Three Essays on the Financial Advisory Industry: Diversification, Competition, and Misconduct

by

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Submitted to

Research School of Finance, Actuarial Studies & Statistics

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at

THE AUSTRALIAN NATIONAL UNIVERSITY

August 2025

Dhammapada Verses 153 and 154

Declaration

I hereby certify that this thesis is entirely my own work, except where I have explicitly indicated otherwise. In such cases, the contributions of others and the extent of any joint work are clearly identified.

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Associate Supervisor : Associate Professor Jozef Drienko

Acknowledgements

Every journey begins with a first step. I was already a lecturer of finance at Thammasat Business School (TBS) prior to joining the PhD program at RSFAS and received generous support in the form of funding, a monthly salary in Thailand, on-campus accommodation, and supportive colleagues. Together with TBS, RSFAS also provided me with ample stipends throughout my time in Canberra. In addition, TBS secured an assistant professor position for me. Being financially worry-free allowed me to fully devote myself to research and study. I would like to thank TBS and ANU's RSFAS for making my PhD journey so enjoyable.

Teachers light the path. I am deeply grateful to Dr. Nhan Le for her exceptional guidance throughout my PhD journey. Her insightful feedback, rigorous approach to research, and unwavering support were pivotal in enhancing the quality of my work and fostering a strong commitment to scholarly excellence. Dr. Nhan was consistently available for research discussions and encouraged me to push beyond initial ideas. Her mentorship and dedication to academic excellence will continue to inspire my future teaching and research. I am also grateful to Professor Takeshi Yamada and Associate Professor Jo Drienko for their valuable contributions as members of my thesis panel. Professor Yamada provided constructive feedback that strengthened the overall quality of my research, while Associate Professor Drienko offered insightful suggestions on early drafts of the thesis and on presentation materials. Their guidance and support played a significant role in shaping this work.

At the end of the day, you need family. I would like to thank Ajarn Barney Hope, a Fulbright scholar, for his rock-solid belief in me: "If you don't go, you won't know, and you won't know if you don't go." I am deeply grateful to Manaschai, Rojana, and Nuansri Chatchawan for their lifetime of unconditional love, endless support, and sacrifice, which allowed me to pursue my dream of becoming a lecturer — a goal that takes great time away from home and requires lifetime dedication. Without their understanding, I might not have been able to remain in academia. I would also like to pay respect to the Most Ven. Phrarat

Vajarasuttiwong (Arayawangso) for his endless blessings and support since my childhood. Last but not least, I thank Ananyapon, my lifetime supporter, for her unwavering patience, single-mindedness, and love.

Time to begin new *chapters*...

Abstract

The first chapter examines how geographic diversification of financial advisory firms influences adviser misconduct. We find that diversification significantly increases both misconduct and customer complaints, an effect robust to alternative diversification measures and endogeneity concerns stemming from firms' non-random expansion decisions. The impact is strongest after branch openings, and in remote, small, or newly established branches, but it weakens when branches are located near regulatory offices. Our results underscore the governance challenges of geographic expansion, offering the first empirical evidence on its consequences in the financial advisory industry. These findings have practical implications for firms seeking to balance growth with internal controls and service quality.

The second chapter investigates how the adoption of the Broker Protocol—a voluntary non-solicitation agreement—shapes competition in local financial advisory markets. We find that a higher share of Protocol-member firms intensifies local market competition, leading to greater talent mobility. Firms joining the Protocol experience significant growth in Assets Under Management (AUM) and employment, but larger firms face a talent drain as advisers disproportionately move to smaller competitors. These results highlight the Protocol's role in reallocating human capital toward smaller firms, thereby reshaping local competitive dynamics in the industry.

The third chapter examines how early career exposure to high-misconduct financial advisory firms shapes advisers' long-term professional conduct. We find that advisers who start their careers at such firms are more likely to engage in subsequent misconduct, face greater likelihood of being barred from the industry, and experience prolonged job transitions—effects that persist after addressing endogeneity. These results provide robust evidence of negative career imprinting, demonstrating how early professional environments exert lasting influence on ethical behavior. Our findings underscore the need for targeted interventions,

such as enhanced supervision of early-career training and mentorship, to disrupt the cycles of misconduct in the financial advisory industry.

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Chapter 1

Branching Out, Weakening Watch: How Geographic Diversification affects Adviser Misconduct

Sapphasak Chatchawan and Nhan Le[1]

Abstract – This paper investigates the impact of geographic diversification on financial adviser misconduct. We document that greater geographic diversification significantly increases both misconduct incidents and customer complaints. These effects are robust across various diversification measures and persist when accounting for endogeneity using an instrumental variable approach. The increase in misconduct is more pronounced in remote, small, and newly established locations, or following branch expansions, but is attenuated when branches operate near regulatory offices. Our findings underscore the governance challenges of geographic expansion and offer practical insights for firms seeking to strengthen internal controls and safeguard service quality amid physical network growth.

Keywords: Financial misconduct; Diversification; Corporate governance; Branching network; Financial adviser

JEL classification: G23, G24; G34; L22, L23

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> "Financial crises are often exacerbated by the inability of firms to monitor their dispersed operations, as weaker branches tend to act with less accountability in their decision-making."
>
> Shiller (2015). *Irrational Exuberance*

1 Introduction

The investment advisory industry has experienced significant growth over the past two decades. According to the IAA Investment Adviser Industry Snapshot 2024, the number of SEC-registered investment adviser firms reached a record 15,396, collectively managing over US$128 trillion in assets—reflecting an average annual growth rate of 8.4% over the last 20 years and serving more than 64 million clients. This expansion has been accompanied by increasing industry concentration, with the top 1% of firms accounting for over 66% of total assets under management, and the most substantial growth occurring among the largest firms.[2] The rapid scaling of operations raises important questions about internal governance and oversight. In particular, as firms expand across a broader geographic footprint, they may face greater challenges in monitoring, enforcement, and incentive alignment—factors that could heighten the risk of adviser misconduct. This paper examines how network diversification affects misconduct, exploring whether geographically dispersed branch networks exacerbate agency problems or, alternatively, strengthen governance through greater economies of scale, standardized compliance processes, and the diffusion of best practices.

The effect of network diversification on financial misconduct can operate through two opposing channels. On one hand, geographic expansion increases organizational complexity, heightening coordination and monitoring costs and exacerbating agency problems and in-

[2] https://www.investmentadviser.org/industry-snapshots/

formation asymmetries between headquarters and branch offices (Aghion and Tirole, 1997; Alonso et al., 2008). These frictions may create enforcement gaps, weaken peer oversight, and hinder the uniform application of governance standards. Moreover, incentive misalignments within diversified organizations can further intensify agency conflicts (Aghion and Tirole, 1997; Brickley et al., 2003; Stein, 2002). Larger and more dispersed teams often dilute managerial accountability and reduce individual incentives to excel. Managers in such settings may be less motivated to gather local soft information or cultivate market-specific expertise, impairing risk assessment and raising the likelihood of misconduct.

On the other hand, network diversification may reduce misconduct by leveraging economies of scale. As firms expand geographically, they can invest in formalized compliance systems and enhance governance, monitoring, and risk management capabilities, thereby improving oversight efficiency (Bolton and Dewatripont, 1994; Murray and White, 1983; Radner, 1993). Geographic diversification also facilitates the diffusion of best practices and specialized expertise across branches (Garicano, 2000; Radner, 1993). Accordingly, we hypothesize that more geographically diversified firms are associated with lower levels of misconduct due to enhanced monitoring, better resource allocation, and greater knowledge sharing.

To study misconduct by financial advisers, we construct a comprehensive panel dataset of over 900,000 individual financial advisers registered in the United States from 2012 to 2022. This dataset includes each adviser's employment history, customer disputes, and disciplinary events from public disclosures available through the Financial Industry Regulatory Authority's (FINRA) BrokerCheck website and the Securities and Exchange Commission's (SEC) Investment Adviser Public Disclosure (IAPD) database.

To construct the Geographic Diversification Index (GDI), we first calculate the share of a firm's total employment located in each ZIP code, then sum the squared values of these shares. This generates a Herfindahl index, ranging from zero to one, where a higher value indicates greater network concentration. A firm with only one branch has a Herfindahl index of one. We then subtract this index from one to construct our diversification measure, such that a higher value reflects dispersed geographic branching. As robustness checks, we supplement our analysis with alternative measures of geographic diversification, including the entropy index and the number of ZIP codes, cities, and states in a firm's branch network.

We begin by examining the time-series pattern of GDI. Despite a significant increase in average firm size over the sample period, GDI steadily declines, indicating a trend toward greater geographic concentration among financial adviser firms. To assess whether this decline is driven by a shift in the composition of firms (i.e. more single-branch firms) or by a reduction in GDI within multi-branch firms, we analyze the time-series trends of both the proportion of single-branch firms and the GDI values for multi-branch firms. Our findings suggest that the overall decline in GDI is primarily driven by the increasing share of single-branch firms. The GDI of multi-branch firms only begins to show a downward trend during the latter part of the period, from 2018 to 2022.

Our analysis shows that greater network diversification is associated with increased adviser fraud and customer complaints. This finding holds both across firms and within firms over time.[3] Moreover, the result is robust to a variety of alternative diversification measures.

[3] In our sample, the GDI has a standard deviation of 0.27, equivalent to 173% of the average index value. Within firms and over time, the index has an average range of 0.12, equivalent to 77.42% of the average value, suggesting that there is sufficient variation of the branching network over time.

We further examine the asymmetric effects of branch openings and closures on adviser misconduct. Rapid branch expansion may strain oversight resources, particularly in newly established locations, increasing the risk of undetected fraud. New branches may also attract less-experienced advisers, further elevating misconduct risk. Conversely, branch closures may consolidate operations into fewer locations and improve oversight, but in the short term, the logistical demands of closures—such as client reassignment, resource allocation, and staff transitions—may temporarily reduce compliance attention, leading to a short-term rise in misconduct. Over time, as operations stabilize, we expect the effect of closures to weaken or disappear. Consistent with this expectation, we observe the negative effect of opening new branches persists over time, while the closure of branches is only significant in the first year and dissipates in the following year.

To address potential endogeneity—specifically, that branch expansion decisions may be driven by local economic, cultural, or demographic factors that also influence fraud risk—we implement two identification strategies. First, we exclude single-branch firms, as their location decisions are more likely influenced by local economic conditions. By restricting the sample to multi-branch firms, we enhance comparability and strengthen the causal interpretation of our results.

Second, we use an instrumental variables (IV) approach that exploits variation from the introduction of new airline routes between firm headquarters and branch locations, following the methodology in Giroud (2013) and Ellis et al. (2020). The rationale is that the availability of direct flights reduces travel costs and facilitates monitoring visits, potentially strengthening oversight and deterring misconduct. Thus, the introduction of a direct flight can be viewed as an exogenous shock to internal governance capacity.

Our first-stage results show that the introduction of new flights is negatively associated with network diversification, consistent with the idea that improved travel accessibility reduces the need for expanding physical branch networks. Firms can more effectively manage distant operations from existing locations, decreasing the incentive to open new branches. In the second stage, we find that the instrumented measure of network diversification remains positively and significantly related to adviser misconduct, reinforcing the conclusion that geographic expansion increases fraud risk.

Building on these causal results, we explore the monitoring mechanism underlying the diversification effect. A highly diversified network complicates centralized oversight and strains compliance resources, particularly as physical and organizational distance from headquarters increases. To test this, we use data from Mapbox to calculate the driving distance and travel time between each branch and its headquarters. Our results indicate that the effect of likelihood of misconduct intensifies with greater geographic distance and accessibility between branch and headquarters, consistent with reduced monitoring capacity.

We further explore how internal resources and operational complexity influence misconduct. Small branches may lack adequate compliance infrastructure, peer oversight, and training, making them more susceptible to fraud. Our analysis confirms that the effect of network diversification is stronger in smaller branches, suggesting that firms should allocate more oversight resources to such locations within a dispersed network.

Next, we examine how branch age moderates the relationship between diversification and misconduct. Newly opened branches may lack established compliance routines and experienced staff, and face heightened revenue pressures, all of which can elevate fraud risk. Older branches, in contrast, are more likely to have well-developed oversight systems and long-standing client relationships that reduce the likelihood of misconduct. Our findings confirm that the adverse effect of network diversification worsens in younger branches.

Lastly, we investigate whether external regulatory oversight moderates the diversification effect. We assess whether proximity to regional offices of the SEC and FINRA reduces misconduct in highly diversified firms. Our analysis shows that closer proximity to regulators provides an additional layer of monitoring, mitigating the negative governance effects of network complexity.

Together, our findings suggest that geographic diversification increases the likelihood of adviser fraud and customer complaints. This effect is strongest following branch openings, more pronounced in remote, small, and young branches, and attenuated by proximity to regulatory offices. These results offer practical insights for firms seeking to strengthen internal controls and improve service quality in the context of expanding physical networks.

This paper contributes to several strands of the literature. First, it adds to the growing body of research on financial adviser misconduct. Dimmock and Gerken (2012) and Egan et al. (2019) examine recurring investment fraud and the career consequences for advisers with misconduct records. Dimmock et al. (2018) document how fraud transmits through peer networks, while Charoenwong et al. (2019) show that regulatory scrutiny affects adviser behavior. Clifford and Gerken (2021) demonstrate that the assignment of property rights to client ownership reduces adviser misconduct, and Dimmock, Gerken, and Van Alfen (2021) link real estate shocks to financial misconduct, highlighting the role of personal financial stress. Our paper extends this literature by introducing the geographic branching structure of firms as a new determinant of adviser misconduct, thereby contributing to the understanding of how organizational structure influences the efficiency of corporate governance.

In addition, our work contributes to research on firm boundaries. Prior studies have examined the effect of diversification on firm value and returns (García and Norli, 2012; Gomes and Livdan, 2004; Laeven and Levine, 2007), operating performance (J. Chen et al., 2004; James et al., 2025), risk-taking (Allen et al., 2012; Berger et al., 2017; Chu et al., 2019; Goetz et al., 2016; Goldstein et al., 2024; Ibragimov et al., 2011; Wagner, 2011), lending and funding (Bord et al., 2021; Levine et al., 2021), labor outcomes (Landier et al., 2007; Tate and Yang, 2015), and internal capital markets (Lamont, 1997; Scharfstein and Stein, 2000; Shin and Stulz, 1998; Stein, 1997). While much of this evidence focuses on banks, non-financial firms, and mutual funds, our study is the first to investigate the diversification effect in the financial advisory industry. Moreover, due to data limitation in other sectors, prior work has largely focused firm-level outcomes. Leveraging the granular adviser-level data, we provide novel evidence linking organizational structure to individual employee behavior and performance, offering direct insights into how geographic diversification shapes internal governance.

The paper proceeds as follows: Section 2 introduces the data and empirical strategy. Sections 3 and 4 present the main results and address endogeneity. Section 5 investigates the mechanisms and interactions between internal and external governance. Section 6 concludes.

2 Data and Empirical Methodology

In this section, we discuss the three data sources utilized in the study, our method to estimate the gender of financial advisers and the physical distance between branches and their headquarters, and our empirical strategy.

2.1 Data construction

We construct our data set of financial advisers using disclosures from the Investment Adviser Public Disclosure (IAPD) and BrokerCheck websites.

A financial adviser can register dually as both a broker and an investment adviser or to register solely in one capacity or the other. Individual professionals employed by Registered Investment Adviser (RIA) firms to provide investment advice to clients are known as Investment Adviser Representatives (IARs) while Broker-dealer firms engage in buying and selling securities, with their registered representatives, commonly known as brokers. Regulation of investment advisers falls under the jurisdiction of the U.S. Securities and Exchange Commission (SEC) and state securities regulators while the Financial Industry Regulatory Authority (FINRA), the self-regulatory organization governing broker-dealers in the United States.

The information pertaining to financial advisers is maintained on both the BrokerCheck and the IAPD websites. BrokerCheck database houses the records of financial advisers who are registered solely as brokers or are dually registered as brokers and investment advisers, while the SEC's IAPD contains the data of financial advisers who are registered solely as investment advisers or are dually registered as both brokers and investment advisers. The data stored on BrokerCheck is extracted from historical Form U4 filings submitted to FINRA. While the data from the IAPD website is collected from the Uniform Application for Investment Adviser Registration (SEC Form ADV).[4]

Both BrokerCheck and IAPD websites provide information regarding each financial adviser's employment history, employment location, qualification examinations, and disclosures of financial misconduct and customer complaints. Each financial adviser is assigned a unique CRD number, enabling detailed tracking of the adviser's professional career. The information related to a financial adviser can be retrieved by querying their CRD number on both the BrokerCheck and IAPD websites.

The disciplinary events include civil, criminal, and regulatory events and disclosed investigations, which FINRA classifies into 23 disclosure categories. Because disclosures are not always indicative of wrongdoing, we conservatively isolate six of the 23 categories as misconduct including regulatory offenses, criminal offenses, and customer disputes that were resolved in favor of the customer.

Following prior literature, we refer to both investment advisers and brokers as "financial advisers" (Egan et al., 2019; Gurun et al., 2021). This spelling is mandated by the Investment Advisers Act of 1940, which governs the registration and regulation of investment advisers in the United States. In our final dataset, the data set contains 969,410 financial advisers and includes roughly million adviser-year observations over the sample period.

[4]The FINRA BrokerCheck website can be accessed at https://brokercheck.finra.org/, and the SEC's IAPD website is available at https://adviserinfo.sec.gov/.

In addition to controlling for advisers' qualification and experience, we additionally control for advisers' gender utilizing Namsor's name checking tool to identify the most likely gender of advisers from a first name or a combination of a first name and a last name. Accuracy can be improved by adding a country of residence. [5]

To obtain the driving distance and driving time between advisers' branch location to their firm headquarters, we utilize the Mapbox Directions API. Mapbox offers a suite of APIs and software development tools that allow us to estimate the distance and travel time that reflect real-world road networks and traffic conditions. Additionally, Mapbox's APIs are optimized for handling large-scale geographic queries, systematically computing travel times and distances for a large number of firm locations.

Since the adviser data only provide ZIP codes for each location, we first convert these ZIP codes into geographic coordinates (latitude and longitude) using the Mapbox Geocoding API. This process ensures that each firm's headquarters and branch locations are accurately mapped to their respective spatial coordinates. Once the latitude and longitude of each location are obtained, we use the Directions API to calculate the shortest driving route between headquarters and branch offices. Specifically, we submit the coordinate pairs as input to the API, specifying "driving" as the routing mode. The API returns a structured response containing key travel metrics, including the estimated driving duration (in seconds) and driving distance (in meters). We convert seconds to hours and meters to miles.

[5]For more information, please refer to https://www.namsor.com/

2.2 Sample selection

Our sample spans for 10 years, starting from 2012-2022, to ensure our data is free of survivorship bias. As thoroughly discussed in Gurun et al. (2021), the FINRA website maintains information for brokers who have been registered within the last ten years and appears to delete entire adviser histories from the publicly available data once they have been de-registered for ten years.

Our final sample covers financial advisors and over 16,435 firms over the period 2012-2022. Key variables for adviser characteristics are summarized in Panel A, Table 1.

In Panel A, Table 1, at the financial adviser level, the average indicator of adviser misconduct is 0.53% which is relatively comparable to the ratio reported in Dimmock, Gerken, and Van Alfen (2021) of 0.63%. With regards to gender, on average, approximately 70% of the financial advisors are male. The average physical and driving distance (in natural logarithm) between branch and their headquarters office is 4.7 and 5, approximately equivalent to 110 and 150 miles, respectively. Among the professional certificates, Investment Company Representative (Series 6) and General Securities Principal Qualification Exam (Series 24) appear to be the ones with least advisers having that certificates. Investment Advisers Law Examination (Series 65) is the most popular certificates for every advisers.

Insert Table 1 here

2.3 Empirical design

We begin our analysis of the impact of network diversification on adviser misconduct at the firm level by estimating the following regression model:

$$(1) \qquad \textit{Adviser misconduct ratio}_{i,t} = \alpha + \beta \times GDI_{i,t} + \lambda \times X_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t}$$

where i,t represents firm i in year t. The term γ_i represents the firm fixed effects, while η_t captures the year fixed effects.

The dependent variable, *Adviser misconduct ratio* is defined as the number of financial advisers with at least one misconduct-related disclosure during the year, divided by the total number of financial advisers in the firm for that year, and multiplied by 100. The vector $X_{i,t}$ includes firm and adviser control variables. We include the natural logarithm of total employment to control for firm size. We additionally include adviser gender, experience and the various number of adviser certificates including Investment Company Representative (Series 6), General Securities Representative (Series 7), General Securities Principal Qualification Exam, Uniform Securities State Law Examination (Series 63), Investment Advisers Law Examination (Series 65), and Uniform Combined State Law Examination (Series 66). Definitions of these variables are detailed in the Appendix.

Moreover, our regression specifications include firm fixed effects, γ_s, to control for time-invariant firm characteristics such as long-standing management and internal control practices or corporate culture that may affect adviser fraud. For example, some firms might focus on high-net-worth clients, while others target mass-market consumers, leading to different misconduct patterns. Some firms have a stronger ethical framework or conservative policies that affect both branch expansion and misconduct likelihood. In other words, we compare the effect within firms, instead of cross-section of different firms. We rely the comparison on the same firms that vary their network branch over times.

Finally, we include year fixed effects, η_t, to control for macroeconomic conditions, such as economic recession or expansion, that could affect the adviser fraud. Standard errors are clustered at the firm level.

The primary explanatory variable, *GDI*, is the Geographic Diversification Index, defined as one minus the sum of squared employment shares of each ZIP location of a firm. The index reflects how geographically diversified a firm's branch network. The higher the value, the more widespread the branch network is. We later show in robustness tests that our results are not sensitive to specific measures of network diversification. For example, we obtain similar robust results using the number of cities, ZIP codes, states or the firm's entropy index which is an alternative index to measure geographic diversification.

