indicates that branch managers use the soft information accumulated through relationships, at least in part, to accommodate misconduct that generates shared financial gains. While we do not observe direct coordination between managers and

advisors, the pattern of results is consistent with models of supervisory collusion in which managers endowed with private information and discretion implicitly tolerate misconduct when incentives are aligned (Tirole, 1986, 1992). The death of a branch manager disrupts this arrangement, leading to a sharp decline in revenue-generating misconduct.

5 Regulatory Oversight and Policy Implications

The prior sections present evidence that branch managers use soft information to facilitate profitable misconduct. We now examine whether regulatory oversight can constrain this behavior. Rule 3110 enables FINRA to sanction branch managers for “failure-to-supervise” when their subordinates commit misconduct. When regulators credibly hold supervisors accountable for their subordinates’ violations, managers’ incentives shift away from enabling misconduct toward ensuring compliance. We hypothesize that stringent regulatory enforcement should deter branch managers from exploiting their accumulated soft information, thereby reducing the treatment effect of manager death on misconduct.

To test this prediction, we use variation in failure-to-supervise enforcement across FINRA’s 11 geographic districts.³⁸ For each district, we use data for the four-year period prior to the event-year to construct three district-level measures using customer complaints and FINRA regulatory actions against registered representatives. We first compute the fraction of regulatory actions that involve failure-to-supervise (*Supervisory Action Share*). We also construct two intensity measures that distinguish the *target* of enforcement: the number of supervisory actions per customer complaint (*Supervisory Actions per Complaint*) and the number of non-supervisory actions per customer complaint (*Non-Supervisory Actions per Complaint*). By using ratios, we normalize across districts for overall enforcement activity and for the volume of customer complaints. All three measures are standardized to have a

³⁸For the geographic makeup of the districts see <https://www.finra.org/rules-guidance/rulebooks/corporate-organization/schedule-finra-regulation-laws>.

mean of zero and standard deviation of one.

Column (1) of Table 8 shows the results for *Supervisory Action Share*. The triple difference term is positive and significant (at the 10% level), implying the treatment effect of branch manager death is weaker in districts where regulators devote a larger fraction of their attention to supervisory violations. This pattern is consistent with supervisory accountability limiting the scope for branch managers to exploit soft information.

Columns (2) and (3) compare how the effect of regulatory oversight depends on the *target* of enforcement. Although failure-to-supervise cases comprise only 9.2% of FINRA regulatory actions in our sample, only the triple-difference coefficient on *Supervisory Actions per Complaint* is significant at the 10% level. The corresponding coefficient on *Non-Supervisory Actions per Complaint* is much smaller and not statistically significant at conventional levels. Taken together, these results suggest that oversight is most effective at limiting the misuse of soft information when it directly raises expected sanctions on supervisors for their subordinates' misconduct, rather than when enforcement is directed primarily at advisors.

6 Robustness Tests

This section presents robustness tests that address potential threats to the identification of the baseline treatment effect. These tests examine whether the decline in misconduct could be explained by generic co-worker effects rather than the loss of a supervisory relationship, whether anticipation of branch manager death confounds our results, and whether business disruption among advisors drives the observed patterns.

6.1 Placebo Tests Using the Deaths of Non-Branch Managers

We interpret our baseline results as evidence that misconduct declines because of the loss of the supervisory relationship when a branch manager dies. This interpretation is specific

to advisor-supervisor relationships and does not predict a decrease in misconduct following the death of a non-branch-manager co-worker. Accordingly, we estimate placebo tests that substitute branch manager deaths with deaths of non-branch-manager co-workers. These tests rule out alternative explanations that would apply to any co-worker death, not just those of supervisors.

We identify non-branch manager deaths using Form U5 filings. Aside from using non-branch manager deaths, the matching procedure and tests are identical to those in the baseline specification in column (2) of Table 3. We create three placebo samples. First, we include all deaths of advisors who are not branch managers. This is the broadest of the placebo samples, and it addresses possible peer co-worker effects. This is important, as Dimmock et al. (2018) show there are peer effects in advisor misconduct.³⁹ Second, we include only the deaths of non-branch managers who hold at least one supervisory license.⁴⁰ This restriction limits the sample to deceased advisors who hold the same qualifications and are thus similar to branch managers, but do not hold the actual position. Third, we include only the deaths of non-branch managers who worked at the firm for at least 10 years. This sample addresses whether the death of a long-term colleague causes a change in behavior. For example, bereavement effects (e.g., Liu et al., 2023) could be stronger following the death of a long-term colleague.

Panel A of Table 9 shows that in all three placebo samples, the treatment effect is not significantly different from zero. Given that the placebo samples are much larger than the main sample, the null result occurs because the effect sizes are economically small and not because of low power. Indeed, the placebo coefficients are all less than one-tenth that in the baseline specification. These placebo results provide evidence against alternative explanations

³⁹Dimmock et al. (2018) find that advisors are influenced by the misconduct histories of their peers. In contrast, our findings are not dependent on the misconduct history of the deceased branch manager. Internet Appendix Table 6 shows the results are robust regardless of whether the deceased branch manager had a history of misconduct.

⁴⁰Advisors who have Series 8, Series 9/10, Series 24, or Series 26 licenses.

that are unrelated to the supervisory role of the deceased.

6.2 Premature Death and Exogeneity

A potential threat to our identification is that some branch manager deaths are anticipated, such as due to a protracted illness, rather than sudden. Anticipation could increase misconduct because of either reduced vigilance by the ailing branch manager or because advisors become less concerned about their reputation with the manager. However, these possibilities seem unlikely for three reasons. First, Figure 3 shows no pre-trend in misconduct preceding the branch managers' deaths. Second, the deceased branch managers remain registered and employed until their date of death, suggesting that protracted illnesses are unlikely to drive our results. Third, if the anticipation of branch manager death increased the misconduct rate, we would expect a positive relation between branch manager age and misconduct. Internet Appendix Table 7 tests this prediction and fails to find a significant relation. Nonetheless, we estimate two additional robustness tests to address the issue of anticipation.

Following Jaravel et al. (2018), we use age cutoffs to identify premature deaths that are relatively likely to be unanticipated. Columns (1) and (2) of Panel B of Table 9 restrict the sample to include only deaths (or pseudo-deaths for the control sample) of branch managers who are 65 or younger and 60 or younger, respectively. Aside from these age cutoffs, the regressions follow the baseline specification in equation (2.2). Even with these sample restrictions, the treatment effect remains negative and significant, suggesting that anticipated deaths do not drive the results.