Panel B, Table 1 reports the statistics of the firm characteristics at the firm-year level. The average misconduct ratio at the firm level is 0.153%. The average index of *Network diversification* is 0.156 with a standard deviation of 0.27. The average adviser experience is 1.68, equivalent to 5.4 years. Among firms, the certificate "Uniform Securities State Law Examination (Series 63)" has the highest average number, indicating that firms tend to have the highest number of advisers with this certificate. The certificate, Investment Company Representative (Series 6), has the lowest average values among all certificates, suggesting that firms are less likely to have advisers with this certificate.

2.4 Geographic Diversification Index

Figure 1 illustrates the evolution of the average geographic diversification index (GDI) over the sample period 2012-2022. The average GDI steadily declines over times from 0.16 to 0.13, reflecting an increasing geographic concentration among financial adviser firms. To further explore whether the declining trend in GDI is driven by the growing number of single-branch firms or by increasing concentration within multi-branch firms, we present these patterns separately in Figures 2 and 3.

Insert Figure 1 here

Figure 2 shows the time trend in the proportion of single-branch firms relative to the total number of firms. The share of single-branch firms steadily rises from 65% in 2012 to above 74% in 2022, suggesting that the growing prevalence of single-branch firms contributes significantly to the overall decline in GDI observed in Figure 1.

Insert Figure 2 here

Figure 3 depicts the trend in the average distance (in miles) between branch offices and headquarters for multi-branch firms. We identify each firm's headquarters using the ZIP code provided for the "Principal Office and Place of Business" in Form ADV's Item 1. The physical distance between each branch office and its headquarters is calculated using the Haversine formula. For each firm, we first calculate the average distance across all branches, and then compute the average across all multi-branch firms for each year.

As shown in Figure 3, the average branch-headquarters distance increased significantly from approximately 405 miles in 2012 to about 445 miles in 2018, but has since declined to around 430 miles by 2022. This pattern is particularly interesting in light of the broader shift toward remote work, supported by advances in technology.

Insert Figure 3 here

The differing patterns of GDI and the average branch-headquarters distance, as shown in Figures 1 and 3, indicate that the two measures are correlated, but not perfectly so. From 2012 to 2018, the average distance increased, suggesting that firms were expanding into more distant locations. However, GDI continued to decline during this period, indicating that firms remained geographically concentrated in a small number of branches.

In contrast, from 2018 to 2022, both GDI and the average distance exhibit a similar downward trend, suggesting that firms reduced their presence in distant locations while becoming increasingly concentrated within more localized areas.

2.5 Comparison of firm characteristics: Multi- and single-branch firms

Table 2 presents a comparison of average firm characteristics between multi-branch and single-branch firms. As expected, multi-branch firms are significantly larger in both GDI and overall size. They also display higher ratios of advisers with misconduct records and customer complaints. Moreover, multi-branch firms employ a greater proportion of female advisers and have advisers with stronger qualifications on average. Given that female and betterqualified advisers are generally associated with lower levels of misconduct and complaints, these patterns suggest that differences in gender composition and adviser qualifications are unlikely to explain the higher misconduct ratios observed in multi-branch firms.

Insert Table 2 here

3 Financial Misconduct and Customer Complaints

In the following sections, we examine the effect of network diversification on financial misconduct and customer complaints. We begin by analyzing the impact of network diversification on adviser misconduct (Section 3.1) and then present robustness checks using alternative measures of network diversification (Section 3.2). Next, we explore the differential effects of branch openings and closures on adviser misconduct. Finally, we assess whether network diversification influences the quality of customer services based on customer complaints (Section 3.4).

3.1 Geographic diversification and financial misconducts

Table 3 presents the results of our regression analysis. We report the findings progressively: Column (1) does not include any fixed effects, Column (2) introduces firm fixed effects, and Column (3) incorporates both firm and year fixed effects for our most stringent specification.

Across all models, the coefficient for *GDI* is positive and statistically significant. In Column (3), which presents our tightest specification, a one-standard-deviation increase in GDI is associated with an 0.03% increase in adviser fraud ratio, equivalent to 20% of the average adviser fraud ratio. This finding supports our hypothesis that branch network expansion is positively associated with higher adviser fraud.

Other coefficients exhibit expected signs. The positive coefficient for *Adviser Gender* suggests that male advisers are more likely to commit fraud, while the negative coefficient for *Adviser Experience* indicates that more experienced advisers are less prone to misconduct. Interestingly, obtaining a *Uniform Securities State Law Examination (Series 63)* certification reduces fraud probability, whereas holding a *General Security Representative (Series 6)* certification appears to increase fraud incidence.

Insert Table 3 here

3.2 Alternative measures of geographic concentration

To ensure that our baseline results are not driven by misspecification, we adopt several alternative measures of geographic concentration. Specifically, we estimate a firm's geographic dispersion by counting the number of ZIP codes, cities, and states in which it operates and by computing an Entropy index.

Table 4 presents the results. Panel A considers ZIP code diversification, Panel B examines city diversification, and Panel C focuses on state diversification. *ZIP Diversification* is defined as the natural logarithm of the number of unique ZIP codes in a firm's branch network, while *City (State) Diversification* is similarly defined for cities and states. Across all three panels, the coefficients for geographic diversification remain positively correlated with adviser misconduct, suggesting that a widely dispersed branch network exacerbates fraud commission.

Panel D introduces a more sophisticated measure of geographic diversification: an Entropy index weighted by the relative importance of each branch within a firm's network. Following Jacquemin and Berry (1979), we compute the entropy index as:

$$\text{Entropy index} = -\sum_{i=1}^{n} s_{ijt} \times ln(1/s_{ijt}) \tag{2}$$

where s_i is the share of employees in ZIP i of firm j in year t, calculated by dividing the number of employees in each ZIP code by the firm's total employees. n is the number of the ZIP locations of a firm. A higher Entropy index reflects greater network diversification. As shown in Panel D, the coefficients for *Entropy index* remain positive and significant, reinforcing the relationship between branch network dispersion and adviser fraud.

Insert Table 4 here

3.3 Opening and closing branches

We investigate whether branch openings and closures have asymmetric effects on adviser misconduct. Rapid branch expansion may weaken oversight, particularly in newly established locations, as compliance resources become stretched, increasing the likelihood of fraudulent behavior going undetected. Additionally, newly opened branches may attract less-experienced advisers, further elevating misconduct risk. In contrast, branch closures could enhance fraud detection by consolidating operations into fewer, more tightly monitored locations. However, as headquarters staff focus on managing logistical and administrative tasks associated with branch closures—such as reassigning clients, reallocating resources, and handling employee transitions—monitoring and compliance activities may be temporarily deprioritized. Branch closures may introduce temporary disruptions, leading to a short-term increase in misconduct. Over time, as operations stabilize, we expect branch closure effect to diminish or turn insignificant.

To test these effects, we modify our baseline specification by replacing *Network Diversification* with the ratio of branch openings and closures in both the current and previous year. Specifically, *Opening Branch* and $Opening\ Brancht - 1$ represent the proportion of newly opened branches in the current and previous year, while *Closing Branch* and $Closing\ Brancht - 1$ measure branch closures in the current and previous year, respectively.

Results in Table 5 indicate that the coefficients for *Opening Branch* and *Closing Branch* are both positive and statistically significant in Columns (1) and (4), suggesting that both network expansion and contraction increase misconduct likelihood. However, in Columns (2) and (5), the effect of *Opening Branch* remains significant over time, while that of *Closing Branch* dissipates, implying that expansion has a more persistent adverse effect on misconduct.

The results in Columns (3) and (6) confirm our findings when combining the variables for *Opening branch* and *Closing branch* in both the current and previous years. The effect of *Opening branch* remains significant, indicating a persistent impact on misconduct, whereas the effect of *Closing branch* diminishes after one year, suggesting that any initial disruptions from branch closures are temporary and become insignificant over time.

Insert Table 5 here

3.4 Customer Complaints

Finally, we assess whether network diversification influences customer complaints. Customer complaints often involve allegations of misconduct or negligence, typically arising when advisers prioritize commission-driven behavior over client interests. Following Dimmock et al. (2018), we construct a *Customer complaints ratio* variable based on disputes that either result in arbitration rulings favoring the customer or settlements exceeding a minimum threshold. We exclude unresolved or withdrawn complaints to focus on substantiated cases.

We hypothesize that a diversified branch network may intensify customer complaints due to weaker oversight and greater operational complexity. As firms expand, maintaining consistent service quality, compliance procedures, and advisor training across dispersed locations becomes challenging, leading to inconsistencies and increased customer dissatisfaction. Additionally, decentralized operations may hinder the enforcement of uniform ethical and professional standards, further contributing to a higher incidence of customer complaints. To test this, we reestimate our baseline model, replacing adviser fraud ratio with the customer complaints ratio which is the number of financial advisers with at least one customer complaint during the year, divided by the total number of financial advisers in the firm that year, and multiplied by 100.

Results in Table 6 show that the coefficient for *Network Diversification* is positive and statistically significant, confirming our expectation. This finding suggests that branch network expansion not only exacerbates adviser fraud but also increases customer complaints, highlighting broader compliance and governance issues associated with network diversification.

Insert Table 6 here

4 Endogeneity test

In this section, we address potential endogeneity issues in the relationship between branch network diversification and financial misconduct. The decision to expand a firm's branch network is not random; it may be influenced by local economic conditions, cultural or demographic factors, or governance structures, all of which could simultaneously affect misconduct risk. For instance, firms with weaker governance may aggressively expand their branch network while also exhibiting higher levels of misconduct, making both outcomes endogenous to poor oversight. Conversely, more risk-averse firms may pursue a conservative expansion strategy while also maintaining stricter compliance, resulting in lower misconduct rates.

To establish a causal link between branch network diversification and adviser misconduct, we employ two empirical strategies: (1) restricting our sample to multi-branch firms to control for structural differences between single- and multi-branch firms, and (2) leveraging the introduction of new airline routes between headquarters and branch locations as an exogenous shock to monitoring intensity.

4.1 Multi-branch firm

First, we narrow our sample to multi-branch firms, excluding single-branch firms to mitigate confounding effects from local economic conditions. Single-branch firms operate within a single geographic market, making their expansion decisions highly sensitive to local factors such as demand, competition, and regulatory environments. In contrast, multi-branch firms distribute their operations across multiple regions, reducing dependence on any single local economy. By focusing on multi-branch firms, we minimize the risk that our findings are driven by regional economic conditions rather than firm-level expansion strategies. Restricting our analysis to firms with multiple branches ensures that expansion incentives are more comparable across firms, allowing us to better isolate the effect of further geographic diversification on misconduct risks and strengthen the causal interpretation of our results.

After applying this restriction, our final sample consists of 5,135 multi-branch firms. We re-estimate our baseline model using this refined dataset and present the results in Table 4. Across all specifications, the coefficient for GDI remains positive and statistically significant. A one-standard-deviation increase in GDI of multi-branch firms, which equals to 0.226, is associated with an increase of 0.07% in fraud commission, equivalent to 18% of the average fraud ratio of multi-branch firms. These findings reinforce the robustness of our baseline results and suggest that the observed relationship between network expansion and misconduct is not solely driven by fundamental differences between single- and multi-branch firms or local economic conditions.

Insert Table 4 here

4.2 Introduction of new airline routes

As a second approach, we follow prior literature (Ellis et al., 2020; Giroud, 2013) and exploit exogenous variation in travel time caused by the introduction of new airline routes between firm headquarters and branch locations. Research suggests that reduced travel time improves internal monitoring and governance (Giroud, 2013). The availability of direct flights reduces both the cost and inconvenience of travel between headquarters and branches, potentially leading to more frequent visits and closer oversight. If network diversification increases misconduct due to weaker monitoring, then the introduction of new flights should mitigate this effect by strengthening headquarters' ability to oversee branch operations.

To track the introduction of direct flights, we use T-100 data from the Bureau of Transportation Statistics,[6] which records all domestic flights from 1990 onward. The T-100 data set begins in 1990 and tracks all domestic flights on a monthly basis, and includes origin, destination, total ramp-to-ramp travel times, and total number of flights, as well as a host of other variables. We consider only flights that are listed as Class F or scheduled passenger service. This eliminates cargo-only flights as well as a number of other miscellaneous categories of air service. We add a 1-hour layover, based on the literature, to make the estimation more conservative. When a new flight is introduced to shorten the flying time lower than driving time, we code the *New flight introduction* equal to one from the year of introduction and subsequent years, and zero otherwise.

Exploiting the new flight introduction, we conduct a two-stage least square regression model. Since we need to identify a new flight introduction for each branch of the firm's

[6] https://www.transtats.bts.gov/DL_SelectFields.aspx?gnoyr_VQ=GEE&QO_fu146_anzr=Nv4+Pn44vr45

network, we conduct this test at the advisor-year level. In the advisor dataset, not all firms disclose the information of their headquarters. For this test, we label the single-branch of a firm is its headquarters. Firms with missing headquarters information will be excluded from this test. Our final sample yields to 3.4 million observations for 969,140 advisors.

Using this exogenous variation, we estimate a two-stage least squares (2SLS) regression model. In the first stage, we regress *New flight introduction* on *Network diversification* to capture the effect of reduced travel time on firms' branch expansion decisions. In the second stage, we use the fitted values of *Network diversification* to predict adviser misconduct, ensuring that our estimates reflect only exogenous changes in network size rather than unobserved firm-level characteristics. The dependent variable in the second stage is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. Other control variables are measured at the advisor-year level.

Since we need to identify a new flight introduction for each branch of the firm's network, we conduct this test at the advisor-year level. In the financial adviser dataset, not all firms disclose the information of their headquarters. For this test, we label the single-branch of a firm is its headquarters. Firms with missing headquarters information will be excluded from this test. Our final sample yields to 3.4 million observations for 969,140 advisors.

Due to the refined level of financial adviser-year data, we are able to additionally introduce the inclusion of ZIP code fixed effect to account for the heterogeneity in demography or rural/urban areas that may affect advisor fraud commission.

As shown in Table 8, the first-stage results indicate a negative and significant relationship between *New flight introduction* and *Network diversification*, consistent with the notion that easier travel reduces firms' incentives to expand their physical branch network. If flights reduce travel time, it becomes easier for headquarters to monitor and manage existing branches. Shorter travel time may allow firms to serve more regions from existing branches rather than expanding their permanent physical footprint. In the second stage, we find that the fitted value of *Network diversification* remains positively and significantly associated with adviser misconduct, reinforcing the conclusion that branch expansion contributes to higher fraud risk.

Insert Table 8 here

By leveraging both the multi-branch firm subsample and an instrumental variable approach based on new airline routes, we confirm the causal relationship between branch network diversification and adviser misconduct. Our findings suggest that firms with wider geographic footprints face greater challenges in maintaining effective oversight, increasing the risk of fraudulent behavior. These results highlight the importance of internal monitoring mechanisms and regulatory scrutiny, particularly for firms undergoing rapid expansion.

5 Internal and External Governance

In this section, we continue exploring the interplay between internal and external governance mechanisms in shaping the effects of network diversification. First, we account for branch-specific characteristics, recognizing that internal governance structures and operational conditions vary across branches. Since our analysis of governance factors is conducted at the branch level, we perform these tests at the advisor-year level, incorporating advisor-level characteristics as control variables rather than firm-level controls used in the baseline model.

5.1 Distance from firm headquarters

First, we examine how geographic distance from headquarters influences the relationship between network diversification and adviser misconduct. Distant branches face higher monitoring costs, making it more challenging to enforce compliance and maintain oversight. The farther a branch is from headquarters, the more difficult it becomes to conduct regular site visits, internal audits, and in-person supervision, increasing the risk of misconduct due to weaker enforcement.

To test this hypothesis, we construct three distance-based proxies: (1) physical distance using the haversine formula, which calculates the shortest straight-line distance between two points based on latitude and longitude; (2) driving distance, which captures real-world accessibility and infrastructure differences that affect travel time; and (3) driving hours, which accounts for road conditions, traffic, and speed limits, providing a practical measure of monitoring effort.

Importantly, by conducting this analysis at the advisor level, we introduce location fixed effects in Columns (2) and (3) of each panel to control for demographic and rural-urban differences that could otherwise confound the results. This allows us to compare misconduct levels among advisors in the same area but with varying degrees of accessibility to headquarters.

Table 9 presents the results, with Panel A showing estimates for physical distance, Panel B for driving distance, and Panel C for driving hours. Across all three measures, the coefficient remains positive and statistically significant, confirming the robustness of our baseline findings. By incorporating driving-based proxies, we demonstrate that geographic frictions in monitoring accessibility contribute to the misconduct risks associated with network expansion.

Insert Table 9 here

5.2 Branch size

Next, we investigate the role of branch size in moderating the relationship between network diversification and adviser fraud. Larger branches may have more resources to implement internal controls, potentially mitigating misconduct risks. However, they also introduce operational complexities that could weaken centralized oversight.

To examine this, we extend our baseline specification by interacting *Network diversification* with *Branch size*, measured as the natural logarithm of the number of advisers per branch. This test includes 6.1 million observations, significantly larger than the sample in Table 9, as it does not require headquarters location data.

Table 10 presents the results. The negative and statistically significant coefficient on the interaction term suggests that network complexity exacerbates misconduct risks primarily in smaller branches. The results suggest that firms should prioritize oversight efforts on smaller branches within diversified networks, as these branches may pose a higher fraud risk.

Insert Table 10 here

5.3 Branch age

We further explore how branch age influences the network effect. Newly established branches may lack strong compliance frameworks and well-defined operational routines, making them more susceptible to misconduct. Younger branches may also face revenue pressures, increasing the likelihood of aggressive or unethical sales tactics. In contrast, older branches are more likely to have refined monitoring systems, experienced staff, and established customer relationships that discourage fraudulent behavior.

To obtain the first operating year of a branch, we rely on the whole dataset starting from 1971 from BrokerCheck & IAPD. We estimate the establishment year as the first year when a firm's branch appear in the dataset.

We define *Branch age* as the natural logarithm of the number of years since a branch was first observed in the dataset. Table 11, Column (1), replaces *Network diversification* with *Branch age* and finds a negative and statistically significant coefficient, consistent with our hypothesis that misconduct risk decreases as branches mature.

In Column (2), we introduce an interaction term between GDI and *Branch age*. The negative and statistically significant coefficient suggests that the adverse effect of network diversification diminishes as branches become more established. Given the average branch age of 2.78 years, this attenuation effect reduces the adverse impact of GDI by 66%.[7]

Insert Table 11 here

5.4 Distance from regional regulatory authority

Finally, we extend our analysis to external governance by assessing the role of regulatory oversight. We test whether proximity to regional regulatory offices, such as those of the SEC and FINRA, moderates the impact of network diversification on misconduct. Firms with highly diversified networks may struggle with internal monitoring, but proximity to regulatory offices could provide an additional layer of oversight, reducing the likelihood of misconduct.

To conduct this test, we estimate the physical distance between each branch and the nearest FINRA and SEC regional office. Regulation of investment advisers falls under the jurisdiction of the U.S. Securities and Exchange Commission (SEC) and state securities regulators, while the Financial Industry Regulatory Authority (FINRA) serves as the self-regulatory organization governing broker-dealers in the United States. Since advisers in our sample may be subject to supervision by both the SEC and FINRA, we obtain the addresses of their regional offices from https://www.finra.org/about/locations and https://www.sec.gov/about/regional-offices, respectively.

For states with more than two regional offices, we select the regional office with the shortest distance from the financial advisory branch location. We then calculate the average of the

[7] $(2.78 \times 0.112)/0.468$

distances from each adviser's branch to the two regional authority offices. Since regulatory jurisdictions remain stable over time, we exclude firm and ZIP code fixed effects but confirm that our results remain robust when single-branch firms are excluded.

Table 12 presents the findings. In Columns (1) and (3), *Proximity to regulatory offices* is negatively and significantly associated with misconduct, consistent with prior literature on the deterrent effect of proximate regulatory scrutiny (Kedia and Rajgopal, 2011). In Columns (2) and (4), we introduce an interaction between *Network diversification* and *Proximity to regulatory offices*, finding a positive and significant effect. This suggests that while regulatory proximity helps mitigate fraud risks, its effectiveness weakens as firms expand their branch networks.

Insert Table 12 here

This section highlights the complementary roles of internal governance and external oversight in shaping the effects of network diversification on adviser misconduct. The adverse impact of network expansion is mitigated in branches that are closer to headquarters, larger in size, and more established. Moreover, proximity to regulatory offices provides additional deterrence, though its effectiveness diminishes in highly diversified networks. These findings emphasize the importance of targeted compliance efforts in managing misconduct risks within complex branch structures.

6 Conclusion

This paper investigates the relationship between network diversification and adviser fraud, providing new insights into the unintended consequences of diversified branch networks in financial institutions. We show that network diversification exacerbates both adviser fraud and customer complaints, and this effect remains robust to alternative measures of diversification and efforts to address endogeneity concerns related to branching networks.

Taken together, our paper suggests that diversified network increases the likelihood of fraud commission and the number of customer complaints. The effect strengthens for opening branches and gradually disseminates for closing branch. The effect is more pronounced in remote, small, and young branches and moderated by the proximity of regulatory authority offices. The findings provide insights for firms in tailoring their monitoring and compliance efforts more effectively to improve service quality and lower the rate of financial misconducts.

Further analysis reveals that the observed effects are largely driven by the accessibility between branches and their headquarters. Specifically, the negative impact of network diversification intensifies with greater physical distance or driving hours between a branch and its headquarters and is more pronounced for smaller branches.

Overall, these findings highlight the need for enhanced monitoring systems and targeted oversight in geographically dispersed branch networks. Institutions with highly diversified networks should prioritize resource allocation to branches that are smaller or farther from headquarters, as these branches are more vulnerable to fraud risks. From a regulatory perspective, the findings underscore the importance of considering network structures in designing compliance guidelines. Regulators could encourage institutions to report their monitoring practices for distant branches or mandate the adoption of technological solutions like real-time compliance monitoring to address oversight challenges.