As an additional robustness test, we collect cause of death information by searching online obituaries using branch managers' names, ages, and dates of death. We then flag the 19.2% of deaths that we classify as either protracted or likely protracted.⁴¹ We then drop the

⁴¹We flag a death as protracted if the obituary uses a phrase like "after a long struggle." We flag a death as "likely protracted" if the obituary indicates the cause of death was a chronic disease or request donations for a non-profit related to a chronic disease.

treated advisors affiliated with these protracted deaths (and their matched control advisors) and estimate our baseline specification on this restricted sample. Column (3) of Panel B of Table 9 shows that the treatment effect remains negative and significant even in this sample, providing further evidence that protracted deaths do not drive the results.

Another potential concern is reverse causality. For example, if supervising a high-misconduct branch contributes to deteriorating health for the manager, the treatment effect could capture selection rather than a response to the loss of a branch manager. To address this possibility, Internet Appendix Table 9 tests whether branch-level misconduct predicts branch manager death. We collapse the matched sample to one observation per branch, and regress the treatment indicator on misconduct and prior misconduct history with match-group fixed effects. Although we did not use misconduct information when forming the matched groups, neither measure is individually or jointly significant (p -value = 0.468), providing no evidence consistent with reverse causality.

6.3 Branch Manager Death and Business Disruption

An alternative explanation for our results is that the death of a branch manager disrupts the business activities of affected advisors, mechanically reducing misconduct by limiting the client interactions that can generate complaints. If this were the case, the decline in misconduct would reflect reduced production volume rather than a lower propensity to commit misconduct. We evaluate this hypothesis using two complementary tests.

First, we examine employment transitions. If business disruption following a manager’s death reduces the attractiveness of an advisor’s current position, affected advisors should be more likely to seek opportunities elsewhere. However, treated advisors are 1.76 percentage points less likely to separate from their firm and 0.23 percentage points less likely to exit the industry during the four-year period after branch manager death, with neither difference statistically significant (p -values of 0.275 and 0.814, respectively). Advisors do not appear to

respond to the loss of a branch manager by changing employers or leaving the industry.

Second, we examine whether branch manager death affects advisors' personal financial outcomes using credit bureau data from Experian. Even if advisors remain at their firms, business disruption could reduce their earnings. Because advisors are compensated primarily through commissions and fees, if branch manager death materially disrupts advisors' business activities, their credit outcomes should deteriorate in the post-treatment period (Keys, 2018). Internet Appendix Table 10 estimates treatment effects on four credit outcomes: Vantage credit scores, an indicator for subprime credit (scores below 600), credit inquiries, and collection inquiries. Across all four measures, we find no evidence consistent with business disruption. The estimated treatment effects are economically small and, where statistically significant, are directionally inconsistent with the disruption hypothesis. Treated advisors experience a 2.8-point increase in credit scores (p -value = 0.006) and a marginally significant decline in credit inquiries (p -value = 0.095). These patterns, if anything, suggest a modest improvement in advisors' financial circumstances rather than deterioration.

Collectively, this evidence fails to support the business disruption hypothesis. Advisors' employment patterns remain stable and their credit outcomes do not deteriorate, indicating that branch manager death does not materially disrupt advisors' business activities or earnings.

Taken together, the robustness tests in this section show that the decline in misconduct following branch manager death is not explained by generic co-worker effects, anticipation of death, or business disruption. These tests reinforce the baseline findings and the mechanism results presented in the preceding sections.

7 Conclusion

Misconduct involving customers generates substantial profits for employees in industries where compensation depends on sales performance, such as financial services. In the financial advisory industry, branch managers shoulder the primary responsibility for monitoring advisors. Their proximity allows them to accumulate soft information about advisors' behaviors, ethics, and client interactions, which could be used to enhance monitoring. However, branch managers face a conflict of interest, as their compensation is directly tied to their advisors' revenues. Because both parties can financially benefit from misconduct, they may use their soft information to enable, rather than prevent, misconduct (Tirole, 1986, 1992; Faure-Grimaud et al., 2003). Through repeated interactions, branch managers learn which advisors can generate revenue aggressively without attracting regulatory scrutiny, while advisors learn their managers' monitoring style and tolerance for pushing ethical boundaries. This mutual learning reduces uncertainty, and can facilitate tacit or explicit understandings that enable misconduct.

This paper tests how exogenous changes in branch supervisors affect misconduct by financial advisors. We show that misconduct falls significantly following the death of a branch manager, although this effect fades over time. This pattern is consistent with branch manager death disrupting the soft information between managers and advisors, leading to reduced misconduct. The effects are stronger where the decrease in soft information is likely largest: for advisors who had a longer work overlap with the deceased branch manager, shared the manager's race, engaged in more complex business activities, and for firms with smaller investments in RegTech. The effects are also stronger for misconduct that financially benefits the branch manager. These results challenge the intuitive assumption that soft information improves monitoring quality. Instead, our findings show the dark side of soft information: it can facilitate misconduct when there are conflicting incentives.

Our findings suggest several approaches that regulators could take to curb financial misconduct. First, regulators could focus on longstanding supervisor-advisor relationships when allocating monitoring resources, as such relationships may increase the risk of misconduct. Second, strengthening regulatory penalties—whether fines, suspensions, or industry expulsion—for “failure to supervise” violations could reduce misconduct. Third, implementing compensation clawback provisions for branch managers could help align incentives by forcing supervisors to internalize the long-term costs of overlooking misconduct. Such provisions would reduce the tension between revenue generation and compliance by making supervisors personally liable for the costs of discovered misconduct. Finally, our work suggests that firms can mitigate these agency problems internally by reducing their reliance on subjective judgment; investments in auditable compliance technologies that formalize processes can limit the scope for managerial discretion in the gray areas where collusive behavior thrives.

More broadly, our findings highlight how conflicts of interest and accumulated soft information can interact to facilitate misconduct. This suggests that regulatory frameworks should carefully consider how supervisory relationships and compensation structures might enable rather than prevent misconduct, particularly in settings where supervisors have revenue-based incentives. Understanding these dynamics is crucial for designing effective oversight systems across various financial and professional service industries.