Table 1: **Summary statistics**

This table reports summary statistics for the variables used in the analysis for the sample period from 2012-2022. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix A.

Variable	N (1)	Mean (2)	SD (3)	P25 (4)	P50 (5)	P75 (6)
Panel A: Adviser level						
Adviser misconduct indicator	3,498,555	0.527	7.241	0.00	0.00	0.00
Adviser experience	3,498,555	1.673	0.966	1.10	1.79	2.40
Adviser gender	3,498,555	0.712	0.453	0.00	1.00	1.00
Investment Company Representative (Series 6)	3,498,555	0.006	0.076	0.00	0.00	0.00
General Securities Representative (Series 7)	3,498,555	0.021	0.143	0.00	0.00	0.00
General Securities Principal Qualification Exam (Series 24)	3,498,555	0.008	0.087	0.00	0.00	0.00
Uniform Securities State Law Examination (Series 63)	3,498,555	0.021	0.142	0.00	0.00	0.00
Investment Advisers Law Examination (Series 65)	3,498,555	0.025	0.155	0.00	0.00	0.00
Uniform Combined State Law Examination (Series 66)	3,498,555	0.017	0.129	0.00	0.00	0.00
Physical distance	3,498,555	4.503	3.413	2.17	6.20	6.95
Driving distance	3,498,555	4.765	3.256	2.50	6.39	7.12
Driving hours	3,498,555	1.276	2.334	0.00	2.25	2.95
Network diversification	3,498,555	0.852	0.285	0.92	0.98	0.99
Panel B: Firm level						
Adviser misconduct ratio	123,993	0.153	0.972	0.00	0.00	0.00
Customer complaint ratio	123,993	0.034	0.252	0.00	0.00	0.00
Geographical diversification	123,993	0.156	0.270	0.00	0.00	0.30
Firm size	123,993	1.143	1.491	0.00	0.69	1.79
Adviser gender	123,993	1.405	1.229	0.69	0.69	1.79
Adviser experience	123,993	1.682	0.826	1.10	1.79	2.30
Investment Company Representative (Series 6)	123,993	0.130	0.329	0.00	0.00	0.00
General Securities Representative (Series 7)	123,993	0.395	0.549	0.00	0.00	0.69
General Securities Principal Qualification Exam	123,993	0.138	0.344	0.00	0.00	0.00
Uniform Securities State Law Examination (Series 63)	123,993	0.427	0.615	0.00	0.00	0.69
Investment Advisers Law Examination (Series 65)	123,993	0.375	0.518	0.00	0.00	0.69
Uniform Combined State Law Examination (Series 66)	123,993	0.195	0.428	0.00	0.00	0.00

Table 2: **Multi- and Single-branch firms - Comparison**

This table presents the comparison of the average firm characteristics between multi- and single-branch firms for the period from 2012-2022. Additional variables are defined as in Appendix A.

Variable	Multi-branch (1)	Single-branch (2)	Difference (3)	t-statistic (4)
Geographical diversification	0.528	0.000	0.528***	-695.61
Misconduct adviser ratio	0.387	0.055	0.332***	-55.56
Customer complaint adviser ratio	0.099	0.007	0.092***	-59.19
Firm size	2.691	0.495	2.195***	-318.91
Adviser gender	2.612	0.901	1.711***	-289.37
Adviser experience	1.589	1.720	-0.131***	25.56
Investment Company Representative (Series 6)	0.195	0.102	0.093***	-45.58
General Securities Representative (Series 7)	0.555	0.329	0.226***	-67.27
General Securities Principal Qualification Exam (Series 24)	0.276	0.080	0.196***	-94.50
Uniform Securities State Law Examination (Series 63)	0.723	0.303	0.421***	-115.62
Investment Advisers Law Examination (Series 65)	0.479	0.331	0.147***	-46.11
Uniform Combined State Law Examination (Series 66)	0.348	0.131	0.217***	-83.64

Table 3: **Network diversification and adviser misconduct**

This table presents estimates from the regressions of adviser misconduct on geographic diversification for the period from 2012-2022. The dependent variable is the proportion of financial advisers with at least one misconduct-related disclosure in a year relative to total employees. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
GDI	0.394***	0.124***	0.119***
	(12.83)	(2.95)	(2.80)
Firm size	-0.006	0.027	0.035
	(-0.61)	(1.02)	(1.30)
Adviser gender	0.141***	0.110***	0.106***
	(10.69)	(3.45)	(3.30)
Adviser experience	-0.007*	-0.015***	-0.002
	(-1.68)	(-2.81)	(-0.21)
Investment Company Representative (Series 6)	-0.030**	0.001	-0.002
	(-2.50)	(0.06)	(-0.13)
General Securities Representative (Series 7)	0.048***	0.032***	0.026**
	(4.93)	(2.66)	(2.12)
General Securities Principal Qualification Exam (Series 24)	-0.099***	-0.013	-0.012
	(-7.04)	(-0.68)	(-0.64)
Uniform Securities State Law Examination (Series 63)	-0.130***	-0.030**	-0.027*
	(-11.01)	(-2.08)	(-1.84)
Investment Advisers Law Examination (Series 65)	-0.043***	-0.021	-0.018
	(-5.77)	(-1.08)	(-0.94)
Uniform Combined State Law Examination (Series 66)	-0.021	-0.031	-0.028
	(-1.64)	(-1.33)	(-1.22)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	123,993	123,993	123,993
Adj. R-squared	0.047	0.263	0.263

Table 4: **Alternative measures of network diversification**

This table presents estimates from the regressions of adviser misconduct on geographic concentration for the period from 2012-2022. The dependent variable is the proportion of financial advisers with at least one misconduct-related disclosure in a year relative to total employees. *ZIP diversification* is defined as the natural logarithm of the total number of unique ZIP code locations in a firm's branch network. *City diversification* is defined as the natural logarithm of the total number of unique cities in a firm's branch network. *State diversification* is defined as the natural logarithm of the total number of unique states in a firm's branch network. *Entrophy index* is the summation of the product of each employment share in a ZIP code location and the natural logarithm of its reciprocal. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - ZIP diversification

	(1)	(2)	(3)
ZIP diversification	0.189***	0.091***	0.087***
	(13.74)	(3.65)	(3.48)
Firm size	0.014	0.027	0.034
	(1.52)	(1.06)	(1.31)
Adviser gender	0.071***	0.084***	0.082**
	(5.66)	(2.66)	(2.57)
Adviser experience	-0.013***	-0.015***	-0.003
	(-3.02)	(-2.86)	(-0.40)
Investment Company Representative (Series 6)	-0.044***	-0.003	-0.006
	(-3.62)	(-0.17)	(-0.33)
General Securities Representative (Series 7)	0.067***	0.031**	0.025**
	(6.64)	(2.54)	(2.04)
General Securities Principal Qualification Exam	-0.113***	-0.015	-0.014
	(-7.95)	(-0.80)	(-0.75)
Uniform Securities State Law Examination (Series 63)	-0.141***	-0.031**	-0.028*
	(-11.86)	(-2.14)	(-1.92)
Investment Advisers Law Examination (Series 65)	-0.057***	-0.024	-0.021
	(-7.68)	(-1.21)	(-1.08)
Uniform Combined State Law Examination (Series 66)	-0.075***	-0.036	-0.034
	(-5.27)	(-1.55)	(-1.44)
Constant	0.066***	0.009	-0.014
	(5.89)	(0.33)	(-0.50)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	123,993	123,993	123,993
R-squared	0.050	0.361	0.361

Geographic diversification and adviser fraud - Con't

Panel B - City diversification

	(1)	(2)	(3)
City diversification	0.181***	0.090***	0.089***
	(13.27)	(3.48)	(3.43)
Firm size	0.013	0.025	0.033
	(1.43)	(0.97)	(1.25)
Adviser gender	0.078***	0.084***	0.081**
	(6.17)	(2.68)	(2.56)
Adviser experience	-0.012***	-0.016***	-0.002
	(-2.78)	(-3.06)	(-0.26)
Investment Company Representative (Series 6)	-0.045***	-0.003	-0.007
	(-3.74)	(-0.17)	(-0.37)
General Securities Representative (Series 7)	0.069***	0.033***	0.026**
	(6.77)	(2.70)	(2.11)
General Securities Principal Qualification Exam	-0.112***	-0.015	-0.014
	(-7.86)	(-0.79)	(-0.75)
Uniform Securities State Law Examination (Series 63)	-0.139***	-0.031**	-0.028*
	(-11.74)	(-2.18)	(-1.92)
Investment Advisers Law Examination (Series 65) l	-0.058***	-0.024	-0.021
	(-7.82)	(-1.23)	(-1.08)
Uniform Combined State Law Examination (Series 66)	-0.073***	-0.036	-0.034
	(-5.11)	(-1.55)	(-1.44)
Constant	0.058***	0.012	-0.015
	(5.20)	(0.46)	(-0.53)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	123,993	123,993	123,993
R-squared	0.049	0.361	0.361

Geographic diversification and adviser fraud - Con't

Panel C - State diversification

	(1)	(2)	(3)
State diversification	0.140***	0.089***	0.089***
	(7.14)	(3.01)	(3.00)
Firm size	0.037***	0.038	0.046*
	(4.03)	(1.52)	(1.79)
Adviser gender	0.094***	0.084***	0.081**
	(6.91)	(2.68)	(2.54)
Adviser experience	-0.011**	-0.016***	-0.002
	(-2.53)	(-3.12)	(-0.24)
Investment Company Representative (Series 6)	-0.026**	-0.002	-0.006
	(-2.13)	(-0.12)	(-0.33)
General Securities Representative (Series 7)	0.058***	0.034***	0.027**
	(5.69)	(2.82)	(2.22)
General Securities Principal Qualification Exam	-0.113***	-0.015	-0.015
	(-7.89)	(-0.80)	(-0.76)
Uniform Securities State Law Examination (Series 63)	-0.147***	-0.033**	-0.029**
	(-12.03)	(-2.25)	(-1.99)
Investment Advisers Law Examination (Series 65)	-0.037***	-0.022	-0.020
	(-5.15)	(-1.15)	(-1.00)
Uniform Combined State Law Examination (Series 66)	-0.036**	-0.035	-0.033
	(-2.54)	(-1.52)	(-1.40)
Constant	0.036***	0.010	-0.018
	(3.07)	(0.38)	(-0.62)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	123,993	123,993	123,993
R-squared	0.044	0.361	0.361

Geographic diversification and adviser fraud - Con't

Panel D - Firm entrophy

	(1)	(2)	(3)
Entropy index	0.194***	0.089***	0.085***
	(13.37)	(3.33)	(3.18)
Firm size	0.017*	0.028	0.035
	(1.80)	(1.09)	(1.35)
Adviser gender	0.094***	0.095***	0.092***
	(7.44)	(3.00)	(2.89)
Adviser experience	-0.012***	-0.015***	-0.003
	(-2.81)	(-2.86)	(-0.35)
Investment Company Representative (Series 6)	-0.049***	-0.002	-0.006
	(-4.09)	(-0.13)	(-0.30)
General Securities Representative (Series 7)	0.067***	0.032***	0.026**
	(6.64)	(2.61)	(2.09)
General Securities Principal Qualification Exam	-0.108***	-0.014	-0.014
	(-7.68)	(-0.75)	(-0.71)
Uniform Securities State Law Examination (Series 63)	-0.129***	-0.030**	-0.027*
	(-10.98)	(-2.11)	(-1.88)
Investment Advisers Law Examination (Series 65)	-0.063***	-0.024	-0.022
	(-8.37)	(-1.25)	(-1.11)
Uniform Combined State Law Examination (Series 66)	-0.074***	-0.035	-0.033
	(-5.24)	(-1.52)	(-1.41)
Constant	0.044***	0.001	-0.022
	(4.00)	(0.05)	(-0.78)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
_cons	Yes	No	No
Observation	123,993	123,993	123,993
Adj. R-squared	0.049	0.361	0.361

Table 5: **The effect of branch's opening and closing**

This table presents estimates from the regressions of adviser misconduct on branch's opening and closing for the period from 2012-2022. The dependent variable is the proportion of financial advisers with at least one misconduct-related disclosure in a year relative to total employees. *Opening branch* and *Opening branch*$_{t-1}$ represent the ratio of newly opened branches to the total number of branches in the current and previous year, respectively. *Closing branch* and *Closing branch*$_{t-1}$ represent the ratio of closed branches to the total number of branches in the current and previous year, respectively. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Opening branch	0.001**		0.001**			
	(2.03)		(2.38)			
Opening branch$_{t-1}$		0.001***	0.001***			
		(2.73)	(3.02)			
Closing branch				0.002***		0.002***
				(4.70)		(4.58)
Closing branch$_{t-1}$					-0.001	-0.000
					(-1.10)	(-0.53)
Firm size	0.053*	0.056**	0.050*	0.045	0.055**	0.044
	(1.93)	(2.04)	(1.84)	(1.64)	(2.03)	(1.62)
Adviser gender	0.101***	0.097***	0.101***	0.100***	0.098***	0.100***
	(2.91)	(2.81)	(2.92)	(2.89)	(2.82)	(2.89)
Adviser experience	0.001	0.003	0.008	-0.006	-0.003	-0.006
	(0.14)	(0.28)	(0.78)	(-0.59)	(-0.32)	(-0.62)
Investment Company Representative (Series 6)	0.004	0.003	0.002	0.006	0.005	0.006
	(0.20)	(0.17)	(0.12)	(0.32)	(0.23)	(0.32)
General Securities Representative (Series 7)	0.025**	0.026**	0.024*	0.028**	0.027**	0.028**
	(2.03)	(2.05)	(1.90)	(2.26)	(2.12)	(2.25)
General Securities Principal Qualification Exam (Series 24)	-0.013	-0.013	-0.013	-0.014	-0.013	-0.014
	(-0.66)	(-0.67)	(-0.67)	(-0.72)	(-0.66)	(-0.72)
Uniform Securities State Law Examination (Series 63)	-0.023	-0.022	-0.023	-0.023	-0.022	-0.022
	(-1.53)	(-1.47)	(-1.51)	(-1.49)	(-1.48)	(-1.49)
Investment Advisers Law Examination (Series 65)	-0.024	-0.023	-0.025	-0.023	-0.022	-0.023
	(-1.16)	(-1.15)	(-1.20)	(-1.14)	(-1.10)	(-1.14)
Uniform Combined State Law Examination (Series 66)	-0.018	-0.018	-0.017	-0.019	-0.018	-0.019
	(-0.71)	(-0.71)	(-0.70)	(-0.75)	(-0.72)	(-0.75)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	109,705	109,705	109,705	109,705	109,705	109,705
Adj. R-squared	0.275	0.275	0.275	0.275	0.275	0.275

Table 6: **GDI and customer complaints**

This table presents estimates from the regressions of customer complaints on geographic diversification for the period from 2012-2022. The dependent variable is customer complaint ratio which is defined as the number of financial advisers with at least one customer complaint during the year, divided by the total number of financial advisers in the firm that year, and multiplied by 100. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
GDI	0.118***	0.022**	0.019**
	(13.12)	(2.37)	(2.09)
Firm size	-0.024***	-0.006	-0.004
	(-7.87)	(-1.09)	(-0.60)
Adviser gender	0.067***	0.049***	0.048***
	(14.39)	(6.21)	(6.06)
Adviser experience	0.003**	-0.003**	0.002
	(2.47)	(-2.35)	(0.80)
Investment Company Representative (Series 6)	-0.009*	0.001	0.000
	(-1.95)	(0.19)	(0.04)
General Securities Representative (Series 7)	0.015***	0.010**	0.009**
	(4.54)	(2.57)	(2.34)
General Securities Principal Qualification Exam (Series 24)	-0.026***	-0.000	-0.000
	(-5.46)	(-0.03)	(-0.01)
Uniform Securities State Law Examination (Series 63)	-0.039***	-0.006	-0.005
	(-8.80)	(-1.49)	(-1.22)
Investment Advisers Law Examination (Series 65)	0.007***	-0.003	-0.002
	(2.84)	(-0.46)	(-0.35)
Uniform Combined State Law Examination (Series 66)	0.027***	0.001	0.001
	(5.57)	(0.09)	(0.19)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	123,993	123,993	123,993
Adj. R-squared	0.072	0.344	0.344

Table 7: **Geographical diversification and adviser misconduct for multiple-branch firms**

This table presents estimates from the regressions of adviser misconduct on geographic diversification for multiple-branch firms for the period from 2012-2022. The dependent variable is the proportion of financial advisers with at least one misconduct-related disclosure in a year relative to total employees. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
GDI	0.592***	0.326***	0.313***
	(8.37)	(2.95)	(2.84)
Firm size	-0.063	0.066	0.080
	(-1.60)	(0.85)	(1.02)
Adviser gender	0.279***	0.084	0.078
	(6.05)	(1.00)	(0.92)
Adviser experience	-0.066***	-0.052**	-0.032
	(-4.13)	(-2.37)	(-1.12)
Investment Company Representative (Series 6)	-0.067***	0.021	0.016
	(-2.82)	(0.90)	(0.67)
General Securities Representative (Series 7)	0.067***	0.023	0.013
	(4.25)	(1.63)	(0.80)
General Securities Principal Qualification Exam (Series 24)	-0.180***	-0.017	-0.016
	(-7.23)	(-0.73)	(-0.68)
Uniform Securities State Law Examination (Series 63)	-0.231***	-0.041**	-0.035*
	(-11.82)	(-2.19)	(-1.86)
Investment Advisers Law Examination (Series 65)	-0.041***	0.003	0.005
	(-2.63)	(0.11)	(0.18)
Uniform Combined State Law Examination (Series 66)	-0.017	-0.055*	-0.052*
	(-0.73)	(-1.91)	(-1.78)
Constant	-0.162***	-0.065	-0.112
	(-3.81)	(-0.74)	(-1.16)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	36,039	36,039	36,039
Adj. R-squared	0.040	0.320	0.321

Table 8: **Endogeneity test - The introduction of new flights**

This table presents estimates from the 2-stage least squared regressions of adviser misconduct for the period from 2012-2022. In Column 1, the dependent variable in the first stage is GDI, calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. The instrument variable is *New flight introduction* which is an indicator equal to one if there is a new flight that reduces the travel time between the advisor's headquarters city and their branch city. In Column 2, the dependent variable in the second stage is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. *Fitted value - GDI* is the fitted value of GDI, obtained in the first-stage regression. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) 1^{st} stage	(2) 2^{nd} stage
New flight introduction	-0.0779***	
	(-66.96)	
Fitted value - GDI		0.988**
		(2.379)
A-Adviser experience	0.0120***	-0.0524***
	(82.38)	(-8.154)
A-Adviser gender	-0.0269***	0.361***
	(-87.25)	(25.66)
A-Investment Company Representative (Series 6)	-0.103***	0.104
	(-49.11)	(1.443)
A-General Securities Representative (Series 7)	-0.301***	0.210
	(-223.5)	(1.606)
A-General Securities Principal Qualification Exam (Series 24)	-0.0935***	-0.103*
	(-56.14)	(-1.702)
A-Uniform Securities State Law Examination (Series 63)	-0.120***	-0.0374
	(-87.88)	(-0.594)
Investment Advisers Law Examination (Series 65)	-0.301***	0.0975
	(-293.0)	(0.757)
A-Uniform Combined State Law Examination (Series 66)	-0.0437***	-0.165***
	(-36.45)	(-4.340)
	(1,291)	(-0.888)
Observations	3,498,555	3,498,555
Adj. R-squared	0.1667	0.0005
Firm FE	Yes	Yes
ZIP FE	Yes	Yes
Year FE	Yes	Yes

Table 9: **Physical distance and adviser fraud**

This table presents estimates from the regressions of adviser misconduct on physical distance for the period from 2012-2022. The dependent variable is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. *Physical distance* is the natural logarithm of one plus the physical distance between the advisor's firm headquarters and their branch. *Driving distance* is the natural logarithm of one plus the driving distance between the advisor's firm headquarters and their branch. *Driving hours* is the natural logarithm of one plus the number of driving hours between the advisor's firm headquarters and their branch. Additional variables are defined as in Appendix A. *t*-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Physical distance

	(1)	(2)	(3)
Physical distance	0.042***	0.024***	0.024***
	(12.05)	(6.33)	(6.30)
A-Adviser experience	-0.019***	-0.012**	-0.007
	(-3.39)	(-2.43)	(-1.38)
A-Adviser gender	0.328***	0.326***	0.325***
	(27.30)	(26.77)	(26.65)
A-Investment Company Representative (Series 6)	0.039	0.039	0.031
	(0.73)	(0.70)	(0.55)
A-General Securities Representative (Series 7	0.003	-0.007	-0.029
	(0.08)	(-0.17)	(-0.74)
A-General Securities Principal Qualification Exam (Series 24)	-0.150***	-0.110***	-0.112***
	(-4.03)	(-2.95)	(-3.03)
A-Uniform Securities State Law Examination (Series 63)	-0.107***	-0.100***	-0.092***
	(-3.22)	(-2.97)	(-2.75)
A-Investment Advisers Law Examination (Series 65)	-0.060*	-0.065*	-0.065*
	(-1.69)	(-1.82)	(-1.81)
A-Uniform Combined State Law Examination (Series 66)	-0.187***	-0.194***	-0.187***
	(-6.12)	(-6.40)	(-6.20)
Firm FE	Yes	Yes	Yes
ZIP FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	3,498,555	3,498,555	3,498,555
Adj. R-squared	0.006	0.011	0.011