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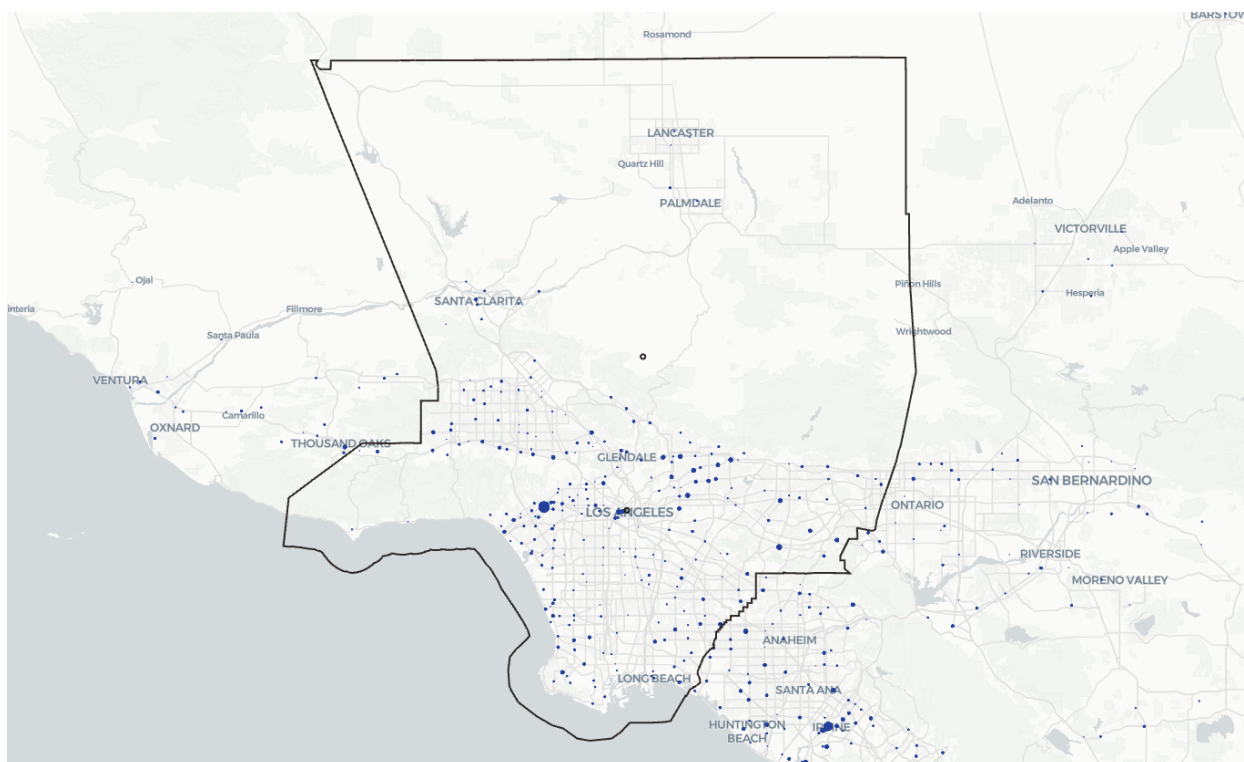


Figure 1: **J.P. Morgan Branches in Los Angeles County**

This figure plots J.P. Morgan branch locations in the Los Angeles metropolitan area as of 2023. The black border surrounds Los Angeles County. The size of the circle corresponds to the number of advisors at the branch.

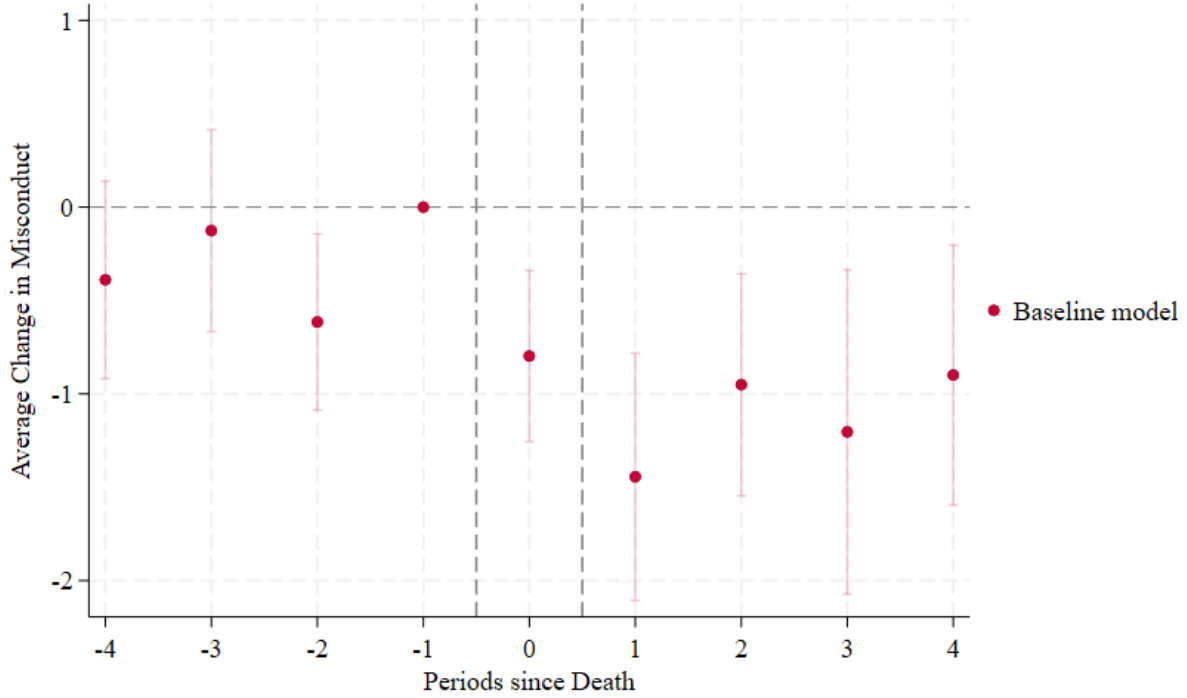


Figure 2: **Dynamic Difference-in-Differences**

This figure presents dynamic difference-in-differences estimates of the effect of branch manager deaths on advisor misconduct using the baseline OLS specification from model (2) in Table 2 with match-group-year and advisor fixed effects. The y-axis represents the average change in the probability of advisor misconduct (in percent), and the x-axis indicates event periods relative to the branch manager's death ($k = 0$). The model includes controls for licensing and investment advisor status. Vertical bars represent 95% confidence intervals based on standard errors clustered by event-branch.