Physical distance and adviser fraud - Con't

Panel B - Driving distance

	(1)	(2)	(3)
Driving distance	0.044***	0.025***	0.025***
	(11.49)	(6.08)	(6.05)
A-Adviser experience	-0.018***	-0.012**	-0.007
	(-3.33)	(-2.42)	(-1.38)
A-Adviser gender	0.328***	0.326***	0.325***
	(27.21)	(26.77)	(26.65)
A-Investment Company Representative (Series 6)	0.039	0.039	0.031
	(0.73)	(0.70)	(0.55)
A-General Securities Representative (Series 7)	0.003	-0.007	-0.029
	(0.08)	(-0.17)	(-0.74)
A-General Securities Principal Qualification Exam (Series 24)	-0.151***	-0.110***	-0.113***
	(-4.07)	(-2.96)	(-3.03)
A-Uniform Securities State Law Examination (Series 63)	-0.107***	-0.100***	-0.092***
	(-3.21)	(-2.97)	(-2.75)
A-Investment Advisers Law Examination (Series 65)	-0.059*	-0.065*	-0.064*
	(-1.67)	(-1.82)	(-1.80)
A-Uniform Combined State Law Examination (Series 66)	-0.186***	-0.194***	-0.187***
	(-6.09)	(-6.40)	(-6.20)
Firm FE	Yes	Yes	Yes
ZIP FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	3,498,555	3,498,555	3,498,555
Adj. R-squared	0.006	0.011	0.011

Physical distance and adviser fraud - Con't

Panel C - Driving hours

	(1)	(2)	(3)
Driving hours	0.057***	0.031***	0.031***
	(11.32)	(6.03)	(6.00)
A-Adviser experience	-0.018***	-0.012**	-0.007
	(-3.22)	(-2.41)	(-1.37)
A-Adviser gender	0.328***	0.327***	0.325***
	(27.17)	(26.78)	(26.66)
A-Investment Company Representative (Series 6)	0.038	0.038	0.030
	(0.72)	(0.69)	(0.55)
A-General Securities Representative (Series 7)	0.002	-0.007	-0.029
	(0.06)	(-0.18)	(-0.75)
A-General Securities Principal Qualification Exam (Series 24)	-0.152***	-0.110***	-0.113***
	(-4.10)	(-2.97)	(-3.04)
A-Uniform Securities State Law Examination (Series 63)	-0.107***	-0.100***	-0.092***
	(-3.22)	(-2.97)	(-2.75)
A-Investment Advisers Law Examination (Series 65)	-0.059*	-0.065*	-0.064*
	(-1.67)	(-1.82)	(-1.80)
A-Uniform Combined State Law Examination (Series 66)	-0.185***	-0.194***	-0.187***
	(-6.06)	(-6.40)	(-6.20)
Firm FE	Yes	Yes	Yes
ZIP FE	No	Yes	Yes
Year FE	No	No	Yes
Observation	3,498,555	3,498,555	3,498,555
Adj. R-squared	0.006	0.011	0.011

Table 10: **The interaction effect between network diversification and branch size**
This table presents estimates from the regressions of adviser misconduct on geographic diversification and branch size for the period from 2012-2022. The dependent variable is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. *Branch size* is the natural logarithm of the number of employees in the advisor's branch. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
GDI × Branch size		-0.080***
		(-4.96)
GDI		0.472***
		(3.62)
Branch size	-0.065***	0.003
	(-14.32)	(0.23)
A-Adviser experience	-0.010*	-0.010*
	(-1.87)	(-1.85)
A-Adviser gender	0.281***	0.281***
	(31.74)	(31.73)
A-Investment Company Representative (Series 6)	0.047	0.048
	(1.02)	(1.06)
A-General Securities Representative (Series 7)	0.000	0.001
	(0.01)	(0.05)
A-General Securities Principal Qualification Exam (Series 24)	-0.122***	-0.120***
	(-4.62)	(-4.54)
A-Uniform Securities State Law Examination (Series 63)	-0.168***	-0.167***
	(-7.90)	(-7.86)
A-Investment Advisers Law Examination (Series 65)	-0.056*	-0.056*
	(-1.88)	(-1.87)
A-Uniform Combined State Law Examination (Series 66)	-0.205***	-0.204***
	(-8.42)	(-8.39)
Firm FE	Yes	Yes
ZIP FE	Yes	Yes
Year FE	Yes	Yes
Observation	6,128,821	6,128,821
Adj. R-squared	0.018	0.018

Table 11: **The effect of branch's age**

This table presents estimates from the regressions of adviser misconduct on branch's opening and closing for the period from 2012-2022. The dependent variable is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. *Branch age* is measured as the natural logarithm of the number of years since the advisor's branch was established. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. Additional variables are defined as in Appendix A. *t*-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
GDI × Branch age		-0.112***
		(-3.40)
GDI		0.468***
		(3.27)
Branch age	-0.138***	-0.037
	(-15.47)	(-1.22)
A-Adviser experience	0.015***	0.016***
	(2.87)	(2.92)
A-Adviser gender	0.282***	0.282***
	(31.85)	(31.87)
A-Investment Company Representative (Series 6)	0.037	0.038
	(0.82)	(0.83)
A-General Securities Representative (Series 7)	-0.002	-0.002
	(-0.07)	(-0.06)
A-General Securities Principal Qualification Exam (Series 24)	-0.126***	-0.125***
	(-4.78)	(-4.74)
A-Uniform Securities State Law Examination (Series 63)	-0.157***	-0.157***
	(-7.39)	(-7.38)
A-Investment Advisers Law Examination (Series 65)	-0.049*	-0.050*
	(-1.67)	(-1.69)
A-Uniform Combined State Law Examination (Series 66)	-0.190***	-0.190***
	(-7.81)	(-7.80)
Firm FE	Yes	Yes
ZIP FE	Yes	Yes
Year FE	Yes	Yes
Observation	6,128,821	6,128,821
Adj. R-squared	0.018	0.018

Table 12: **The moderating effect of the regulatory authority**

This table presents estimates from the regressions of adviser misconduct on geographic diversification for the period from 2012-2022. The dependent variable is an indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise. *GDI* is calculated as one minus the sum of the squared employment shares across all ZIP code locations within a firm's branch network. *Proximity to regulatory authority* is measured as the natural logarithm of the average distance between the advisor's branch and its corresponding regional regulatory offices, including the SEC and FINRA. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Proximity to regulatory offices	-0.060**	-0.165***	-0.058**	-0.158***
	(-2.11)	(-3.74)	(-2.00)	(-3.53)
Proximity to regulatory offices × GDI		0.266***		0.258***
		(4.14)		(3.94)
GDI		0.327***		0.323***
		(12.47)		(12.41)
A-Adviser experience	-0.050***	-0.058***	-0.043***	-0.051***
	(-11.05)	(-12.78)	(-9.65)	(-11.38)
A-Adviser gender	0.313***	0.326***	0.311***	0.324***
	(37.32)	(38.08)	(36.96)	(37.76)
A-Investment Company Representative (Series 6)	0.038	0.079**	0.031	0.071*
	(0.99)	(2.04)	(0.81)	(1.85)
A-General Securities Representative (Series 7)	-0.030	0.066***	-0.062**	0.033
	(-1.19)	(2.59)	(-2.48)	(1.30)
A-General Securities Principal Qualification Exam (Series 24)	-0.220***	-0.173***	-0.220***	-0.174***
	(-8.80)	(-6.80)	(-8.83)	(-6.83)
A-Uniform Securities State Law Examination (Series 63)	-0.246***	-0.211***	-0.233***	-0.199***
	(-11.84)	(-10.14)	(-11.23)	(-9.55)
A-Investment Advisers Law Examination (Series 65)	-0.142***	-0.067***	-0.129***	-0.055***
	(-6.88)	(-3.13)	(-6.26)	(-2.59)
A-Uniform Combined State Law Examination (Series 66)	-0.191***	-0.200***	-0.172***	-0.182***
	(-8.24)	(-8.72)	(-7.45)	(-7.92)
Year FE	No	No	Yes	Yes
Observation	6,047,604	6,047,604	6,047,604	6,047,604
Adj. R-squared	0.001	0.001	0.001	0.001

Figure 1: **Geographic Diversification Index over time**
This figure displays the average geographic diversification idex (GDI) over time for the sample period from 2012-2022. GDI is defined as one minus the sum of squared employment shares of all ZIP code locations within a firm's branch network.

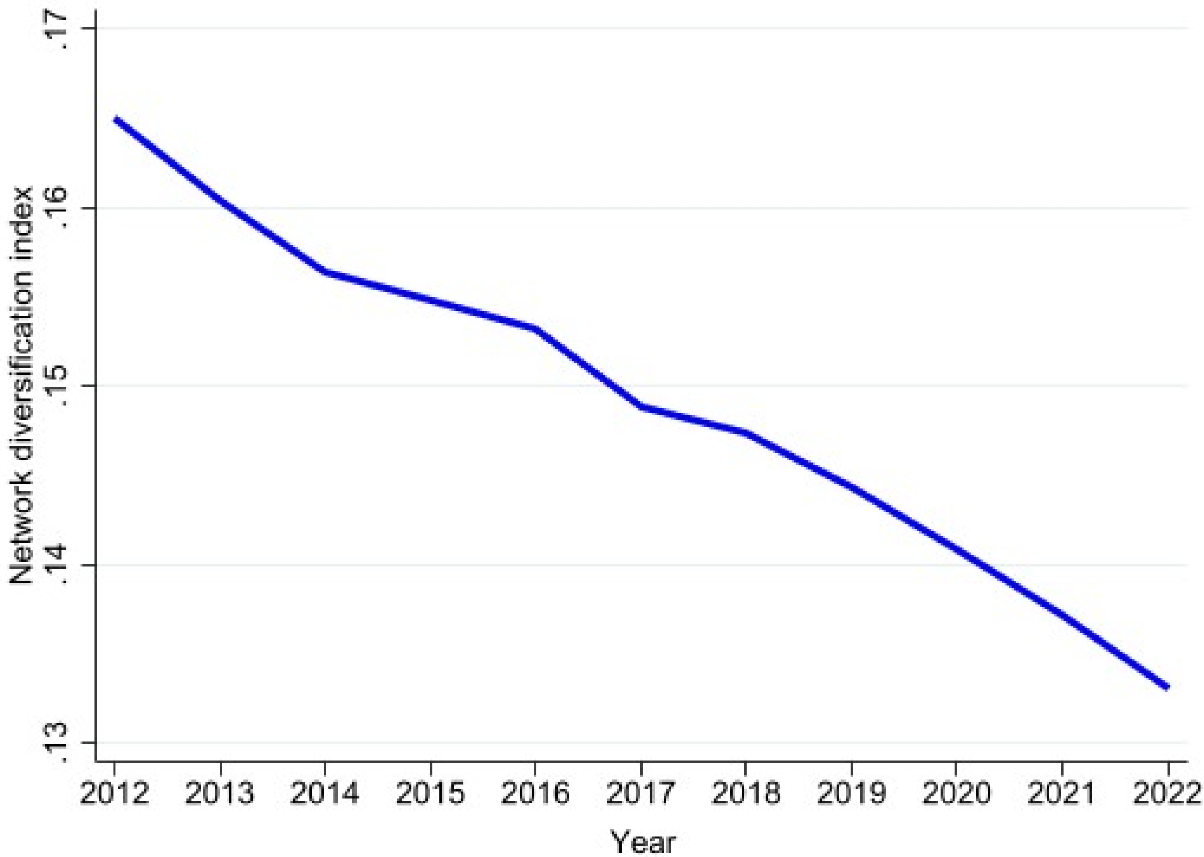

Figure 2: **Single-branch firms**
This figure displays the ratio of single-branch firms over time for the sample period from 2012-2022.

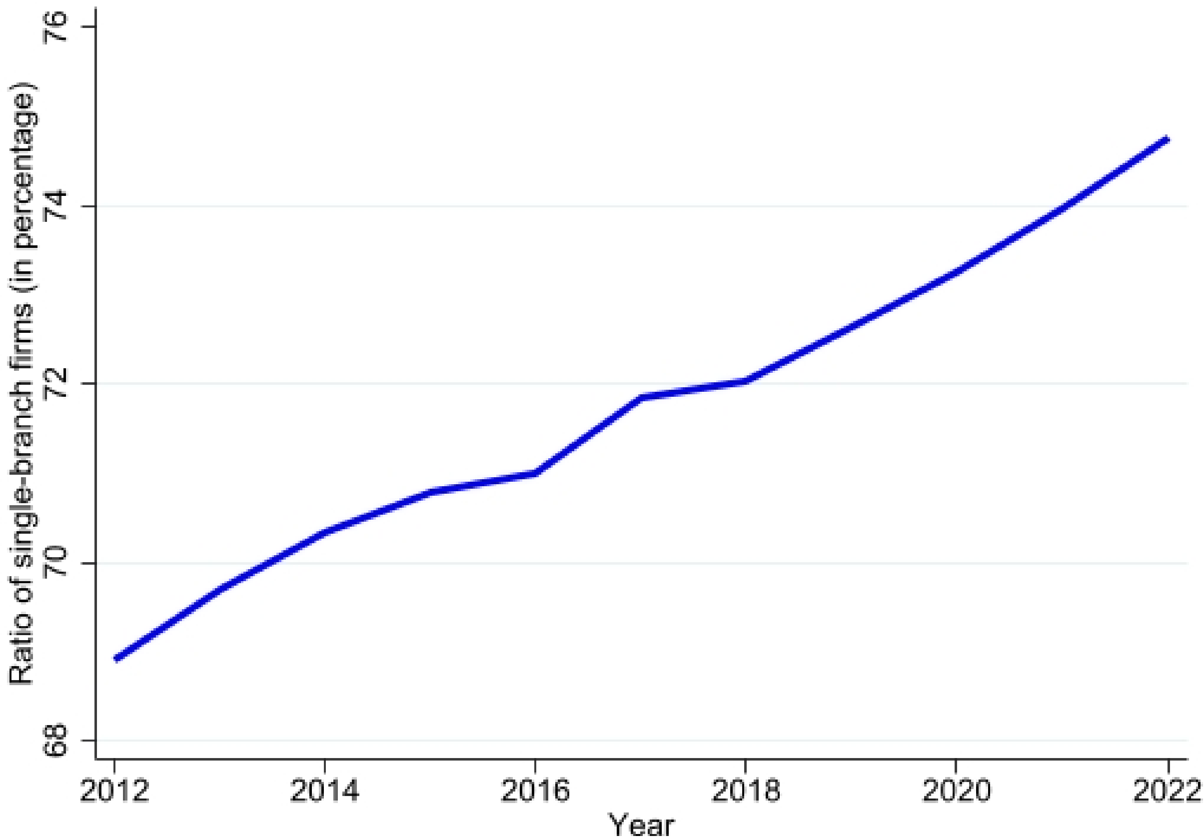

Figure 3: **Multi-branch firms - Branch-headquarters distances**
This figure displays the average distance (in miles) between branch and its headquarters of multi-branch firms over time for the sample period from 2012-2022.

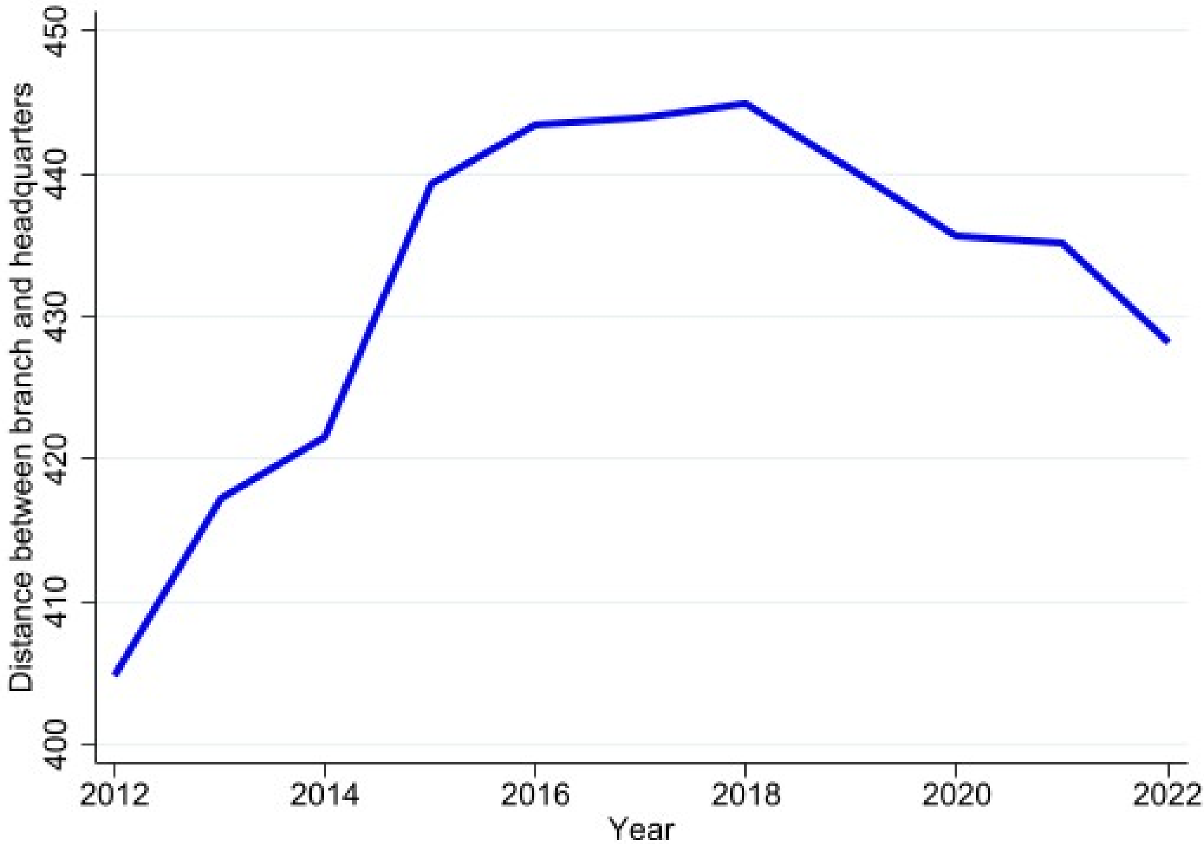

Table 13: **Appendix A - Variable definitions**

Variable	Description
Firm-level variables	
Adviser misconduct ratio	The number of financial advisers with at least one misconduct-related disclosure during the year, divided by the total number of financial advisers in the firm for that year, and multiplied by 100.
Customer complaint (%)	The ratio of the number of financial advisers who receives at least one misconduct-related disclosure during the year over the total number of employees
GDI	One minus the sum of squared employment shares of all ZIP code locations within a firm's branch network.
Adviser gender	The natural logarithm of one plus the total number of male adviser in a firm
Adviser experience	The natural logarithm of the average years of work experience among all advisors in a firm
Firm size	The natural logarithm of the total number of financial advisers within a firm
Investment company representative (Series 6)	The natural logarithm of one plus the number of such professional licenses within a firm. This license allows financial professionals to sell mutual funds, variable annuities, and other investment products
General securities representative (Series 7)	The natural logarithm of one plus the number of such professional licenses within a firm. This license allows financial professionals to trade a wide range of securities, including stocks, bonds, options, and mutual funds.
General securities principal qualification exam (Series 24)	The natural logarithm of one plus the number of such professional licenses within a firm. This FINRA-administered exam qualifies individuals to supervise and manage a firm's general securities business.
Uniform securities state law examination (Series 63)	The natural logarithm of one plus the number of such professional licenses within a firm. This FINRA exam qualifies individuals to solicit orders for securities and provide investment advice within a specific state.
Investment advisers law examination (Series 65)	The natural logarithm of one plus the number of such professional licenses within a firm. This FINRA exam qualifies individuals to act as an investment advisor. An indicator variable equal to one if a financial adviser holds this license and zero otherwise.
Uniform combined state law examination (Series 66)	The natural logarithm of one plus the number of such professional licenses within a firm. This FINRA exam qualifies individuals to act as both securities agents and investment adviser representatives.

Appendix A - Variable definitions (Con't)

Variable	Description
Firm-level variables - Con't	
ZIP diversification	The natural logarithm of the total number of unique ZIP code locations in a firm's branch network
City diversification	The natural logarithm of the total number of unique cities in a firm's branch network
State diversification	The natural logarithm of the total number of unique states in a firm's branch network
Entropy index	The sum of the product of each employment share of a ZIP code location in a firm's branch network and the natural logarithm of its reciprocal
Opening branch	The ratio of newly opened branches to the total number of branches in the current year
Opening branch$_{t-1}$	The ratio of newly opened branches to the total number of branches in the previous year
Closing branch	The ratio of closed branches to the total number of branches in the current year
Closing branch$_{t-1}$	The ratio of closed branches to the total number of branches in the previous year
Advisor-level variables	
A-Flow of financial misconduct (%)	An indicator equal to one when a financial adviser receives at least one misconduct-related disclosure during the year and zero otherwise
A-Gender	An indicator equal to one if a financial adviser is male and zero otherwise
A-Experience	The natural logarithm of the advisor's total years of work experience
A-Investment company representative (Series 6)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This license authorizes financial professionals to sell mutual funds, variable annuities, and other investment products
A-General securities representative (Series 7)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This license allows financial professionals to trade a wide range of securities, including stocks, bonds, options, and mutual funds.
A-General securities principal qualification exam (Series 24)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA-administered exam qualifies individuals to supervise and manage a firm's general securities business.
A-Uniform securities state law examination (Series 63)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to solicit orders for securities and provide investment advice within a specific state.