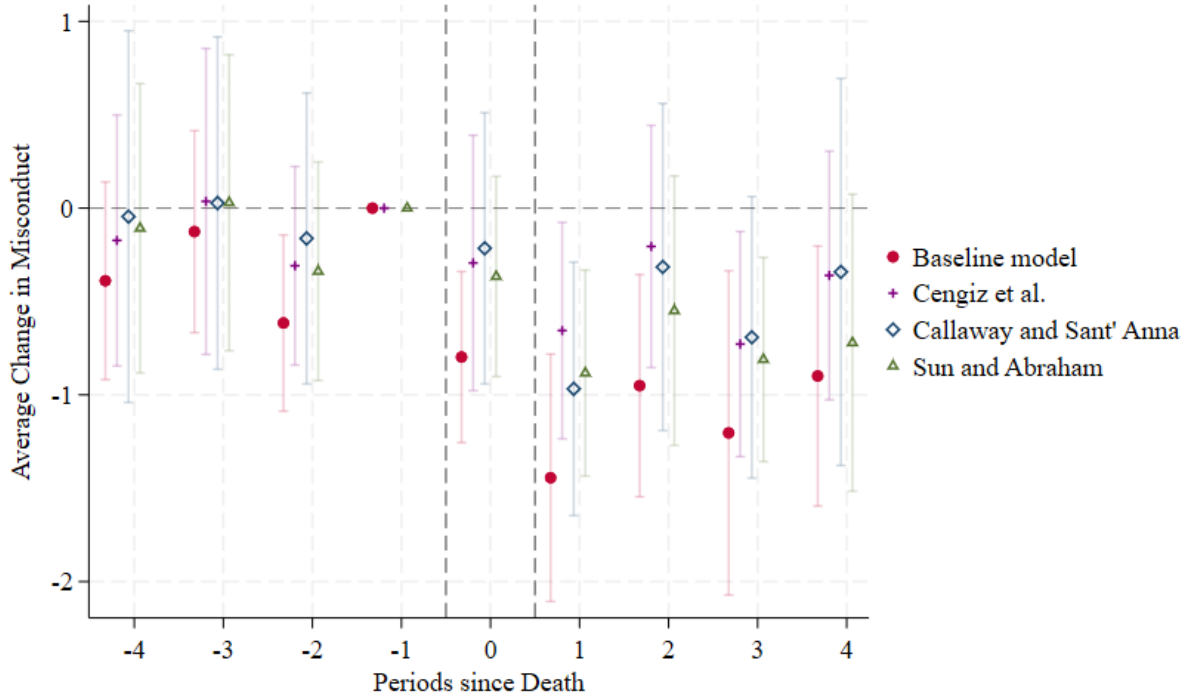


Figure 3: **Comparison of Dynamic Difference-in-Differences Methods**

This figure compares the dynamic treatment effects of branch manager deaths on advisor misconduct using different difference-in-differences estimation methods. The methods include: the baseline fixed effects model, [Cengiz et al. \(2019\)](#), [Callaway and Sant'Anna \(2021\)](#), and [Sun and Abraham \(2021\)](#). The y-axis represents the average change in the probability of advisor misconduct (in percent), and the x-axis denotes the event periods relative to the branch manager's death ($k = 0$). Vertical bars indicate the 95% confidence intervals for each method.

Table 1: **Comparison of Treated vs. Control Advisors at $k = 0$**

This table compares treated advisors with matched control advisors at the treatment date, $k = 0$.

	Treatment		Control	
	Mean	Std. Dev.	Mean	Std. Dev.
Branch Manager Age	61.92	8.99	62.66	8.40
Branch Manager Experience	30.97	8.94	32.73	7.98
Number of Advisors at Branch	28.60	18.32	33.28	25.28
Age	53.39	12.71	51.40	12.65
Experience	21.09	11.94	19.74	11.92
Investment Advisor	0.61	0.49	0.62	0.49
Series 6	0.21	0.41	0.20	0.40
Series 7	0.83	0.37	0.83	0.37
Series 24	0.15	0.36	0.09	0.28
Series 63	0.70	0.46	0.68	0.47
Series 65/66	0.66	0.47	0.68	0.47
Misconduct	0.73	8.52	0.81	8.94
Past Misconduct	17.82	38.29	15.54	36.23
Observations	1,094		5,586	

Table 2: **Dynamic Difference-in-Differences**

This table presents dynamic difference-in-differences estimates of the effect of branch manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in that year. The event time $k = 0$ corresponds to the year the branch manager died, and $k = -1$ is the omitted category. Pre-treatment periods are denoted by negative values ($k = -2, -3$, etc.), while post-treatment periods are denoted by positive values ($k = +1, +2$, etc.). The event window is $[-4, +4]$. Column 2 adds controls for licensing and investment advisor status; coefficients are omitted for brevity. All models include match-group-year and advisor fixed effects. Standard errors are clustered by event-branch, and t -statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
K = -4	-0.104 (-0.32)	-0.102 (-0.32)
K = -3	0.164 (0.51)	0.160 (0.50)
K = -2	-0.337 (-1.24)	-0.335 (-1.23)
K = 0	-0.524** (-2.06)	-0.525** (-2.06)
K = +1	-1.162*** (-3.35)	-1.164*** (-3.35)
K = +2	-0.668** (-2.06)	-0.669** (-2.06)
K = +3	-0.889* (-1.86)	-0.890* (-1.87)
K = +4	-0.554 (-1.26)	-0.557 (-1.26)
Controls	No	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.212	0.212
Observations	47,173	47,173

Table 3: **Branch Manager Death and Misconduct**

This table presents static difference-in-differences estimates of the average effect of branch manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in that year. The sample uses an event window of $[-4, +4]$ around the branch manager's death. The variable $\text{Treated} \times \text{Post}$ captures the average effect during the four years following the branch manager's death ($k = +1$ to $k = +4$). Both columns include match-group-year and advisor fixed effects. Column (2) also includes controls for licensing and investment advisor status, but the coefficients are omitted for brevity. Standard errors are clustered by event-branch, and t -statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Treated $\times$ Post	-0.713*** (-3.10)	-0.714*** (-3.10)
Controls	No	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.212	0.212
Observations	47,173	47,173