Appendix A - Variable definitions (Con't)

Variable	Description
Adviser-level variables (Con't)	
A-Investment advisers law examination (Series 65)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to act as an investment advisor.
A-Uniform combined state law examination (Series 66)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to act as both securities agents and investment adviser representatives.
Physical distance	The natural logarithm of one plus the physical distance between the advisor's firm headquarters and their branch
Driving distance	The natural logarithm of one plus the driving distance between the advisor's firm headquarters and their branch
Driving hours	The natural logarithm of one plus the number of driving hours between the advisor's firm headquarters and their branch
New flight introduction	An indicator equal to one if there is a new flight that reduces the travel time between the advisor's headquarters city and their branch city.
Proximity to regulatory offices	The natural logarithm of the average distance between the advisor's branch and its corresponding regional regulatory offices, including the SEC and FINRA.
Branch age	The natural logarithm of the number of years since the advisor's branch was established

Chapter 2

Talent in Motion: How the Broker Protocol Reshapes Competition in Financial Advisory Markets

Sapphasak Chatchawan and Nhan Le[1]

Abstract – This chapter examines how the adoption of the Broker Protocol—a voluntary solicitation agreement—affects competition in local financial advisory markets. We find that greater local penetration of Protocol-member firms is associated with intensified market competition. This competitive effect is robust across alternative definitions of geographic units, measures of Protocol participation, and indicators of market competition. Furthermore, firms that join the Protocol experience substantial growth in Assets Under Management (AUM) and employment, while larger firms disproportionately lose high-quality advisers. These patterns suggest that the Protocol facilitates a reallocation of human capital toward smaller firms, thereby reshaping industry competition dynamics. More broadly, the findings offer insights into how institutional arrangements governing labor mobility can influence market structure—particularly in human-capital-intensive sectors where talent is a core driver of competitive advantage and market power is highly concentrated.

Keywords: Broker Protocol; Local market competition; Labor mobility; Financial adviser

JEL classification: D23; D40; G23; G24; J41; J42; J63; K31; L10

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1 Introduction

The U.S. financial advisory industry has experienced significant consolidation over the past decade. As Figure 1 illustrates, the Herfindahl-Hirschman Index (HHI) increased from approximately 800 (indicating an unconcentrated market) to over 1,000—a threshold the FTC and DOJ classify as moderately concentrated.[2] Concurrently, the collective market share of the top decile of firms grew substantially from 52% to 72%, reflecting the increasing dominance of a small number of national players. This trend toward greater concentration has raised concerns about deteriorating customer service, reduced product diversity, and increased incidence of misconduct (Bennett et al., 2013; Gelman et al., 2021; Saidi and Streitz, 2021). Against this backdrop, our paper investigates how the *Protocol for Broker Recruiting* (the "Broker Protocol")—a voluntary firm agreement governing the ownership and solicitation of client relationships—shapes local market competition. By analyzing this unique institutional mechanism, we shed light on how labor mobility rules can influence market structure in an increasingly consolidated industry.

Launched in 2004, the Broker Protocol is a voluntary agreement among participating firms that standardizes the rules governing adviser mobility. Specifically, it allows departing advisers to take limited client information—such as names, addresses, phone numbers, email addresses, and account titles—when moving to another signatory firm, without facing legal action. By relaxing firm's property rights over client relationships, the Protocol reduces legal frictions, lowers transaction costs and litigation risks, and shifts bargaining power toward individual advisers. This institutional arrangement facilitates smoother client transitions

[2] https://www.justice.gov/atr/herfindahl-hirschman-index

and enhances adviser mobility (Gurun et al., 2021). By altering the portability of client relationships, the Broker Protocol provide a unique setting to study how changes in labor mobility, property rights of client information affect local market competition.

However, the effect of the Protocol on local market competition can operate through two opposite channels. First, by reallocating residual control rights over client relationships from firms to individual advisers, the Broker Protocol mitigates hold-up problems (Grossman and Hart, 1986; Hart and Moore, 1990). This reallocation reduces firms' monopsony power in the labor market and weakens their monopoly powers in the product market. Simultaneously, by enhancing adviser mobility and client portability, the Protocol accelerates cross-firm knowledge spillovers. Mobile advisers serve as conduits of institutional knowledge transfer, disseminating best practices—such as advanced risk management frameworks, compliance innovations, and fintech solutions—to recipient firms. This dynamic undermines incumbents' informational advantages and lowers entry barriers, ultimately driving Schumpeterian creative destruction through the disruption of entrenched knowledge monopolies (Jovanovic and Rob, 1989). We refer to this channel as "Labor mobility hypothesis."

On the other hand, the Broker Protocol may also reinforce scale advantages, potentially stiffing market competition. According to network effects theory (Katz and Shapiro, 1985), the Protocol's standardized portability rules could disproportionately benefit larger firms by enabling them to leverage existing client networks and brand recognition. This dynamic may lead to an equilibrium where top advisory talent concentrates at dominant firms. The Protocol may further exacerbate this trend through superstar effects (Rosen, 1981). By allowing high-performing advisers to capture disproportionate returns on scalable platforms, it could intensify market concentration and threaten mid-sized and smaller firms' viability. In this scenario, rather than dispersing talent, labor mobility might reinforce dominant players and create a bifurcated market structure. We refer to this channel as "Scale advantage hypothesis."

Given these competing hypotheses—that the Protocol may either enhance competition by reducing frictions or suppress it through scale advantages— empirical investigation becomes crucial. The implications are significant for policymakers and industry stakeholders. As a voluntary, self-regulatory arrangement operating outside traditional enforcement channels, the Protocol's future—whether it should be maintained, modified, or limited—depends on its net effect on market competition. This paper aims to provide the necessary evidence to inform these decisions and guide the design of similar industry-wide agreements.

To test these two competing hypotheses, we construct a comprehensive panel dataset on financial advisers and advisory firms by combining public disclosure records from the Financial Industry Regulatory Authority's (FINRA) BrokerCheck website and the Securities and Exchange Commission's (SEC) Investment Adviser Public Disclosure (IAPD) databases. These sources provide detailed information on adviser employment histories, firm headquarters and branch office locations (by ZIP code), and firm-level assets under management (AUM). We supplement this dataset with Broker Protocol participation records—including firm join and withdrawal dates—sourced from the official J.S. Held website. We use commuting zones as our geographic unit of analysis, as they better capture economically integrated labor and client markets than traditional administrative boundaries such as counties.[3] As of

[3]See Autor and Dorn (2013) for discussion of commuting zones as effective units of analysis in labor economics.

2022, 2,196 firms had signed the Protocol. Our final panel covers the period 2012–2022 and includes 7,156 commuting zone-year observations and 3,229,765 adviser-year observations. The number of unique commuting zones is 741 unique commuting zones.

We measure local market competition using the Herfindahl-Hirschman Index (HHI), calculated as the sum of squared employment shares of financial advisory firms within each commuting zone. We use employment shares as our primary metric due to more complete data coverage, but confirm the robustness of our results when using AUM-based shares, despite their higher rate of missing observations. To capture the local presence of Broker Protocol firms, we compute the employment share of Protocol-participating firms relative to total adviser employment in each commuting zone. We obtain similar results when using AUM-based shares as an alternative measure of Protocol penetration.

Our results indicate that greater penetration of Broker Protocol firms intensifies local market competition. A one-standard-deviation increase in Protocol firms – Employment corresponds to a 0.45% decline in the local Herfindahl-Hirschman Index (HHI), equivalent to roughly 8% of the average local HHI. This effect persists across both within- and across-location specifications and remains robust to alternative measures of market competition, Protocol firm size, and geographic definitions.

A key empirical challenge is potential endogeneity, as firms may endogenously join the Broker Protocol in response to local competitive conditions—for example, to facilitate adviser poaching in anticipation of heightened market pressures. To address this reverse causality concern, we implement two identification strategies, both of which support our baseline findings.

First, we restrict our sample to multi-branch firms and exclude single-branch firms, whose decisions to join the Broker Protocol are more likely to be heavily influenced by conditions in their single local market. In contrast, multi-branch firms are better positioned to make such decisions based on firm-wide strategic considerations rather than the competitive dynamics of any one location. Focusing on multi-branch firms also improves the comparability between Protocol and non-Protocol firms.[4] Second, we further refine our sample to include only firms that operate in heterogeneous competitive environments—specifically, those with branches located in both highly competitive and highly concentrated commuting zones. By exploiting this within-firm variation in local market conditions, we reduce the risk that Protocol adoption is driven by localized market characteristics. Our baseline results remain robust under both sample restrictions, strengthening the causal interpretation of the pro-competitive effects associated with Broker Protocol participation.

Having established causal identification, we next examine how the Protocol affects firm-level performance, focusing on adviser employment and assets under management (AUM). Using a stacked difference-in-differences regression framework, we find that firms experience a significant post-adoption increase in both employment and AUM relative to non-Protocol firms. These results suggest that the Protocol not only enhances local market competition but also facilitates firm growth. After adopting the Broker protocol, small firms significantly benefit from increasing employment and AUM.

We next explore the mechanisms through which Broker Protocol penetration enhances local market competition, with a focus on labor mobility as a key channel. Following a firm's

[4] Our analysis shows that Protocol firms tend to be larger in terms of employment and AUM compared to non-Protocol firms.

entry into the Protocol, we observe a significant rise in turnover among talent advisers with long tenure and advanced professional credentials, particularly at large firms. This pattern indicates that the Protocol facilitates the mobility of highly skilled advisers who were previously constrained by legal and contractual barriers. Increased talent adviser mobility in large firms promotes the transfer of adviser expertise and client relationships to rival firms, weakening labor market power of large incumbent firms and hence intensifying competitive pressures across the industry. Importantly, when examining the destination of adviser movements, we find that transitions from large to smaller firms accelerate following the entry of the adviser's firm into the Broker Protocol. This pattern suggests that the resulting mobility disproportionately benefits smaller firms. Together, the two turnover analysis suggests that the Protocol not only increases the mobility of talent advisers—particularly at large firms—but also facilitates the reallocation of advisers toward less dominant market participants. By enabling such redistribution, the Protocol promotes market decentralization and strengthens local competition.

In brief, we find that a higher local presence of Protocol-member firms intensifies market competition. Firms that join the Broker Protocol experience significant growth in both assets under management (AUM) and employment. However, large firms also face a significant outflow of talent advisers, and adviser transitions from large to smaller firms increase following Protocol adoption. These results collectively underscore the Protocol's role in reallocating human capital toward smaller firms, thereby reshaping competitive dynamics in the industry.

This paper makes three primary contributions. First, we advance the emerging research on the Broker Protocol in the U.S. financial advisory industry. While prior work have examined its effects on adviser-level behaviors—including misconduct (Gurun et al., 2021) and professional certification incentives (Clifford and Gerken, 2021)—we shift the focus to its broader market-level implications. By linking firm participation in the Protocol to local market-level competition, we extend the analysis from individual adviser outcomes to the macro-level dimensions of industry competitive dynamics.

Second, we contribute to the literature on the determinants of local market competition. Existing research has identified various structural drivers including sunk costs (Stiglitz et al., 1987), economies of scale (Wright, 1978), firm entry barriers (Bresnahan and Reiss, 1991; Fama and Laffer, 1972; Stiglitz, 1987), foreign competition (Claessens and Laeven, 2004; Owen et al., 2007), and technological diffusion (Hauswald and Marquez, 2015; Vives and Ye, 2025), regulatory barriers across multiple industries—from healthcare Certificate of Need (CON) laws (Ni et al., 2017) to banking deregulation (Carlson and Mitchener, 2006; Huang, 2008).

Building on this body of work, we introduce a labor-market perspective by examining firm-level adoption of the Broker Protocol—a voluntary solicitation agreement—as a novel and underexplored determinant of local market competition. Our analysis complement the findings of Abramova (2024), who show that labor supply shocks in the accounting profession can drive audit firm M&A activity and increase market concentration. While their study links labor scarcity to industry consolidation in the audit industry, our work highlights how institutional labor arrangements that govern the ownership and transferability of client relationships can shape competitive outcome in the financial advisory industry.

Third, our research contributes to the growing debate on how employee mobility restrictions, such as no-poach and non-solicitation agreements, influence firm strategy and labor market outcomes. For instance, Callaci et al. (2024) show that Washington State's 2018–2020 enforcement campaign against no-poach clauses in franchise agreements led to a 6% increase in posted annual earnings and a 4% rise in worker-reported wages. Conversely, Battiston et al. (2025) find that restricting poaching can improve employee productivity by reducing turnover. Shy and Stenbacka (2019) theoretically demonstrate that anti-poaching agreements can enhance industry profits but at the expense of worker welfare. While prior literature examines labor turnover and worker welfare in the security service and franchising industries, our paper extends the analysis to the financial advisory industry and emphasizes the broader implications of solicitation agreements on market power and competitive dynamics.

The paper is structured as follows. Section 2 describes the data sources and outlines the empirical strategy. Section 3 and 4 present the baseline results and address endogeneity. Section 5 investigates the underlying mechanisms driving this effect. Section 6 summarizes the findings and concludes.

2. Data and Empirical Strategy

This section begins by outlining the institutional framework of the Broker Protocol, then describes the construction of our sample, and finally details the empirical methodology used to analyze the competition effects.

2.1 The Protocol for Broker Recruiting

In 2004, Smith Barney (now part of Morgan Stanley), Merrill Lynch, and UBS Financial Services created *The Protocol for Broker Recruiting* or *Broker Protocol* to reduce legal disputes when financial advisers switched to new firms. Under the Broker Protocol, signatory firms agreed to remove certain non-solicitation clauses and allow financial advisers to take limited client information—such as names, addresses, phone numbers, and emails—when transitioning between signatory firms. This arrangement aims to reduce legal friction in advisor transitions while giving clients more freedom to choose where they receive financial services.

As of March 2024, the official list of Broker Protocol signatory firms is maintained by J.S. Held,[5] which assumed this role from Carlile, Patchen, and Murphy LLP. The list is updated weekly and distributed to member firms every Monday by 1:00 PM Central Time. We downloaded the full list in March 2024, which includes each firm's current and former names as well as their join and withdrawal dates. At that time, over 2,000 firms had signed the Protocol.

2.2 Sample selection

We obtain data of financial advisers from two public disclosure sources: the Securities and Exchange Commission (SEC) Investment Adviser Public Disclosure (IAPD) database[6] and Financial Industry Regulatory Authority (FINRA) BrokerCheck website[7]. Throughout the

[5] https://www.jsheld.com/markets-served/financial-services/broker-recruiting/the-broker-protocol
[6] https://adviserinfo.sec.gov/
[7] https://brokercheck.finra.org/

paper, we use the spelling "financial adviser" with an "e," consistent with the terminology in the Investment Advisers Act of 1940. Following Egan et al. (2019) and Gurun et al. (2021), we use the term "financial adviser" to refer broadly to both investment advisers and brokers.

Individuals who provide investment advice on behalf of financial advisory firms are classified as Investment Adviser Representatives (IARs), while the firms themselves are known as Registered Investment Advisers (RIAs). In contrast, registered representatives—or brokers—work for broker-dealer firms. The key distinction lies in regulatory standards: IARs and RIAs are held to a fiduciary standard, obligating them to act in the client's best interest, while brokers and broker-dealer firms are bound by a suitability standard, requiring recommendations to be suitable but not necessarily in the client's best interest. Many individuals are dually registered as both an advisers and a brokers.

Each financial adviser is uniquely identified by a Central Registration Depository (CRD) number, which allows retrieval of their registration records from both BrokerCheck and IAPD websites. To construct our sample, we queried CRD numbers from 0 to 10 million on both platforms. As of Q2 2023, highest CRD numbers extended into the 7–8 million range. These databases provide detailed information on adviser names, licenses, registration and employment histories, geographic locations, and any misconduct disclosures. We supplement this with SEC form Form ADV filings, which contain firm-level data on assets under management (AUM), client accounts, and size classification.

We supplement the adviser and firm datasets with Broker Protocol participation records—including firm join and withdrawal dates—sourced from the official J.S. Held website. Firm names from the J.S. Held list are manually matched to those in our dataset.

When exact matches were unclear—especially for independent advisers—we traced those firm names to their parent companies using their firm websites.[8]

We use commuting zones as our geographic unit of analysis because they more accurately reflect economically integrated labor and client service markets than traditional administrative boundaries such as counties.[9] Our main dataset is organized at the ZIP code level, which we map to county FIPS codes using the HUD-USPS ZIP-County Crosswalk,[10] and then to commuting zones using mappings from the Integrated Public Use Microdata Series (IPUMS).[11]

We measure local market competition using the Herfindahl-Hirschman Index (HHI), calculated as the sum of squared employment shares of financial advisory firms within each commuting zone. Employment share is our preferred metric due to more comprehensive data coverage. However, in section 3.2, we confirm that our results are robust to using AUM-based market shares, despite the higher rate of missing observations. To quantify local Broker Protocol penetration, we compute the employment share of Protocol-participating firms relative to total adviser employment in each commuting zone. Our findings are consistent when using AUM shares as an alternative measure.

Figure 1 depicts a steady rise in the cumulative number of firms joining the Broker Protocol from 2004 to 2023, surpassing 2,000 signatory firms to date.

[8] For example, Raymond James operates a hybrid model in which advisers maintain independent branding but are registered under Raymond James, which manages regulatory and operational functions. These advisers are therefore matched to the Raymond James parent firm.

[9] See Autor and Dorn, 2013 for a discussion of commuting zones as effective units of analysis in labor economics.

[10] https://www.huduser.gov/apps/public/uspscrosswalk/home

[11] https://usa.ipums.org/usa/volii/1980LMAascii.txt

Insert Figure 1 here

To avoid survivorship bias, our final sample covers the period from 2012 to 2022. According to FINRA, BrokerCheck retains information on financial advisers registered within the past 10 years, except for those with a record of financial misconduct, whose data are retained indefinitely. Because we began web scraping data from FINRA's BrokerCheck and the SEC's IAPD databases in Q2 2023, including data prior to 2012 would disproportionately capture advisers with misconduct histories, introducing survivorship bias. Our sample spans 605,719 financial advisers, 17,315 unique firms, and 2,292 Broker Protocol firms during the 2012–2022 period.

2.3 Empirical design

We analyze the impact of the Broker Protocol on local market competition at the commuting zone level by estimating the following regression.

$$(1)\ \textit{Local HHI}_{c,t} = \alpha + \beta \times \textit{Protocol firms - Employment}_{c,t} + \lambda \times X_{c,t} + \delta_c + \gamma_t + \varepsilon_{c,t}$$

Here, c, t index commuting zone c in year t. The term δ_c captures commuting zone fixed effects, while γ_t denotes year fixed effects.

The dependent variable, *Local HHI*$_{c,t}$, is calculated as the sum of squared employment shares of financial advisory firms in each commuting zone, multiplied by 100. The vector $X_{c,t}$ includes firm-level and local economic controls. Specifically, we control for the natural logarithm of average firm age and firm AUM, as well as local economic conditions, including the natural logarithm of total local adviser employment, local adviser employment growth, and state-level real GDP growth.

Furthermore, our regression specifications include commuting zone fixed effects, δ_c, to account for time-invariant characteristics specific to each location, such as geographic features, regional economic structures, and local industry composition that may affect labor market competition. For example, a metropolitan area like New York City—with a dense concentration of financial firms—likely exhibits different competitive dynamics than a rural zone with limited financial services.

We also include year fixed effects, γ_t, to control for factors common to all commuting zones in a given year, such as nationwide regulatory changes or macroeconomic policy. Examples include the introduction of federal financial regulations or the impact of a relaxing monetary policy. Standard errors are clustered at the commuting zone level.

The key independent variable, *Protocol firms - Employment*, is defined as the ratio of financial advisers employed by protocol firms to the total number of financial advisers across all firms within a commuting zone in a given year. In robustness checks in section 3.2, we show that our results remain consistent when using AUM-based shares as an alternative measure.

The coefficient β captures the effect of Protocol firms – Employment on local market competition. Under the labor mobility hypothesis, we expect β to be negative: greater penetration of Protocol firms should reduce market concentration. By mitigating hold-up problems, the Protocol facilitates adviser mobility and smoother client transitions, thereby weakening firms' monopsony power in the labor market and diminishing their monopoly power in the product market. Enhanced mobility and client portability also foster cross-firm knowledge spillovers—such as the dissemination of best practices—which erode incumbents' informational advantages, lower entry barriers, and disrupt entrenched knowledge monopolies, ultimately promoting greater competition (Grossman and Hart, 1986; Hart and Moore, 1990; Jovanovic and Rob, 1989).

In contrast, the scale advantage hypothesis predicts a positive β. The Protocol may reinforce the scale advantages of large firms—those with strong client networks and brand recognition—talent advisers may increasingly cluster at dominant players. By enabling high-performing advisers to extract returns on scalable platforms, the Protocol may intensify market concentration and threaten the competitiveness of mid-sized and smaller firms. In this scenario, labor mobility consolidates rather than disperses talent, potentially entrenching market dominance (Katz and Shapiro, 1985; Rosen, 1981).

Table 1 presents summary statistics for all variables used in our analysis, reported at the commuting zone level (Panel A) and the adviser-year level (Panel B). In Panel A, the average local market HHI is 8.536, or 0.08536 when scaled between 0 and 1, with a standard deviation of 5.656. According to U.S. Department of Justice (DOJ) guidelines, markets with an HHI below 0.08 are considered competitive. This indicates that, on average, the financial advisory industry operates under relatively competitive conditions at the local level. The average employment and AUM shares of Protocol firms are 0.421 and 0.747, respectively, suggesting that Protocol-participating firms control a significant portion of the industry's human and AUM at the local level.

In Panel B, the average workplace turnover level is 7.492. The average *Broker Protocol - Adviser* is 0.625, indicating that 62% of advisers are in Protocol firms. The variable *Large firm* has an average value of 0.987, indicating that approximately 1% of firms have AUM larger than $100 million The average *Talent adviser* indicator is 0.281.

Insert Table 1 here

Table 2 presents average firm characteristics for Broker Protocol and non-Broker Protocol firms over the 2012–2022 period. Broker Protocol firms are, on average, larger in size, employing more staff, managing more client accounts, and overseeing higher assets under management (AUM). They also tend to be slightly older than non-Protocol firms. All reported differences are statistically significant.

Insert Table 2 here

3 The Effect of Broker Protocol on Local Competition

In this section, we examine how the presence of Broker Protocol firms affects local competition. We begin by presenting our baseline analysis, which estimates the impact of Broker Protocol firms on competitive dynamics at the local level. We then conduct robustness checks to assess the reliability of our baseline findings.

Table 3 presents the results of our regression analysis. Panel A reports the estimates across model specifications. Column (1) shows the baseline model without fixed effects, Column (2) adds year fixed effects, and Column (3) incorporates both year and commuting zone fixed effects, representing our most stringent specification, as outlined in Equation (1).