Table 4: **Interpersonal Familiarity**

This table presents estimates examining how the strength of the advisor–manager relationship conditions the effect of branch-manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Columns (1) and (2) use match-group-year and advisor fixed effects. Columns (3) and (4) replace the match-group-year fixed effects with Branch at death $\times$ event-year fixed effects, restricting identification to within the branch where the manager died. In columns (1) and (3), the connection measure is *Shared Tenure*, defined as the number of years the advisor and branch manager worked at the event firm at the same time, z-scored to have mean zero and standard deviation one. In columns (2) and (4), the connection measure is *Shared Race*, an indicator equal to one if the advisor and the deceased manager share the same race. All specifications include controls for licensing and investment-advisor status, advisor fixed effects, and the interaction of *Post* with the relevant connection measure (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated $\times$ Post	-0.733*** (-3.29)	0.385 (1.03)		
Treated $\times$ Post $\times$ Shared Tenure	-0.359** (-2.04)		-0.624*** (-3.23)	
Treated $\times$ Post $\times$ Shared Race		-1.406*** (-3.06)		-1.073** (-2.06)
Controls	Yes	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	No	No
Branch at death $\times$ event-year FE	No	No	Yes	Yes
Advisor FE	Yes	Yes	Yes	Yes
R^2	0.212	0.212	0.270	0.270
Observations	47,173	47,034	46,454	46,315

Table 5: **Complexity**

This table presents estimates examining the role of the complexity of the advisor’s business activities on the effect of branch manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Both columns include a triple-differences term with a variable proxying for complexity. In column (1), the complexity measure is *High Product Complexity*, an indicator variable equal to one if the advisor works for a firm that offers an above-average number of different investment products such as debt, derivatives, mutual funds, private placements, and variable life insurance, as in [Kowaleski et al. \(2024\)](#). In column (2), the complexity measure is the Form CRS *Complexity Index*, which aggregates scores across three dimensions: service scope, product diversity, and account customization, as detailed in Internet Appendix [IA-1.1](#). This index is z-scored to have mean zero and standard deviation one. All specifications include controls for licensing and investment-advisor status, advisor fixed effects, and the interaction of *Post* with the relevant complexity measure (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Treated $\times$ Post	-0.112 (-0.45)	-0.739*** (-3.20)
Treated $\times$ Post $\times$ High Product Complexity	-2.208** (-2.11)	
Treated $\times$ Post $\times$ Complexity Index		-0.508** (-2.55)
Controls	Yes	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.213	0.212
Observations	47,173	47,173

Table 6: **Hard vs. Soft Information Environment**

This table presents estimates of how the effect of branch manager death on advisor misconduct varies according to the firm's information environment. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. *Low RegTech* equals one if a firm's RegTech index, measured as of the treatment period, is below median. The RegTech index is based on Charoenwong, Kowaleski, Kwan, and Sutherland (2024), which captures firm-level technological investment in compliance-related tools, such as ERP software, IT infrastructure, and customer relationship management systems. All specifications include controls for licensing and investment-advisor status, advisor fixed effects, and the interaction of *Post* with *Low RegTech* (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Treated $\times$ Post	-0.496** (-2.50)
Treated $\times$ Post $\times$ Low RegTech	-1.209* (-1.92)
Controls	Yes
Match-Group-year FE	Yes
Advisor FE	Yes
R^2	0.214
Observations	46,813

Table 7: **Advisor-Only versus Shared Benefit Misconduct**

This table presents estimates examining the effect of branch manager deaths on different categories of advisor misconduct based on who primarily benefits. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Column (1) shows results for advisor-only benefit misconduct (such as theft of client funds and outside business activities) that primarily benefits the advisor without generating branch revenue. Column (2) shows results for shared benefit misconduct (such as excessive trading and fee/commission abuse) that generates revenue for both the advisor and the branch/firm. All specifications include controls for licensing and investment-advisor status, match-group-year fixed effects, and advisor fixed effects (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Treated $\times$ Post	-0.0195 (-0.40)	-0.631*** (-2.74)
Misconduct Type	Advisor-Only Benefit	Shared Benefit
Controls	Yes	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.199	0.220
Observations	47,173	47,173

Table 8: **Regulatory Oversight Focus and Supervisory Accountability**

This table reports how external regulatory oversight moderates the effect of branch manager death on advisor misconduct. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. *Supervisory Action Share* is the share of FINRA-initiated regulatory actions in the district that involve a supervisory issue, computed as the number of such actions over the four years preceding the treatment period divided by the total number of FINRA actions over the same period. *Supervisory Actions per Complaint* is the number of FINRA supervisory actions in the district over the same four-year period divided by the number of customer complaints, and *Non-Supervisory Actions per Complaint* is defined analogously using non-supervisory FINRA actions. All FINRA oversight variables are z-scored to have mean zero and standard deviation one. All specifications include controls for licensing and investment-advisor status, advisor fixed effects, and the interaction of *Post* with the relevant oversight measure (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Treated $\times$ Post	-0.550*** (-2.81)	-0.774*** (-3.22)	-0.728*** (-2.78)
Treated $\times$ Post $\times$ Supervisory Action Share	0.595* (1.84)		
Treated $\times$ Post $\times$ Supervisory Actions per Complaint		0.374* (1.90)	
Treated $\times$ Post $\times$ Non-Supervisory Actions per Complaint			0.0348 (0.17)
Controls	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes
R^2	0.212	0.212	0.212
Observations	47,173	47,173	47,173

Table 9: **Robustness Tests: Placebo and Sample Restrictions**

This table reports robustness tests for the effect of deaths in the workplace on advisor misconduct. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Panel A reports placebo tests where the “treatment” is the death of a non-branch manager coworker. Columns vary by additional coworker characteristics: (1) any non-branch manager; (2) non-branch manager with supervisory license; (3) non-branch manager with tenure ≥ 10 years. Panel B reports estimates for the main branch manager death analysis under alternative sample restrictions: (1) branch managers 65 or younger; (2) branch managers 60 or younger; (3) excluding protracted deaths. All specifications include controls for licensing and investment-advisor status, match-group-year fixed effects, and advisor fixed effects (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Placebo: Non-Branch Manager Death			
	(1)	(2)	(3)
Treated $\times$ Post	-0.0686 (-1.53)	-0.0648 (-0.89)	-0.0395 (-0.81)
Placebo Treatment Sample	All Non-BMs	Supervisor Non-BMs	Long Tenured Non-BMs
Controls	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes
R^2	0.195	0.199	0.201
Observations	722,721	337,230	485,080
Panel B: Sample Restrictions: Premature and Sudden Branch Manager Death			
	(1)	(2)	(3)
Treated $\times$ Post	-0.684** (-2.41)	-0.536** (-2.06)	-0.672** (-2.54)
Sample	BM age ≤ 65	BM age ≤ 60	Non-protracted deaths
Controls	Yes	Yes	Yes
Match-Group-Year FE	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes
R^2	0.191	0.176	0.201
Observations	28,553	16,683	37,921

Internet Appendix

IA-1.1 Form CRS and Firm-Level Complexity

Form CRS (customer relationship summary) is a regulatory disclosure document mandated by the SEC since June 30, 2020, as part of the Regulation Best Interest framework.⁴² It provides retail investors with a concise summary of a firm’s services, fees, conflicts of interest, and other critical information. In October 2021, we downloaded these forms, which we then use to create firm-level measures for 114 firms in our matched sample that had filed a Form CRS that year. Because Form CRS disclosures were introduced in 2020, all measures derived from Form CRS are constructed from this 2021 cross-section of filings and treated as time-invariant firm characteristics applied to all sample years.

Form CRS contains standardized sections that ensure comparability across firms, but its natural language descriptions vary significantly. This variation allows us to analyze and quantify the complexity of the firms’ offerings.

We use ChatGPT (OpenAI GPT-4.0, accessed January 28, 2025) to systematically extract key sections of Form CRS, apply predefined scoring criteria for firm-level attributes, and generate a structured **Complexity Index**, to quantify this characteristic and facilitate cross-firm comparisons. The process involved uploading each Form CRS document, extracting the relevant section, and assigning scores for each of the three components based on the disclosed breadth of services, range of products, and level of account customization.

IA-1.1.1 Complexity Index

The “What investment services and advice can you provide me?” section is particularly relevant to understanding the scope, diversity, and customization of a firm’s offerings, making it useful for constructing measures of firm-level complexity. Each category is scored between

⁴²See <https://www.investor.gov/CRS>.

1 and 3 based on the level of detail and sophistication provided in the firm’s disclosures, with the total Complexity Index ranging from 3 (low complexity) to 9 (high complexity). Below is an overview of the scoring:

Service Scope

Captures the breadth of services, from basic brokerage services (1) to highly comprehensive offerings that include financial planning, discretionary accounts, and wrap programs (3).

Product Diversity

Measures the range of investment products, from simple offerings like mutual funds and bonds (1) to highly complex products such as alternative investments, structured notes, and private equity (3).

Account Customization

Reflects how tailored accounts are, from standard, non-discretionary accounts (1) to highly customizable solutions involving wrap accounts, discretionary accounts, or personalized strategies (3).

IA-1.1.2 Exhibit: Prompt Used for Data Extraction

You are a specialized Form CRS analysis assistant. You can read PDFs (including via OCR if needed) to extract text. You will focus on the “What investment services and advice can you provide me?” section of each Form CRS to assign a Product Complexity Index. You will receive PDFs in batches and must continually append results to an Excel table (in CSV format).

Context

- I have 114 Form CRS PDF documents, each with a filename in the format: CRD##.pdf, where ## is the firm’s CRD number.
- The Product Complexity Index is calculated by summing three category

scores (Service Scope, Product Diversity, Account Customization), each on a scale of 1–3, for a total range of 3–9.

- We will define and refine the scoring approach using a pilot batch of 10 PDFs. Then, apply the finalized scoring system to the remaining 104 PDFs, which I will provide in batches of 10 at a time.

Scoring Categories (each scored 1–3):

- **Service Scope**

- 1: Simple (e.g., basic brokerage services only)
- 2: Moderate (e.g., brokerage + limited advisory services or planning)
- 3: Comprehensive (e.g., discretionary accounts, wrap programs, financial planning)

- **Product Diversity**

- 1: Simple (e.g., stocks, bonds, mutual funds)
- 2: Moderate (e.g., adds ETFs, annuities, or basic proprietary products)
- 3: Complex (e.g., alternative investments, structured products, private equity)

- **Account Customization**

- 1: Simple (e.g., standard, non-discretionary accounts only)
- 2: Moderate (e.g., includes some customization, like non-discretionary + discretionary)
- 3: Complex (e.g., wrap accounts, tailored strategies, highly customizable)

Product Complexity Index = Service Scope + Product Diversity + Account Customization (range: 3–9)

Workflow

Pilot Phase (10 PDFs)

- I will provide you with 10 PDFs.
- Focus on the “What investment services and advice can you provide me?” section.
- Assign the three category scores and compute the Product Complexity Index.
- Propose any refinements to the scoring definitions if needed.
- Finalize the scoring system after review.

Full Application

- I will provide the remaining PDFs in batches of 10.
- For each batch, do the same analysis and update the results.
- Append results cumulatively to a CSV file.

Output Format

- The CSV should have one row per firm, with these columns:
 - CRD (extracted from filename, e.g., 12345)
 - ServiceScope (1/2/3)
 - ProductDiversity (1/2/3)
 - AccountCustomization (1/2/3)
 - ProductComplexityIndex (3–9)
 - SummaryParagraph (a 1–3 sentence explanation justifying the scores)
- The CSV must be cumulative after each batch, building toward a final table of all 114 firms.

- Example: After the pilot batch (10 firms), the CSV has 10 rows. After the next batch of 10, the CSV has 20 rows, and so on.

Handling Missing or Incomplete Sections

- If the “What investment services and advice can you provide me?” section is missing or incomplete, note this in the SummaryParagraph so I can follow up.
- Use OCR if text extraction fails. If both methods fail, let me know so I can provide another copy.

Final Check

- Once all batches are processed, the final CSV should contain 114 rows, serving as the consolidated Product Complexity Index results.

Do you understand these instructions, and can you proceed with the pilot batch now?

The scoring prompt was developed through a small pilot review to clarify how predefined categories map to Form CRS language. After this pilot, the scoring rules were finalized and applied uniformly to all filings, including a re-processing of the pilot documents. The resulting index reflects a fixed, cross-sectional measure of firm-level complexity.