Across all models, the coefficient for *Protocol firms - Employment* is negative and statistically significant. This effect persists across both within- (Column 3) and across-location (Column 2) specifications. In Column (3), which presents our tightest specification, a one-standard-deviation increase in *Protocol firms - Employment* is associated with an 0.21% decrease in local HHI, equivalent to 3% of the average local HHI. This finding supports our hypothesis that greater penetration of Protocol firms improves local market competition.

Other coefficients align with expectation. In Column 3, the positive coefficients on Local firm age and Local firm AUM suggest that, within a given location, greater local presence of more established and larger firms is associated with higher market concentration. Notably, the coefficient on Local adviser employment changes sign between the within-location and across-location specifications. Across locations, the coefficient is negative, indicating that in areas with a larger overall financial advisory market, competition is higher (i.e., HHI is lower). However, within a given location, the relationship becomes positive, implying that as the local advisory market grows in size, it tends to become more concentrated. Lastly, in Column 3, the negative coefficient on Local employment growth indicates that faster growth in adviser employment is associated with greater market competition.

To ensure the robustness of our baseline results, we employ an alternative measure of Protocol firm presence: *Protocol firms - AUM*. This metric captures the share of assets under management (AUM) held by Protocol firms relative to the total AUM of all financial advisory firms within each commuting zone in a given year. The results, presented in Panel

B of Table 3, show that the coefficients on *Protocol firms – AUM* remain negative and statistically significant. This reinforces our main finding that greater presence of Broker Protocol firms is associated with increased local market competition.

Insert Table 3 here

4 Endogeneity tests

In this section, we address potential endogeneity concerns in the relationship between the presence of Broker Protocol firms and local labor market competition. Importantly, the decision to join the Broker Protocol is not random. Firms may choose to join the Protocol in anticipation of heightened local competition, rather than their participation causing increased competition—a classic reverse causality issue. Additionally, local markets experiencing economic booms—such as the Shale oil and gas expansion or the tech-driven growth in Austin, Texas—may simultaneously become more competitive and more attractive to Protocol firms, resulting in simultaneity between market size and competitive dynamics.

While our baseline specification accounts for these factors by controlling for local market size, adviser employment growth, and state-level GDP growth, potential endogeneity may still remain. To strengthen the causal interpretation of our results, we implement two complementary identification strategies in this section.

4.1 Single-branch firm removal

First, we narrow our sample to firms operating in geographically diverse locations, excluding those limited to a single market to mitigate the confounding influence of local economic conditions. Firms concentrated in one geographic area are more susceptible to localized factors—such as region-specific demand, regulatory differences, or competitive dynamics—that can obscure the true effect of Broker Protocol participation. In contrast, firms with a broad geographic footprint operate across a range of business environments, reducing reliance on any single local economy. By focusing on these multi-location firms, we improve comparability across firms and more effectively isolate the impact of Broker Protocol adoption on local market competition, thereby strengthening the causal interpretation of our findings. Moreover, since Protocol firms tend to be larger in terms of employment and AUM than non-Protocol firms, focusing on multi-branch firms enhances comparability between the two groups.

We re-estimate our baseline model using the restricted sample of multi-branch firms, and report the results in Table 4. Panels A and B present the results using Protocol penetration measures based on employment and AUM, respectively. Across all specifications, the coefficients on Protocol firms – Employment (Panel A) and Protocol firms – AUM (Panel B) remain negative and statistically significant. The magnitude of the coefficients is comparable to those reported in Table 3, indicating that the relationship is robust to this sample restriction. These findings reinforce the validity of our baseline results and suggest that the observed link between Broker Protocol participation and increased local market competition is not driven by differences between single- and multi-branch firms or by localized economic conditions.

Insert Table 4 here

4.2 Competition-diverse firm

Second, we narrow our sample to firms operating in highly diverse competitive environments. Firms with operations spanning multiple markets face a broader range of competitive conditions, reducing the likelihood that a localized competitive shock drives both Protocol participation and observed market outcomes. By focusing on these firms, we mitigate concerns about reverse causality and ensure that our findings are not driven by idiosyncratic local market conditions. This approach helps isolate the effect of Broker Protocol participation on local competition and strengthens the causal interpretation of our results.

To construct this subsample, we compute, for each firm, the range of Herfindahl-Hirschman Index (HHI) values across all commuting zones in which it operates. Firms are classified as operating in highly diverse markets if this range falls within the top 10% of observed variation in local market competition. We then re-estimate our baseline model using this restricted sample, reporting results based on *Protocol firms–Employment* in Panel A and *Protocol firms–AUM* in Panel B of Table 5.

Across all specifications, the coefficients on both *Protocol firms–Employment* and *Protocol firms–AUM* remain negative and statistically significant, reinforcing the competitive effects of Broker Protocol penetration reported in our baseline results. These findings strengthen the causal interpretation of our main analysis, indicating that the observed relationship between Protocol participation and increased local market competition is not driven by firm geography or localized economic shocks or competition conditions. Instead, they point to a broader institutional mechanism through which the Broker Protocol reshapes competitive dynamics in the financial advisory industry.

Insert Table 5 here

5 Post-Protocol effects and labor mobility mechanism

In this section, we investigate the benefits of firm joining Protocol in terms of employment and AUM, then explore evidence on the labor mobility mechanism that can explain the competition effect of the Protocol on local market competition. In particular, we analyze the workplace turnover post-Protocol and its differential effect regarding to talent adviser and firm size. Finally, we look into the destination of adviser turnover and examine whether adviser are more likely move from large to smaller firms post-Protocol.

5.1 Employment and AUM post-Protocol

To accurately assess the impact of Broker Protocol adoption on firm performance, it is important to account for the fact that firms adopt the protocol at different times. Simply comparing all firms before and after adoption can be misleading, as firms that adopted earlier may already be experiencing changes that influence the results for firms adopting later. We introduce a stacked difference-in-differences approach to address this issue. We construct a separate cohort based on the adoption year and compare each treated group only to firms that have not yet adopted the protocol at that time. Then, we stack these cohort-specific datasets. Our analysis includes cohorts from 2015 to 2019, which allows for a balanced event window of three years before and after adoption.

Table 6 shows that joining the Broker Protocol is associated with significant increases in both firm employment and AUM. The coefficients of Broker Protocol adoption are positive and significant across Column (1) and (2). These findings support that joining Broker Protocol is associated with firm growth in both human and financial capital.

Insert Table 6 here

In addition, we examine whether Broker Protocol adoption benefits small firms. Columns (1) and (2) of Table 7 show that the interaction term between the protocol indicator and the small firm dummy is positive and statistically significant, indicating that small firms experience greater increases in employment and AUM after joining the protocol compared to non-adopting small firms. This suggests that the protocol may help level the playing field for smaller firms by enhancing their ability to attract advisers and retain clients.

Insert Table 7 here

The Broker Protocol seems to improve a signatory's resources by boosting the growth in both AUM and employment, especially small firms. After Protocol adoption, member firms experience an increase in AUM, likely because financial advisers can more easily bring clients with them, expanding the member firm's client base. Adviser headcount also rises, as the Protocol may enhance mobility and make it easier to attract talent. Together, these show how the Protocol enables firms to scale operations and build a more competitive workforce over time.

5.2 Turnover of high quality advisers in large firms

In this section, we examine the labor mobility mechanism as a potential driver of the Protocol's impact on market competition. We hypothesize that by reallocating residual control rights over client relationships from firms to individual advisers, the Broker Protocol increases adviser mobility and facilitates client portability. Mobile advisers act as channels for institutional knowledge transfer, spreading best practices—such as risk management techniques, compliance standards, and technological innovations—to recipient firms. This diffusion of expertise and client relationships weakens incumbents' informational advantages and erodes their client base. By lowering entry barriers and disrupting entrenched knowledge monopolies, the Protocol intensifies local market competition (Jovanovic and Rob, 1989).

To test this mechanism, we analyze post-Protocol workplace turnover, focusing on how turnover rates vary by firm size and adviser quality. Specifically, we estimate a regression at the adviser-year level, where the dependent variable is a binary indicator equal to one if the adviser switched firms in that year, and zero otherwise. We define the treatment variable *Broker Protocol – Adviser* as an indicator equal to one if the adviser's firm was a Protocol signatory in a given year. To examine heterogeneous effects, we interact this indicator with variables capturing firm size and adviser quality, including: *Large firm* is defined as an indicator equal to one if the adviser's firm reports assets under management (AUM) exceeding $100 million, following FINRA classification; *Experienced adviser* equals one if the adviser's tenure is above the 75th percentile of the sample distribution; *Highly credentialed adviser* equals one if the number of professional certifications held by the adviser is at or above the 75th percentile.

Tables 8 and 9 present the regression results for experienced and highly credentialed advisers, respectively. In Table 8, the triple interaction term *Broker Protocol – Adviser* × *Large firm* × *Experienced adviser* is positive and statistically significant, indicating that large firms experience disproportionate outflows of senior talent following Protocol membership. Since senior advisers accumulate knowledge and expertise over times, this increased turnover of these advisers signal evidence of the labor mobility and knowledge transfer drain from large incumbents to competitors in the post-Protocol period.

Insert Table 8 here

Other coefficients exhibit expected signs. The negative coefficient on *Experienced adviser* confirms that senior advisers have lower mobility. Interestingly, while the Protocol appears to increase turnover rate specifically for high-quality advisers at large firms, the double interaction terms—*Broker Protocol – Adviser* × *Large firm* and *Broker Protocol – Adviser* × *Experienced adviser*—are negative and statistically significant. This suggests that the Protocol reduces turnover among other adviser groups. Taken together, the results imply that the Protocol's competitive effects are not driven by broad-based increases in labor mobility, but rather by the selective reallocation of top talent—particularly experienced advisers at large firms.

Table 9 reveals a similar pattern for highly credentialed advisers. The interaction term *Broker Protocol – Adviser* × *Large firm* × *Highly credentialed adviser* is consistently positive and statistically significant across specifications. This finding indicates that, following a firm's Protocol adoption, highly credentialed advisers at large firms exhibit increased mobility. The result supports the view that the Protocol facilitates the reallocation of high-value human capital at large firms and contributes to reshape competitive dynamics.

Insert Table 9 here

5.3 Turnover destination - From large to smaller firms

Finally, to provide additional evidence on the mechanism that the Protocol disproportionate benefits smaller firms by facilitating turnover rate of advisers, we investigate the destination of adviser turnover. We construct a dependent variable of workplace turnover of advisers who move to a smaller firms. This allows us to isolate the direction of the mobility pattern. We conduct the test at the adviser-year level, similarly to those at Table 8 and 9. We adopt the same treatment variable *Broker Protocol – Adviser* from Table 8 and 9 as an indicator equal to one if the adviser's firm was a Protocol signatory in a given year and report the results in Table 10.

The number of observations in Table 10 is smaller than those in Table 8 and 9 because we exclude the turnover cases from small to larger firms. cross all specifications, we observe a a positive coefficient on *Broker Protocol - Adviser*, indicating that the workplace turnover from large to small firms accelerate following the Protocol adoption. The result provide additional evidence to support the mobility mechanism from larger to smaller firms for the Protocol competition effect.

Insert Table 10 here

6 Conclusion

This paper examines how the Broker Protocol—a voluntary non-solicitation agreement—shapes competition in local financial advisory markets. We find that higher local penetration of Protocol-member firms intensifies local market competition. This negative relationship between Protocol participation and local market concentration holds across a range of specifications, geographic definitions, and alternative measures of both Protocol penetration and market competition. The effect remains robust in identification tests that restrict the sample to multi-branch and geographically diverse firms. Moreover, firms that join the Protocol experience significant growth in AUM and employment, while larger firms suffer a talent drain, particularly of high-quality advisers, who disproportionately move to smaller competitors. These findings highlight the Protocol's role in reallocating human capital toward smaller firms, thereby reshaping the competitive landscape.

Our results suggest that the Protocol mitigates hold-up frictions associated with client relationships, thereby weakening firm-level monopsony power through enhanced adviser mobility and reduced entry barriers for rival firms. By relaxing legal constraints on adviser movement, the Protocol promotes more equitable access to talent and contributes to greater market decentralization. This voluntary institutional mechanism facilitates labor mobility without direct regulatory intervention and provides a compelling case of how reconfiguring property rights over human capital can foster more competitive and dynamic market environments. These insights have broader implications for the design of labor market institutions, especially in human-capital-intensive industries where talent is a key source of competitive advantage and market power is concentrated.

Table 1: **Summary statistics**

This table reports summary statistics for the variables used in our empirical analysis. The sample covers 570,036 unique financial advisers affilicated with 15,602 firms across 741 unique commuting zones over the sample period 2012-2022. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. AUM-related variables (million) are reported in CPI-adjusted 2012 U.S. dollars. Variables definition are provided in Appendix A.

Variable	(1) N	(2) Mean	(3) SD	(4) P25	(5) P50	(6) P75
Panel A: Location-year level						
Local HHI	7,156	10.818	6.970	5.15	8.64	14.84
Protocol firms-Employment	7,156	0.420	0.129	0.33	0.42	0.51
Protocol firms-AUM	7,156	0.689	0.201	0.57	0.76	0.85
Local firm age	7,156	3.409	0.169	3.32	3.43	3.54
Local firm AUM	7,156	24.966	0.794	24.45	24.99	25.57
Local adviser employment	7,156	4.612	1.866	3.09	4.29	5.78
Local employment growth	7,156	0.678	9.029	-2.43	0.00	3.49
State GDP growth	7,156	2.059	2.316	0.80	2.00	3.40
Panel B: Adviser year level						
Workplace turnover	3,229,765	7.492	26.327	0.00	0.00	0.00
Broker Protocol - Adviser	3,229,765	0.625	0.484	0.00	1.00	1.00
Large firm	3,229,765	0.987	0.114	1.00	1.00	1.00
Experienced adviser	3,229,765	0.281	0.449	0.00	0.00	1.00
Talent adviser	3,229,765	0.285	0.451	0.00	0.00	1.00

Table 2: **Cross-Sectional Comparison by Protocol Status**
This table compares the average characteristics of Broker Protocol and non-Broker Protocol firms over the period 2012-2022. Broker Protocol firms are those that adopts Broker Protocol in a given year. Non-Broker Protocol are those that do not adopt Broker Protocol in a given year. Firm AUM (million) is reported in CPI-adjusted 2012 dollars. Additional variable definitions are provided in Appendix A.

Variable	Protocol firm	Non-Protocol firm	Diff.	t-stat
	(1)	(2)	(3)	(4)
Number of employees	3.828	2.333	.641	-22.31
Number of accounts	7,866.064	2,640.527	1.979	-30.69
Firm age	13.31	10.401	.28	-23.41
Firm AUM (millions)	9,668.31	5,916.249	.634	-4.65

Table 3: **The effect of Broker Protocol on local market competition**

This table presents regression estimates examining the relationship between Broker Protocol firm presence and local market competition over the 2012–2022 period. The dependent variable is the Herfindahl-Hirschman Index (HHI), computed as the sum of squared employment-based market shares of all advisory firms within each commuting zone and scaled by 100. In Panel A, *Protocol firms – Employment* is defined as the ratio of adviser employment at Protocol firms to total adviser employment in each commuting zone. In Panel B, *Protocol firms – AUM* is defined as the ratio of AUM at Protocol firms to the total AUM of all advisory firms within each commuting zone. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Protocol firms - Employment

	(1)	(2)	(3)
Protocol firms-Employment	-3.478***	-4.872***	-1.591***
	(-3.34)	(-4.90)	(-3.27)
Local firm age	-2.528**	-8.346***	4.010***
	(-2.20)	(-8.57)	(8.31)
Local adviser employment	-2.788***	-3.320***	-0.347
	(-19.28)	(-26.25)	(-0.57)
Local firm AUM	0.381	-0.920***	0.539***
	(1.12)	(-2.76)	(4.22)
State GDP growth	0.045*	0.046	0.018
	(1.67)	(1.24)	(1.55)
Local employment growth	0.014*	0.033***	-0.007***
	(1.84)	(4.38)	(-3.07)
Constant	24.141***	79.493***	-14.083***
	(4.29)	(10.81)	(-2.78)
Observation	7,156	7,156	7,156
Adj. R-squared	0.530	0.563	0.955
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

The effect of Broker Protocol on local market competition - Con't

Panel B - Protocol firms - AUM

	(1)	(2)	(3)
Protocol firms-AUM	-7.968***	-6.549***	-2.207***
	(-8.16)	(-5.72)	(-4.53)
Local firm age	-2.749**	-6.667***	3.777***
	(-2.13)	(-6.83)	(8.04)
Local adviser employment	-2.498***	-2.920***	-0.082
	(-18.97)	(-20.63)	(-0.13)
Local firm AUM	0.480	-0.382	0.602***
	(1.28)	(-0.84)	(4.48)
State GDP growth	0.035	0.048	0.020*
	(1.40)	(1.33)	(1.73)
Local employment growth	0.023***	0.034***	-0.007***
	(2.97)	(4.72)	(-2.93)
Constant	25.141***	60.949***	-15.221***
	(4.41)	(5.64)	(-2.97)
Observation	7,156	7,156	7,156
Adj. R-squared	0.571	0.583	0.955
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Table 4: **Multi-branch firms**

This table reports regression estimates examining the relationship between Broker Protocol firm presence and local market competition for a subsample of multi-branch firms over the 2012–2022 period. Firms are included in the sample if they operate more than one branch. The dependent variable is the Herfindahl-Hirschman Index (HHI), computed as the sum of squared employment-based market shares of all advisory firms within each commuting zone and scaled by 100. In Panel A, *Protocol firms – Employment* is defined as the ratio of adviser employment at Protocol firms to total adviser employment in each commuting zone. In Panel B, *Protocol firms – AUM* is defined as the ratio of AUM at Protocol firms to the total AUM of all advisory firms within each commuting zone. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Protocol firms - Employment

	(1)	(2)	(3)
Protocol firms - Employment	-14.68***	-14.80***	-3.365***
	(-17.12)	(-17.59)	(-6.664)
Local firm age	5.751***	0.307	5.542***
	(5.907)	(0.246)	(7.825)
Local adviser employment	-0.778***	-1.007***	4.305***
	(-8.239)	(-9.265)	(7.728)
Local firm AUM	1.485***	0.941***	0.957***
	(7.222)	(3.440)	(5.056)
State GDP growth	-0.0265	-0.0337	-0.00492
	(-1.054)	(-0.975)	(-0.381)
Local employment growth	0.0646***	0.0912***	-0.0160***
	(3.947)	(5.426)	(-3.150)
Constant	-37.89***	-4.294	-55.33***
	(-8.982)	(-0.470)	(-8.682)
Observations	7,156	7,156	7,156
Adj. R-squared	0.224	0.233	0.939
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Panel B - Protocol firms - AUM

	(1)	(2)	(3)
Protocol firms - AUM	-11.01***	-11.53***	-3.300***
	(-15.32)	(-11.21)	(-6.322)
Local firm age	-0.634	0.264	4.747***
	(-0.506)	(0.203)	(7.136)
Local adviser employment	-0.983***	-0.925***	4.885***
	(-11.36)	(-7.827)	(8.024)
Local firm AUM	1.535***	1.722***	1.216***
	(6.530)	(4.412)	(5.887)
State GDP growth	-0.0334	-0.0173	0.00672
	(-1.313)	(-0.435)	(0.428)
Local employment growth	0.109***	0.110***	-0.0175***
	(7.223)	(6.922)	(-2.838)
Constant	-14.22***	-21.91**	-61.10***
	(-4.838)	(-2.028)	(-8.271)
Observations	7,156	7,156	7,156
Adj. R-squared	0.180	0.182	0.939
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Table 5: **Firms operating in diverse competitive environments**
This table presents regression estimates of the relationship between Broker Protocol firm presence and local market competition for a subsample of firms operating across diverse competitive environments during the 2012–2022 period. Firms are included in the sample if they maintain branches in commuting zones that span the top 10% of the observed range of local market competition within the dataset. The dependent variable is the Herfindahl-Hirschman Index (HHI), computed as the sum of squared employment-based market shares of all advisory firms within each commuting zone and scaled by 100. In Panel A, *Protocol firms – Employment* is defined as the ratio of adviser employment at Protocol firms to total adviser employment in each commuting zone. In Panel B, *Protocol firms – AUM* is defined as the ratio of AUM at Protocol firms to the total AUM of all advisory firms within each commuting zone. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Protocol firms - Employment

	(1)	(2)	(3)
Protocol firms - Employment	-14.48***	-14.37***	-3.340***
	(-15.93)	(-16.17)	(-6.160)
Local firm age	0.565	-9.231***	4.544***
	(0.598)	(-7.715)	(6.605)
Local adviser employment	-0.895***	-1.294***	4.934***
	(-9.414)	(-13.89)	(7.472)
Local firm AUM	1.888***	0.865***	0.945***
	(10.24)	(3.628)	(4.508)
State GDP growth	-0.0320	-0.0511	-0.00293
	(-1.446)	(-1.425)	(-0.219)
Local employment growth	0.0500***	0.0907***	-0.0192***
	(3.330)	(5.632)	(-3.447)
Constant	-29.54***	31.82***	-54.84***
	(-7.610)	(3.731)	(-7.325)
Observations	7,156	7,156	7,156
Adj. R-squared	0.207	0.231	0.939
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Panel B - Protocol firms - AUM