IA-2 Misconduct Classification Algorithm

We classify customer disputes into two categories based on the alleged beneficiary: advisor-only-benefit and shared-benefit misconduct. This distinction allows us to test whether branch managers selectively enable violations from which they financially benefit.

IA-2.1 Classification Methodology

Our classification algorithm uses keyword matching on allegations text from Form U4 customer dispute disclosures to identify whether alleged misconduct primarily benefited the advisor alone or generated revenues for both the advisor and firm.

Advisor-only-benefit misconduct includes violations where the advisor exclusively benefits while the firm receives no revenue: theft and conversion of client funds (“misappropriated,” “converted,” “embezzled”), forgery and falsification of documents (“forged,” “falsified signature”), undisclosed outside business activities (“outside business,” “private securities transaction,” “selling away”), and authorization-related allegations that do not also reference commission- or fee-generating activity. Because these violations harm the firm without generating revenue, branch managers have no financial incentive for leniency.

Shared-benefit misconduct includes violations where both the advisor and firm potentially benefit through revenue generation: unsuitable recommendations (“unsuitable,” “inappropriate recommendation”), misrepresentation of investment risks (“misrepresented,” “failed to disclose”), and churning or excessive trading (“churning,” “excessive trading,” “excessive commissions”). When authorization-related language appears alongside explicit commission/fee or churning/excessive-trading language, we classify the dispute as shared-benefit.

Many allegations contain insufficient information for clear classification. Our algorithm classifies disputes based on the primary violation indicated when diagnostic patterns are present. Among advisor-years with misconduct in our sample, 9.1% are classified as advisor-only, 72.0% as shared-only, 1.7% involve both categories in the same year (reflecting multiple complaints), and 17.2% are unclassified.

Internet Appendix Table 1 presents representative examples from each category. Complete classification code is available in our replication materials.

Internet Appendix Table 1: **Examples of Misconduct Classification from Form U4 Disclosures**

This table presents examples drawn from Form U4 customer dispute disclosures in our data, reproduced verbatim with minor formatting adjustments. Names redacted. Complete classification algorithm available in replication materials.

Allegation Text

Panel A: Advisor-Only-Benefit Misconduct

“Advisor acted as officer for company formed to conduct inspections to determine homeowner policy premiums, for compensation, without providing prompt written notice to member firm.”

“Financial advisor misappropriated income distributions from client account (September-December 2007).”

“Used client’s credit card information without authorization to make personal purchases totaling \$8,500.”

Panel B: Shared-Benefit Misconduct

“Customer alleges advisor did not inform her of 7% penalty on partial withdrawals; surrender charges for 6 withdrawals (10/19/2001-05/09/2002) totalled \$5,564.42.”

“Client alleges unauthorized trading, churning and excessive commissions.”

“Client alleges investments purchased 2013-2019 were not suitable, illiquid, and misrepresented; firm failed to conduct adequate due diligence.”

IA-3 Additional Robustness Tables

Internet Appendix Table 2: **Branch Managers vs. Other Advisors**

This table presents summary statistics comparing branch managers to other advisors in the Discovery Database for the period 2015–2023. The sample includes 65,492 advisor-years for branch managers and 1,589,720 advisor-years for other advisors working at branches with at least one branch manager. The unit of observation is advisor-year. The table reports means and standard deviations for various characteristics, with age values linearly interpolated based on advisor experience when missing.

	Branch Managers		Other Advisors	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	53.89	10.47	45.69	11.84
Experience	24.14	9.59	14.88	10.98
Investment Advisor	0.68	0.47	0.44	0.50
Series 6	0.28	0.45	0.22	0.41
Series 7	0.86	0.34	0.75	0.44
Series 8	0.17	0.37	0.03	0.16
Series 9 and 10	0.35	0.48	0.07	0.25
Series 26	0.10	0.30	0.03	0.18
Series 8, 9/10, 24, or 26	0.90	0.31	0.22	0.42
Series 24	0.41	0.49	0.12	0.33
Series 63	0.84	0.36	0.67	0.47
Series 65/66	0.74	0.44	0.50	0.50
Misconduct	0.65	8.06	0.33	5.74
Past Misconduct	20.08	40.06	7.93	27.02
Observations	65,492		1,589,720	

Internet Appendix Table 3: **Dynamic Difference-in-Differences: Alternative Event Windows**

This table presents dynamic difference-in-difference estimates of the effect of branch manager deaths on advisor misconduct over time. The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in that year. The event time $k = 0$ corresponds to the year the branch manager died. Pre-treatment periods are denoted by negative values ($k = -1$, $k = -2$, etc.), while post-treatment periods are denoted by positive values ($k = +1$, $k = +2$, etc.). All specifications include controls for licensing and investment-advisor status, match-group-year fixed effects, and advisor fixed effects (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
K = -5			-0.0160 (-0.05)
K = -4		-0.102 (-0.32)	-0.0922 (-0.29)
K = -3	0.153 (0.48)	0.160 (0.50)	0.155 (0.48)
K = -2	-0.343 (-1.27)	-0.335 (-1.23)	-0.341 (-1.26)
K = 0	-0.530** (-2.08)	-0.525** (-2.06)	-0.520** (-2.04)
K = +1	-1.163*** (-3.35)	-1.164*** (-3.35)	-1.161*** (-3.35)
K = +2	-0.678** (-2.08)	-0.669** (-2.06)	-0.688** (-2.12)
K = +3	-0.828* (-1.70)	-0.890* (-1.87)	-0.951** (-1.99)
K = +4		-0.557 (-1.26)	-0.569 (-1.30)
K = +5			0.496 (1.02)
Event Window	$[-3, +3]$	$[-4, +4]$	$[-5, +5]$
Controls	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes
R^2	0.250	0.212	0.194
Observations	39,073	47,173	53,491

Internet Appendix Table 4: **Branch Manager Death and Misconduct $k=0$ to $k=+4$**

This table presents estimates of the average effect of branch manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in a given year. The variable Treated $\times$ Post captures the average effect during the five year period including the year the branch manager dies and the four following years ($k = 0$ to $k = +4$). All specifications include controls for licensing and investment-advisor status, match-group-year fixed effects, and advisor fixed effects (coefficients omitted for brevity). Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Treated $\times$ Post	-0.701*** (-3.38)	-0.702*** (-3.39)
Controls	No	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.212	0.212
Observations	47,173	47,173

Internet Appendix Table 5: **Branch Manager Death and Misconduct — Wild Cluster Bootstrap**

This table replicates the baseline specification from Table 3 and reports wild cluster bootstrap p -values following [Cameron et al. \(2008\)](#) and [Roodman et al. \(2019\)](#). The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in that year. The variable $\text{Treated} \times \text{Post}$ captures the average effect during the four years following the branch manager's death ($k = +1$ to $k = +4$). Wild cluster bootstrap p -values are computed using 9,999 replications, clustering by event-branch. Both columns include match-group-year and advisor fixed effects. Column (2) also includes controls for licensing and investment advisor status, but the coefficients are omitted for brevity. Standard errors are clustered by event-branch, and t -statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Treated $\times$ Post	-0.713*** (-3.10)	-0.714*** (-3.10)
Wild Cluster Bootstrap p -value	0.002	0.001
Controls	No	Yes
Match-Group-year FE	Yes	Yes
Advisor FE	Yes	Yes
R^2	0.212	0.212
Observations	47,173	47,173

Internet Appendix Table 6: **Branch Manager Death and Advisor Misconduct – Stratification by Branch Manager Misconduct History**

This table presents estimates examining the role of branch managers' past history of misconduct on the effect of branch manager deaths on advisor misconduct. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Column (1) restricts the sample to branches where the deceased or matched control branch manager had no history of misconduct, while column (2) restricts to cases where the branch manager had a history of misconduct. Column (3) reports results for the full sample and includes an interaction term, BM Past Misconduct, an indicator equal to one if the branch manager has a history of misconduct. The variable Treated $\times$ Post captures the average effect during the years following the branch manager's death ($k = +1$ to $k = +4$). All specifications include controls for licensing and investment-advisor status, match-group-year fixed effects, advisor fixed effects, and the relevant lower-order terms implied by the reported triple interaction (coefficients omitted for brevity). Standard errors are clustered by branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Treated $\times$ Post	-0.453** (-2.43)	-0.554* (-1.76)	-0.561** (-2.35)
Treated $\times$ Post $\times$ BM Past Misconduct			-0.00465 (-0.95)
Sample	BMs no misconduct	BMs with misconduct	Full
Controls	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes
R^2	0.196	0.304	0.212
Observations	32,244	14,876	47,173

Internet Appendix Table 7: **Branch Manager Age and Misconduct Rates**

This table examines the relationship between branch manager age and advisor misconduct, using a sample of advisors working at branches with a branch manager and 100 or fewer advisors. The dependent variable is an indicator equal to 100 if the advisor receives a customer complaint in a given year. Column (1) includes only a linear branch manager age term, while column (2) introduces quadratic and cubic age terms to capture non-linearities. The models include controls for past misconduct, advisor characteristics (investment advisor status; certifications such as Series 6, 7, 24, 63, 65/66; log experience; and an indicator for missing age data), but the coefficients are omitted for brevity. All specifications include year fixed effects to account for time trends. Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Branch Manager Age	-0.0016 (-0.92)	0.0739 (1.00)
Branch Manager Age ²		-0.0013 (-1.00)
Branch Manager Age ³		0.0000 (0.98)
Controls	Yes	Yes
Year FE	Yes	Yes
Advisor FE	No	No
R^2	0.008	0.008
Observations	591,068	591,068

Internet Appendix Table 8: **Firm-Level Complexity from Form CRS**

This table presents estimates examining the impact of firm-level complexity on advisor misconduct following branch manager deaths. The dependent variable is an indicator equal to 100 if an advisor receives a customer complaint in a given year. Firm-level complexity is measured using Form CRS filings and is proxied by the Complexity Index and its three components: Service Scope, Product Diversity, and Account Customization, each scored from 1 (low complexity) to 3 (high complexity). The Complexity Index is the sum of these three scores. Each measure is z-scored to have mean zero and standard deviation one. Firms without a Form CRS filing are assigned the sample mean after standardization. All specifications include controls for licensing and investment-advisor status, advisor fixed effects, and the interaction of *Post* with the relevant complexity measure (coefficients omitted for brevity). Standard errors are clustered by event-branch, and *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Treated $\times$ Post	-0.739*** (-3.20)	-0.746*** (-3.22)	-0.758*** (-3.26)	-0.715*** (-3.14)
Treated $\times$ Post $\times$ Complexity Index	-0.508** (-2.55)			
Treated $\times$ Post $\times$ Service Scope		-0.488** (-2.28)		
Treated $\times$ Post $\times$ Product Diversity			-0.491*** (-2.61)	
Treated $\times$ Post $\times$ Account Customization				-0.530*** (-2.70)
Controls	Yes	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes	Yes
R^2	0.212	0.212	0.212	0.212
Observations	47,173	47,173	47,173	47,173

Internet Appendix Table 9: **Branch Misconduct and Branch Manager Death**

This table tests whether branch-level misconduct predicts branch manager death. The dependent variable is an indicator equal to one if the branch manager dies (treated branch). The sample is collapsed to one observation per branch. *Misconduct* is the branch-level average misconduct rate at the match date. *Prior Misconduct History* is the share of advisors at the branch with at least one prior customer complaint. Standard errors are clustered by match group, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Misconduct	0.00105 (0.36)
Prior Misconduct History	0.00101 (1.08)
Match-Group FE	Yes
Sample Level	Branch
Joint F-statistic	0.77
Joint F p-value	0.468
R^2	0.003
Observations	578

Internet Appendix Table 10: **Credit Outcomes**

This table presents estimates examining the impact of treatment on financial advisors' credit characteristics using Experian data. The dependent variable is Vantage credit scores (column 1), indicators for sub 600 credit scores (column 2), credit inquiries (column 3), and collection inquiries (column 4). The models include controls for licensing (Series 6, 7, 24, 63, 65/66) and investment advisor status. The models also include match-group-year and advisor fixed effects. Standard errors are clustered by event-branch, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Treated $\times$ Post	2.786*** (2.77)	-0.00416 (-1.18)	-0.0321* (-1.67)	0.00115 (0.89)
Dependent Variable	Vantage	Poor Score	Inquiry	Collection
Controls	Yes	Yes	Yes	Yes
Match-Group-year FE	Yes	Yes	Yes	Yes
Advisor FE	Yes	Yes	Yes	Yes
R^2	0.821	0.542	0.335	0.207
Observations	40,288	40,288	40,336	40,336