	(1)	(2)	(3)
Protocol firms - AUM	-12.05***	-10.98***	-3.351***
	(-15.05)	(-9.563)	(-4.949)
Local firm age	-7.592***	-11.24***	3.681***
	(-6.598)	(-9.171)	(4.543)
Local adviser employment	-1.077***	-1.266***	5.454***
	(-13.88)	(-11.15)	(10.21)
Local firm AUM	2.155***	1.639***	1.229***
	(8.468)	(4.001)	(4.813)
State GDP growth	-0.0520**	-0.0697**	-0.00358
	(-2.027)	(-2.119)	(-0.289)
Local employment growth	0.0908***	0.109***	-0.0205***
	(6.004)	(6.592)	(-3.378)
Constant	-4.386	21.29*	-60.61***
	(-1.096)	(1.789)	(-8.090)
Observations	7,156	7,156	7,156
Adj. R-squared	0.177	0.182	0.939
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Table 6: **The effect of Broker Protocol on participating firms - Stacked regression**
This table presents regression estimates of the relationship between Broker Protocol participation on firm performance over the 2012–2022 period. The dependent variable in Column 1 is Firm employment, measured as the natural logarithm of the number of advisers employed by each firm in a given year. The dependent variable in Column 2 is firm AUM, measured as the natural logarithm of the firm's AUM. *Broker Protocol indicator* equals one for the years in which a firm is a Protocol participant. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Firm employment	Firm AUM
	(1)	(2)
Broker Protocol indicator	0.222***	0.262***
	(14.37)	(11.10)
Constant	1.143***	20.00***
	(2,092)	(18,642)
Observations	291,289	97,307
Adj. R-squared	0.967	0.965
Firm-cohort FE	Yes	Yes
Year-cohort FE	Yes	Yes

Table 7: **The effect of Broker Protocol and small firms - Stacked regression**

This table presents regression estimates of the relationship between Broker Protocol participation on firm performance over the 2012–2022 period. The dependent variable in Column 1 is Firm employment, measured as the natural logarithm of the number of advisers employed by each firm in a given year. The dependent variable in Column 2 is firm AUM, measured as the natural logarithm of the firm's AUM. *Broker Protocol indicator* equals one for the years in which a firm is a Protocol participant. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Firm employment	Firm AUM
	(1)	(2)
Broker protocol indicator × Small firm	0.534***	0.922***
	(3.707)	(4.497)
Small firm	-0.218***	-1.807***
	(-16.77)	(-107.4)
Broker protocol indicator	0.277***	0.243***
	(14.21)	(11.02)
Constant	0.918***	20.03***
	(996.3)	(19,452)
Observations	97,770	97,307
Adj. R-squared	0.960	0.970
Firm-cohort FE	Yes	Yes
Year-cohort FE	Yes	Yes

Table 8: **Workplace turnover post-Protocol - Experienced advisers in large firms**

This table presents regression estimates of the relationship between Broker Protocol participation and workplace turnover among financial advisers with long tenure and those employed at large firms during the 2012–2022 period. The dependent variable, *Workplace Turnover* is an indicator equal to one if an adviser changes firm in a given year, and zero otherwise, multiplied by 100. *Broker Protocol - Adviser* is an indicator equal to one if the adviser's firm is a Protocol signatory in that year and zero otherwise. *Experienced adviser* indicator equals one if the adviser's tenure exceeds the 75^{th} percentile of the sample distribution. *Large firm* is an indicator equal to one if the adviser's firm reports AUM greater than US$100 million. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Broker Protocol - Adviser × Large firm × Experienced adviser	7.737**	7.690**	7.580**
	(2.124)	(2.048)	(1.986)
Experienced adviser	-12.44***	-12.41***	-12.28***
	(-5.980)	(-5.951)	(-6.032)
Broker Protocol - Adviser	5.449*	4.358	4.072
	(1.768)	(1.297)	(1.277)
Large firm	-1.309	-1.526	-1.896
	(-0.487)	(-0.592)	(-0.840)
Broker Protocol - Adviser × Large firm	-7.463**	-6.237*	-6.053*
	(-2.005)	(-1.709)	(-1.741)
Broker Protocol - Adviser × Experienced adviser	-5.651*	-5.647*	-5.600*
	(-1.876)	(-1.782)	(-1.751)
Large firm × Experienced adviser	1.300	1.409	1.346
	(0.501)	(0.552)	(0.531)
Constant	12.81***	12.91***	13.33***
	(5.921)	(6.087)	(7.573)
Observations	3,229,765	3,229,765	3,229,765
Adj. R-squared	0.029	0.032	0.035
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Table 9: **Workplace turnover post-Protocol - Highly credentialed advisers in large firms**

This table presents regression estimates of the relationship between Broker Protocol participation and workplace turnover among financial advisers with high qualifications and those employed at large firms during the 2012–2022 period. The dependent variable, *Workplace Turnover* is an indicator equal to one if an adviser changes firm in a given year, and zero otherwise, multiplied by 100. *Broker Protocol - Adviser* is an indicator equal to one if the adviser's firm is a Protocol signatory in that year and zero otherwise. *Highly credentialed adviser* indicator equals one if the number of professional certificates held by an adviser is greater than or equal to the 75^{th} percentile of the sample distribution. *Large firm* is an indicator equal to one if the adviser's firm reports AUM greater than US$100 million. Additional variables are defined as in Appendix A. t-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Broker Protocol - Adviser × Large firm × Highly credentialed adviser	3.951*	3.817*	3.505*
	(1.942)	(1.905)	(1.776)
Highly credentialed adviser	5.754***	5.776***	5.486***
	(5.158)	(5.173)	(5.066)
Broker Protocol - Adviser	6.080**	4.712	4.606
	(2.208)	(1.605)	(1.638)
Large firm	-1.013	-1.336	-1.542
	(-0.455)	(-0.667)	(-0.872)
Broker Protocol - Adviser × Large firm	-7.210**	-5.670*	-5.806*
	(-2.199)	(-1.804)	(-1.937)
Broker Protocol - Adviser × Highly credentialed adviser	-4.492**	-4.363**	-4.016**
	(-2.508)	(-2.399)	(-2.223)
Large firm × Highly credentialed adviser	-3.910***	-3.665***	-3.510***
	(-2.785)	(-2.697)	(-2.651)
Constant	8.758***	8.896***	9.282***
	(5.457)	(6.053)	(7.444)
Observations	3,229,765	3,229,765	3,229,765
R-squared	0.001	0.005	0.008
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Table 10: **Workplace turnover from large to smaller firm**

This table presents regression estimates of the relationship between Broker Protocol participation and workplace turnover among financial advisers moving from large to small firms during the 2012–2022 period. The sample includes advisers that have moved their jobs from large to small firms. The dependent variable, *Workplace Turnover* is an indicator equal to one if an adviser changes firm in a given year, and zero otherwise, multiplied by 100. *Broker Protocol - Adviser* is an indicator equal to one if the adviser's firm is a Protocol signatory in that year and zero otherwise. Additional variables are defined as in Appendix A. *t*-statistics are provided in parentheses. Robust standard errors are clustered at the communiting zone level. The superscript $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Broker Protocol - Adviser	6.872***	7.701***	7.428***
	(3.504)	(3.846)	(3.722)
Constant	10.15***	9.955***	10.02***
	(13.10)	(13.07)	(14.37)
Observations	2,906,193	2,906,193	2,906,193
R-squared	0.008	0.012	0.019
Year FE	No	Yes	Yes
CZs FE	No	No	Yes

Figure 1: **The number of Protocol firms over the 2004–2023 period**
This graph presents the cumulative number of financial advisory firms that joined the Broker Protocol from its inception in 2004 through 2022.

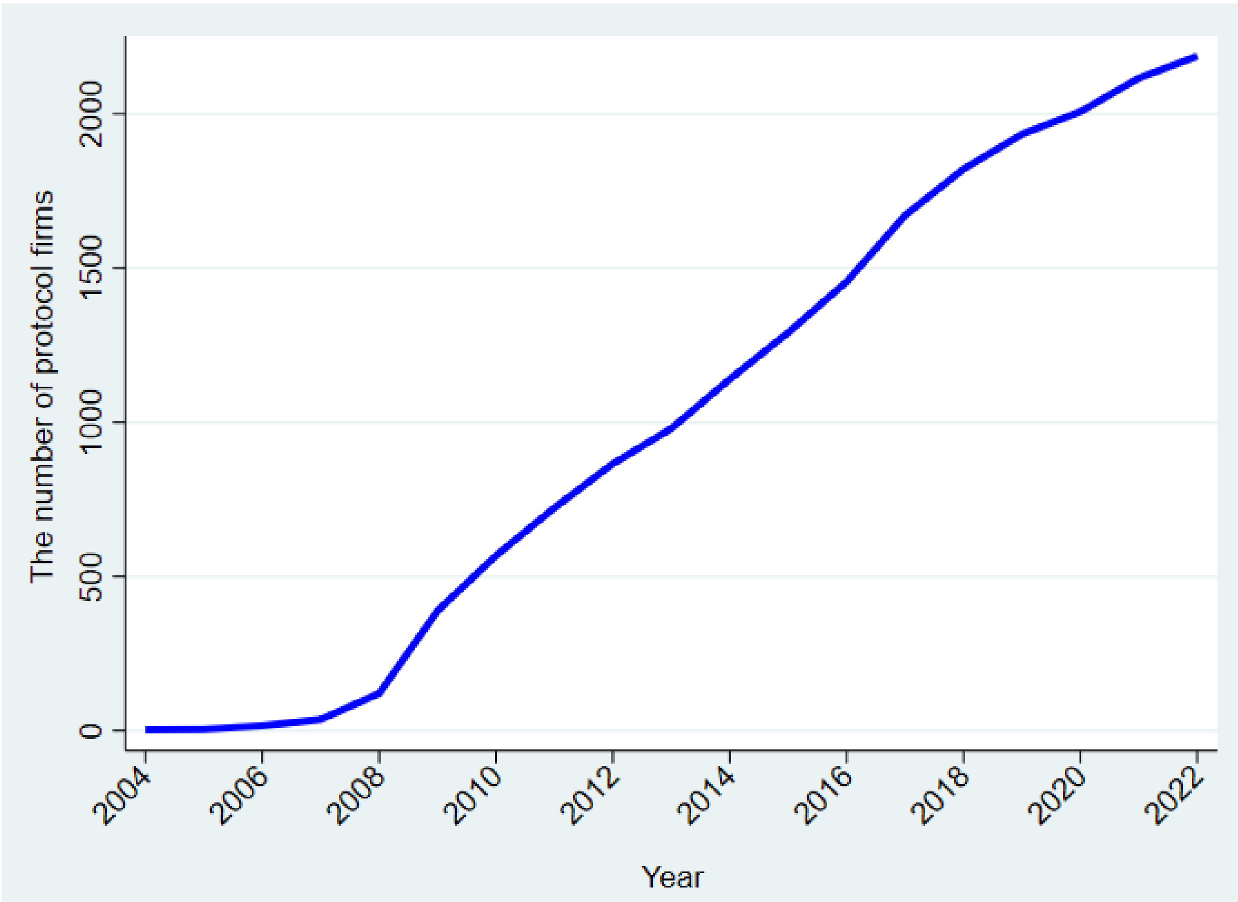

Figure 2: **Industry Herfindahl-Hirschman Index (HHI)**
This graph presents the industry HHI over the 2012-2022 period. The HHI is calculated as the sum of squared employment-based market shares of all financial advisory firms within each commuting zone.

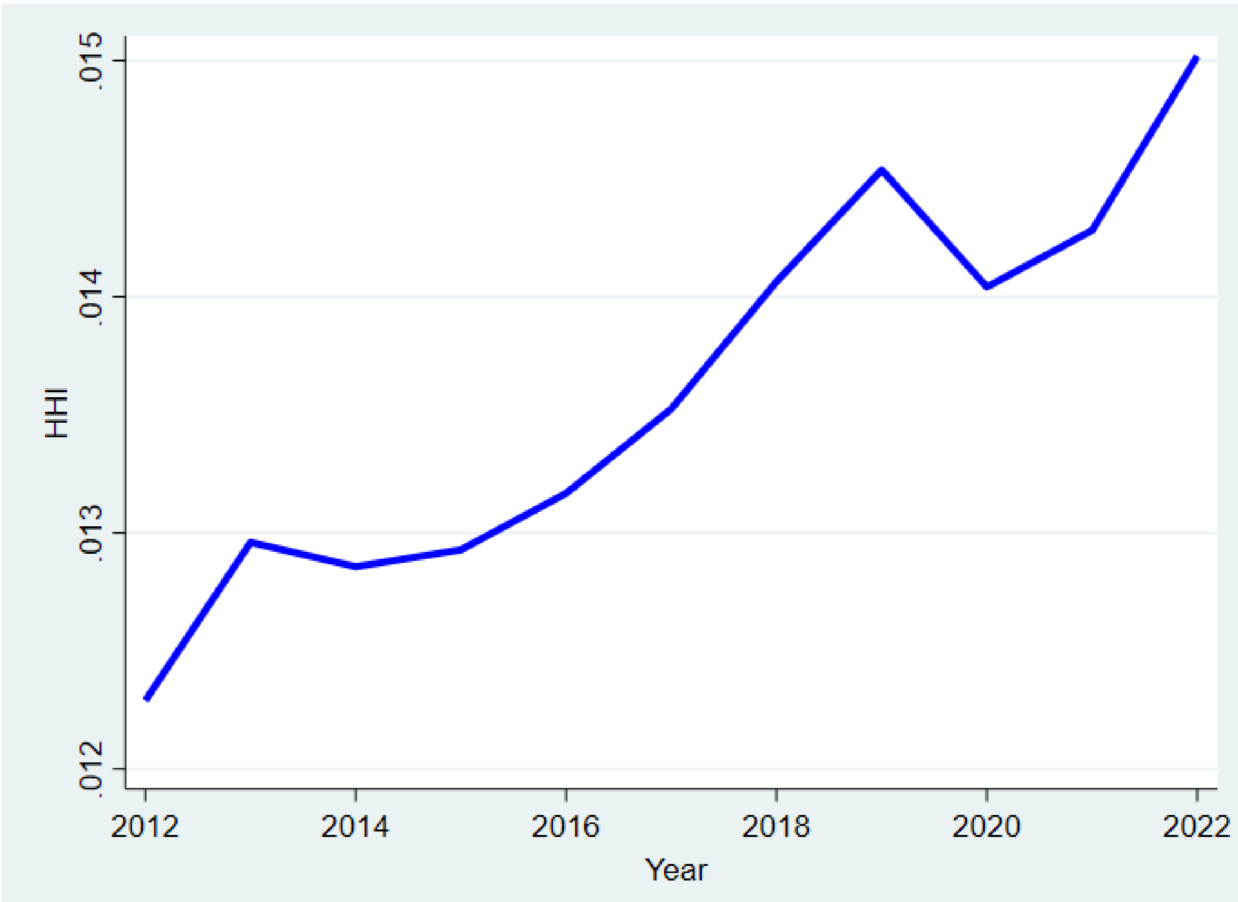

Figure 3: **Market concentration of the top decile of firms**
This graph shows the cumulative market shares of the top 10% largest firms over the 2012-2022 period. The red bars represent the market shares held by the top decile of firms, while the blue bars represent the combined market share of all remaining firms.

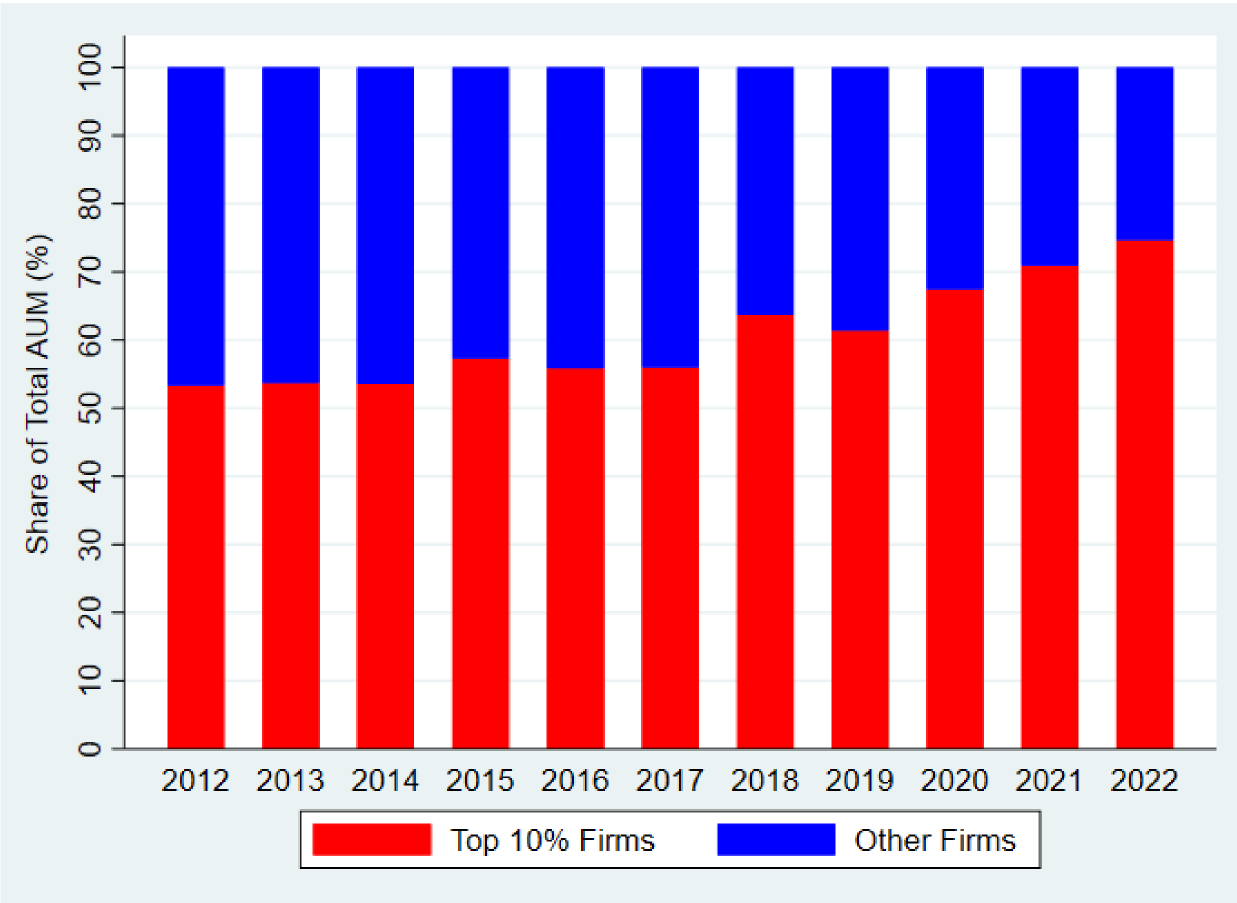

Table 11: **Appendix A - Variable definitions**

Variable	Description	Data sources
Local competition		
Local HHI	The sum of squared employment-based market shares of all adviser firm in each commuting zone, multiplied by 100.	BrokerCheck & IAPD
Broker Protocol		
Protocol firms - AUM	The ratio of AUM by Protocol firms to the total AUM of all advisory firms within each commuting zone.	J.S. Held, BrokerCheck & IAPD
Protocol firms - Employment	The ratio of adviser employment at Protocol firms to total adviser employment in each commuting zone.	J.S. Held, BrokerCheck & IAPD
Broker Protocol indicator	An indicator equals one for the years in which a firm is a Protocol participant	J.S. Held
Broker Protocol - Adviser	an indicator equal to one if the adviser's firm is a Protocol signatory in a given year	J.S. Held
Other firm and state variables		
Local firm age	The natural logarithm of the average firm age, measured as the number of years in operation, across all firms within each commuting zone.	BrokerCheck & IAPD
Local firm AUM	The natural logarithm of the average firm's AUM within a commuting zone	Form ADV
Local adviser employment	The natural logarithm of the total number for advisers in a commuting zone	BrokerCheck & IAPD
Local adviser growth	The growth rate of total financial advisory employment in a commuting zone	BrokerCheck & IAPD
Large firm	An indicator equal to one if the adviser's firm reports AUM greater than US$100 million.	Form ADV

Appendix A - Variable definitions (Con't)

Variable	Description	Data sources
Number of accounts	The firm's number of customer accounts in a given year	Form ADV
Firm AUM (million)	The total value of the firm's assets under management.	Form ADV
Firm AUM	The natural logarithm of a firm's assets under management.	Form ADV
State GDP growth	The growth rate of state real GDP growth rate	U.S. Bureau of Economic Analysis (BEA)
Adviser variable		
Workplace turnover	An indicator equal to one if a financial adviser changes firms in a given year, and zero otherwise, multiplied by 100.	BrokerCheck & IAPD
Talent adviser	An indicator equals one if the number of professional certificates held by an adviser is greater than or equal to the 75^{th} percentile of the sample distribution.	BrokerCheck & IAPD
Experienced adviser	An indicator equals one if the adviser's tenure exceeds the 75^{th} percentile of the sample distribution.	BrokerCheck & IAPD

Chapter 3

From Bad Seed to Rotten Apple: Does Launching a Career in a High-Misconduct Firm Influence Financial Advisers' Misconduct?

Sapphasak Chatchawan[1]

Abstract – I investigate the impact of early career experiences in top misconduct financial advisory firms on the propensity for financial advisers to commit financial misconduct. The findings indicate that financial advisers who begin their careers at high-misconduct firms are more likely to engage in financial misconduct, experience longer job transitions, and face higher likelihood of being barred from the industry. These relationships remain robust even after controlling for endogeneity. Overall, the results provide compelling evidence of negative career imprinting, highlighting the long-term effects of early career environments on professional behavior in the financial advisory sector. Our findings underscore the need for targeted interventions, such as enhanced supervision of early-career training and mentorship, to disrupt the cycles of misconduct in the financial advisory industry.

Keywords: Career imprinting; Corporate governance; Financial adviser industry; Financial fraud

JEL classification: J61, J82; G24, G34

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1 Introduction

Over recent decades, U.S. households have increasingly sought financial advisers for investment and financial decisions, reflecting a growing need for professional expertise. According to the U.S. Survey of Consumer Finance [2], 57% of U.S. households rely on financial professionals for borrowing and investing advice. This demand has led to financial professionals comprising 10% [3] of total employment in the U.S. finance and insurance sector as of 2023. The Investment Adviser Association (IAA)[4] reports a significant rise in assets under management (AUM) by financial advisers, from \$83.7 trillion in 2018 to \$114 trillion in 2022, alongside a 42% increase in clients, from 43.6 million to 61.9 million during the same period.

Despite their critical role, financial professionals have been involved in repeated misconduct scandals. A notable example is Wells Fargo, where thousands of employees engaged in unethical practices—such as opening unauthorized accounts—under pressure from aggressive sales targets and a permissive corporate culture (Tayan, 2019). Against this backdrop, this study investigates whether early-career exposure to such high-misconduct environments, like Wells Fargo, imprints individuals with norms that increase the likelihood of future misconduct in their careers.

The influence of early career exposure to high-misconduct corporate environment on financial misconduct can operate through the following channel. Commencing a career at a firm with widespread misconduct may normalize unethical behavior, increasing the risk of future misconduct through the imprinting effect—where early experiences shape long-term attitudes and actions. Bowlby et al. (1992)'s attachment theory suggests that individuals

[2] https://www.federalreserve.gov/econres/scf-previous-surveys.htm
[3] https://www.bls.gov/oes/current/naics2_52.htm
[4] https://www.investmentadviser.org/wp-content/uploads/2023/06/Snapshot2023_Final.pdf

form emotional bonds with their initial environments, which can anchor behaviors and values over time (Louis, 1980; Ashforth and Saks, 1996; Higgins, 2005). Likewise, Bandura (1986)'s concept of self-efficacy implies that when unethical behavior is rewarded early on, individuals may perceive it as acceptable, reinforcing their confidence in acting similarly in the future (Bandura et al., 2001; Bandura, 2014; Fida et al., 2018). These psychological theories explain how early exposure to unethical firms can leave lasting imprints on advisers' ethical standards.

To study financial misconduct, I construct a comprehensive adviser-year panel dataset of six million observations from 2012 to 2022, based on publicly available disclosures from the Financial Industry Regulatory Authority (FINRA)'s BrokerCheck and the United States Securities and Exchange Commission (SEC)'s the Investment Adviser Public Disclosure (IAPD) database. The dataset includes employment histories, misconduct disclosures, and qualification exam records for all registered financial advisers. Financial misconduct is conservatively defined following Egan et al. (2019), using six specific disclosure categories that clearly indicate wrongdoing: Customer Dispute—Settled, Regulatory Final, Employment Separation after Allegations, Customer Dispute—Award/Judgment, Criminal—Final Disposition, and Civil Final. These categories account for 60% of the total disclosure incidents.

To construct the key independent variable, I identify financial advisers who begin their careers at firms with high levels of misconduct. For each year, I calculate the firm-level misconduct-per-employee ratio (FMPE) by dividing the total number of misconduct incidents by the total number of employees. Firms are then ranked annually based on their FMPE values, and those in the top 20% are classified as top misconduct firms. The indicator variable, *Top misconduct firm*, equals one for newly registered advisers who start their careers at these firms in a given year, and zero otherwise. This variable captures early exposure to high-misconduct organizational settings and serves as a proxy for cultural imprinting shaped by unethical professional norms in the first workplace.

The analysis reveals that starting a financial adviser career at a top misconduct firm is associated with approximately twice[5] the likelihood of committing financial misconduct compared to peers who start at non-top misconduct firms within the same city and year. This finding supports the career imprinting hypothesis, which argues that early exposure to a negative corporate culture significantly shapes future behavior. Moreover, the results are robust across all alternative measures of financial misconduct such as the stock of misconduct (Egan et al., 2019) and cumulative misconduct.

To isolate the effect of the top misconduct firm environment—independent of personal propensity for financial misconduct-—I exclude advisers who committed misconduct during their first job spell. This restriction allows the analysis to focus solely on the broader impact of firm culture. The results confirm that even after excluding those advisers with their own tendency of committing financial misconduct in their own first job, financial advisers who begin their careers at top misconduct firms remain significantly more likely to engage in financial misconduct later in their careers.

To address endogeneity concerns—particularly the possibility that omitted variables such as local market competition, racial concordance, or regional enforcement intensity may influence both the choice of first employer and future misconduct—I implement an instrumental variables (IV) strategy using the historical state unemployment rate at the time of labor market entry. This rate serves as a valid instrument under two conditions. First, it satisfies the relevance condition: during periods of high unemployment, new advisers face fewer job opportunities and are more likely to accept positions at firms with higher misconduct rates

[5]The average probability of fraud is low, but its standard deviation is large—about 6.8, which is over 20 times the mean—indicating a highly dispersed distribution. This implies that the estimated effect, while large, is not implausibly extreme.

due to reduced bargaining power and limited mobility. Second, it meets the exclusion restriction: the unemployment rate at entry affects future misconduct only through its impact on initial job placement, not through any direct channel, as advisers can relocate or change firms after their first job.

Our first-stage result shows that the historical unemployment rate is significant and positively associated with the likelihood of commencing a career at a top misconduct firm. This is plausible because in periods of high unemployment, job seekers face greater competition and fewer opportunities, which reduces their ability to avoid firms with poor reputations. As a result, new advisers are more likely to accept positions at firms with higher misconduct rates simply due to limited alternatives. In the second stage, we find that the historical unemployment rate remains positive and significant, reenforcing the conclusion that early career placement in high misconduct firms increases the likelihood of future misconduct.

Building on the established causal results, I examine whether early-career experiences exert a stronger influence on adviser behavior than later ones. Specifically, I compare advisers who began their careers at top misconduct firms with those who joined such firms as their second employer. Using adviser-level employment histories from 2012–2022, I construct a sample of advisers who switched into top misconduct firms as their second job but had no prior misconduct. The results show that only those exposed to high-misconduct environments at the start of their careers are significantly more likely to commit future misconduct. In contrast, joining a top misconduct firm as a second workplace does not increase subsequent misconduct risk. This supports the mechanism that cultural imprinting occurs during the formative early-career stage, when advisers are more susceptible to adopting workplace norms.

To further understand the factors shaping the imprinting effect of the first workplace, I examine the career outcomes of financial advisers whose first job spell occurs at top misconduct firms. These advisers tend to face long-term disadvantages in the labor market. Specifically, after exiting their initial job spell, they experience slower re-employment, suggesting that the reputational stigma of having started in a high-misconduct environment lingers—even in the absence of personal misconduct. This finding underscores how early exposure to unethical firm culture during the initial job spell can have lasting negative effects on an adviser's career trajectory, limiting both mobility and employability over time.

Lastly, I examine whether starting a career at a top misconduct firm increases the likelihood of being barred by FINRA—the industry's most severe disciplinary action. If early workplace norms shape long-term behavior, then beginning in a firm with a deeply unethical culture may lead financial advisers toward serious violations. The analysis shows that advisers who start in high-misconduct firms face a significantly greater risk of being barred from the industry. This highlights the lasting impact of early exposure to misconduct, which not only influences future behavior and career mobility but also raises the likelihood of the most serious regulatory sanctions.

Together, these findings reveal that launching a career at a high-misconduct firm significantly increases the risk of future misconduct, prolongs job transitions, and raises the likelihood of being permanently barred from the industry. These effects are driven by early cultural imprinting and are strongest when misconduct exposure occurs at the start of a career, rather than later. The results highlight the role of early workplace environments in shaping long-term professional behavior and career outcomes in the financial advisory industry.

This study contributes to the literature on determinants of financial adviser misconduct. Previous research examine location factors like city norms (Parsons et al., 2018), market competition (Gelman et al., 2021), housing returns (Dimmock, Gerken, and Van alfen, 2021), childhood location (Clifford et al., 2019), racial concordance (Clifford et al., 2023), and local corruption (Pham et al., 2024), as well as individual characteristics such as gender (Egan et al., 2018), repeat offenses (Egan et al., 2019), criminal records (Law and Mills, 2019), experiences during recessions (Law and Zuo, 2021), and minority status (Law and Zuo, 2022). This study contributes to this strand of the literature by examining how unfavorable corporate cultures impact financial misconduct.

In addition, this study extends the career imprinting literature in finance. Pertinent research has explored the imprinting effects of adverse experiences like poverty (Du and Ren, 2024), famine (Xu et al., 2024), and disasters (Y. Chen et al., 2021) on CEOs, as well as formative backgrounds such as military service (Zhang et al., 2022). While the majority of this literature focuses on CEOs, this paper provides the first evidence of how early-career exposure to negative corporate culture shapes long-term career outcomes and ethical behavior in the financial advisory industry. This setting offers a unique opportunity to observe a large population of professionals over time, with detailed employment and misconduct records. By shifting the focus from elite executives to rank-and-file financial advisers, the study broadens the scope of imprinting research and demonstrates that early organizational environments can leave persistent marks on individual conduct even outside the executive suite.

The paper proceeds as follows: Section 2 introduces the data and empirical strategy. Sections 3 and 4 present the main results and address endogeneity. Section 5 and 6 investigates the mechanisms and career outcomes. Section 7 concludes.

2 Data and sample construction

In this section, we describe the data sources, the data scraping technique, the method for identifying firms with high misconduct rates, and our empirical strategy.

2.1 Data construction

We collect data on financial advisers from the U.S. Securities and Exchange Commission (SEC)'s Investment Adviser Public Disclosure (IAPD) and the Financial Industry Regulatory Authority (FINRA)'s BrokerCheck websites.[6] We use the spelling "financial adviser" with an "e," in line with the Investment Advisers Act of 1940. Firm-level data are obtained from the SEC's Form ADV. Following Egan et al. (2019), we use the term "financial adviser" to include both investment advisers and brokers.

Our data include both investment advisers and brokers. Individuals who provide investment advice on behalf of Registered Investment Adviser (RIA) firms are known as Investment Adviser Representatives (IARs). Both IARs and RIAs are held to a fiduciary standard. Investment advisers are regulated by the SEC and state securities regulators. In contrast, broker-dealer firms engage in the buying and selling of securities, and their registered representatives, which is known as brokers, are subject to a lower suitability standard. The key difference is that IARs must prioritize their clients' best interests, while brokers are only required to recommend products that are suitable to the client's financial situation. Any individuals can dually register as IARs and Broker.

To construct a survival bias-free dataset, I queried CRD numbers from FINRA's BrokerCheck and the SEC's IAPD, where each financial adviser is assigned a unique CRD number, enabling tracking of their professional history. Both websites provide APIs that return JSON data, which I converted into data frames. After data cleaning, I obtained an unbalanced panel dataset at the adviser level.

The disciplinary events include civil, criminal, and regulatory events and disclosed investigations, which FINRA classifies into 23 disclosure categories. Following Egan et al. (2019),

[6] The FINRA BrokerCheck website is available at https://brokercheck.finra.org/, and the SEC's IAPD website at https://adviserinfo.sec.gov/.

we conservatively isolate six of the 23 categories as misconduct including regulatory offenses, criminal offenses, and customer disputes that were resolved in favor of the customer because disclosures are not always indicative of wrongdoing.

To identify top misconduct firms each year, I calculate *Financial Misconduct Per Employee (FMPE)*, defined as the total number of misconduct incidents divided by the number of financial advisers in a firm for that year. FMPE reflects the firm's propensity for misconduct. Firms are ranked annually by FMPE, and firms above the 80th percentile are classified as top misconduct firms. The process is repeated each year using updated FMPE values.[7]

2.2 Sample construction

To avoid survivorship bias, the final sample spans the period from 2012 to 2022. FINRA's BrokerCheck maintains the records of financial advisers who have registered within the past 10 years. However, after the 10-year reporting period has ended, FINRA continues to hold data on financial advisers with a track record of financial misconduct.

The sample starts in 2012 and ends in 2022 because I started gathering the data through web scraping from FINRA's BrokerCheck and the SEC's IAPD websites in the second quarter of 2023. Because the data prior to 2012 only included financial advisers with a history of misconduct, including the time frame prior to 2012 results in survivorship bias. The final sample covers around 605,719 active financial advisers and 17,315 firms over the period 2012 to 2022.

[7]Alternative cutoffs at the 70th, 75th, 85th, 90th, and 95th percentiles yield consistent statistical results.

2.3 Empirical design

I investigate how starting a career in the top misconduct firms impacts on financial misconduct at the financial adviser level by estimating the following regression.

$$(1)\ \text{Financial misconduct}_{ijlt} = \alpha + \beta \times \text{Top misconduct firm}_{ijlt} + \gamma \times \mathbf{X}^T_{ijlt} + \lambda_l \times \theta_t + \varepsilon_{ijlt}$$

where i, j, l, t represent financial adviser i at firm j in city l in year t. The term λ_l captures the city fixed effects and θ_t represents the year fixed effects. $\lambda_l \times \theta_t$ is high-dimensional fixed effects. I do not include firm fixed effects because the ranking of top misconduct firms is stable overtime.

The dependent variable, *Financial misconduct*, is an indicator variable equal to one if the financial adviser receives a new financial misconduct incident falling into one of the six disciplinary events in a given year, and zero otherwise.

The key independent variable, *Top misconduct firm* is an indicator variable equal to one if financial advisers begin their first employment in one of top misconduct financial advisory firms and zero otherwise.

The vector X_{ijlt} includes financial adviser control variables. Specifically, I control for adviser experience using the natural logarithm of years in the industry. Additional controls include adviser gender and certification indicators, such as the Investment Company Representative (Series 6), General Securities Representative (Series 7), General Securities Principal, Uniform Securities State Law Exam (Series 63), Investment Advisers Law Exam (Series 65), and Uniform Combined State Law Exam (Series 66). Variable definitions are provided in the Appendix.

Finally, I control for city-year fixed effects, $\lambda_l \times \theta_t$, which subsume both city and year fixed effects. Some characteristics, such as the local housing price shocks (Dimmock, Gerken, and Van alfen, 2021) and local corruption (Pham et al., 2024), affect professional financial misconduct. Including city-year fixed effects sweeps out time-invariant characteristics of cities, as well as time-varying city characteristics. Moreover, this specification allows the comparison among the financial advisers who work in the same city during the year.

Table 1 presents descriptive statistics for the final unbalanced panel dataset of 6,636,350 financial adviser-year observations. On average, 0.467% of adviser-years involve financial misconduct. The average incidence of misconduct in this study is marginally lower than those reported in Egan et al. (2019) and Law and Zuo (2021), primarily because the sample period does not include the 2008 Global Financial Crisis (GFC). As a result, the dataset provides a more conservative estimate, unaffected by the spike in misconduct typically associated with the GFC. Approximaltely 0.8% of financial advisers started their careers at top misconduct firms. Men account for 71.70% of the industry, hence it is male-dominated. In terms of credentials, the Series 63 certificate has the highest rate at 4.80% while the Series 24 has the lowest, at 0.70%. This indicates that the Series 63 is the most popular professional certificate among financial advisers. Variable definitions are provided in Appendix 1.

Insert Table 1 here

Table 2 compares average characteristics between advisers who began their careers at top misconduct firms (*Top misconduct firm*) and those who did not (*Non-top misconduct firm*). As expected, 1st workplace advisers exhibit significantly higher misconduct rates across all measures, consistent with the career imprinting hypothesis. They are also more likely to be male rather than female and have less industry experience. Regarding credentials, they are more likely to have passed the Series 7, Series 24, Series 63, and Series 65 exams. These confirm that the impacts of the top misconduct firms are not driven by the the poor quality of financial advisers.

Insert Table 2 here

3 Career imprinting and financial misconduct

In the following sections, we examine the effect of commencing a career in the top misconduct firms on financial misconduct and alternative measures of financial misconduct. We begin by analyzing the impact of commencing a career in the top misconduct firms on adviser misconduct (Section 3.1) and then present robustness tests using alternative measures of financial misconduct (Section 3.2).

3.1 Baseline analysis

Table 3 presents the results of our regression analysis. We report the findings progressively: Column (1) does not include any fixed effects, Column (2) introduces year fixed effects, Column (3) introduces city fixed effects, Column (4) incorporates both year and city fixed effects, and Column (5) incorporates year $\times$ city fixed effects for our most stringent specification.

Across all models, the coefficient on Top misconduct firm is positive and statistically significant. In Column (5), starting a career at a top misconduct firm is associated with approximately twice the likelihood of committing financial misconduct[8].This finding supports our hypothesis that commencing a career at a top misconduct firm increases the likelihood of future misconduct. That is, advisers who start their careers at top misconduct firms are more likely to commit financial misconduct than those who begin at other firms in the same city and in the same year.

[8]Although the average probability of fraud is low, the standard deviation is large—about 6.8, which is over 20 times the mean—indicating a highly dispersed distribution. The effect effectively doubles the likelihood of fraud, representing a large but not extreme increase.

Other coefficients show expected signs. The positive coefficient on adviser gender suggests that male advisers are more likely to engage in misconduct. Adviser experience is negatively associated with misconduct, although the effect is not statistically significant. Professional licensing is associated with a lower likelihood of misconduct.

Insert Table 3 here

3.2 Alternative measurements of financial misconduct

As noted in prior studies (Aliyev et al., 2022; Lausen et al., 2020), measures of financial misconduct may be subject to measurement error, as they rely on reported cases disclosed by advisers and firms. To ensure our baseline results are not driven by such misclassification, I construct several alternative measures of misconduct. Specifically, I estimate misconduct using the total number of cases, the stock of misconduct, and cumulative misconduct.

Table 4 presents the results. Panel A considers total financial misconduct, Panel B examines stock of financial misconduct, and Panel C focuses on accumulative financial misconduct. *Total financial misconduct* is defined as the natural logarithm of one plus the number of total misconduct of a financial adviser in a given year. Following Egan et al. (2019), *Stock of financial misconduct* is defined as a binary indicator for whether the financial adviser has any prior misconduct. *Accumulative financial misconduct* is defined as the cumulative sum of all misconduct incidents by the financial adviser over the career path.

Across all three panels, the coefficients for 1^{st} *workplace adviser* remain positively correlated with adviser misconduct, suggesting that commencing a career in top misconduct firms increases the likelihood of committing financial misconduct.

Insert Table 4 here

3.3 Excluding misconduct adviser

To ensure that the main results are robust, I implement a robustness check by excluding advisers who committed misconduct at their first firm to isolate the impact of an unethical firm from the direct influence of potentially problematic coworkers. By removing these advisers, the analysis focuses on those who began their careers in a top misconduct firm but did not personally engage in misconduct at that time, allowing a cleaner identification of the firm's cultural imprint.

Table 7 presents the results. The coefficient on Top misconduct firm remains positive and significant, indicating that starting a career at a top misconduct firm is associated with a higher likelihood of committing financial misconduct later, even after accounting for and removing the initial influence of early misconduct behavior by the advisers themselves. This reinforces the interpretation that the firm's environment, rather than just individual tendencies, plays a key role in shaping future misconduct.

Insert Table 7 here

4 Endogeneity - Historical state unemployment rate

In this section, we address potential endogeneity issues in the relationship between starting a career in top misconduct firms and financial misconduct. The decision to join top misconduct firms is not random; it may be influenced by unobserved individual characteristics such as risk preferences, ethical standards, or career motivations, which are also correlated with future misconduct.

For instance, individuals with a higher tolerance for risk or lower ethical standards may be more inclined to self-select into firms with a culture tolerant of misconduct. Conversely, highly motivated individuals seeking rapid career advancement may join such firms due to their aggressive sales environments, regardless of their own ethical disposition.

To establish a causal link between starting a career in top misconduct firms and future adviser misconduct, we employ historical state-level unemployment rates at labor market entry as an exogenous shock to job opportunities, which affects the likelihood of starting at a top misconduct firm.

4.1 Historical state unemployment rate

The historical state unemployment rate at the time new financial advisers begin their careers can affect their choice of first workplace and serve as a good instrumental variable (IV) for study. This variable satisfies the two key properties required for a valid instrument: relevance and exclusion restriction.

The historical state-level unemployment rate at the time financial advisers enter the job market can influence where they begin their careers and serves as a valid instrumental variable (IV) for identifying the causal effect of first workplace misconduct exposure. This measure meets the relevance criterion, as higher unemployment weakens job market conditions and increases the likelihood that new advisers accept positions at firms with higher misconduct rates due to limited alternatives.

4.2 Two-stage least square

According to the exclusion restriction, historical state unemployment rates at the entry level should only shape initial job opportunities without directly influencing future misconduct. This exclusion restriction is plausible for the historical state-level unemployment because while high unemployment may force new advisers to accept jobs at firms with poor reputations, it does not inherently make them more likely to commit misconduct.

To establish causality, I use a two-stage least squares (2SLS) regression, instrumenting the indicator for whether an adviser began their career at a top misconduct firm with the historical state unemployment rate at the time of labor market entry. The first stage regresses the first workplace variable on the instrument, controls, and fixed effects, confirming that higher unemployment significantly increases the likelihood of starting at a high-misconduct firm. The second stage regresses financial misconduct on the instrumented first workplace variable.

Insert Table 6 here

Table 6 reports the second-stage results, showing a positive and statistically significant relationship. Advisers who begin their careers at top misconduct firms are more likely to engage in misconduct themselves, providing causal evidence of a career imprinting effect from an initial high-misconduct environment.

5 First vs. Second workplace influence

An important concern is whether a financial adviser's current workplace has a stronger influence on behavior than their first job. Since recent experiences are also more influential, one might expect current firm culture to matter more. To test this, I show that financial advisers with no misconduct record at their first workplace who later joined a top misconduct firm as their second employer are not more likely to commit misconduct.

Insert Table 7 here

Table 7 compares advisers who began their careers at top misconduct firms with those who joined such firms as their second employer. I define *Second-job top misconduct firm* as an indicator equal to one if an adviser moved to a top 10% misconduct firm given these financial advisers have never joined the top misconduct firm as their first workplace. The coefficient of *Second-job top misconduct firm* lose significance after adding location fixed effects, while those on *Top misconduct firm* remain positive and significant, suggesting that the first workplace is stronger than the recent workplace.

6 Career outcomes

In this section, I further explore the career outcome of joining the top misconduct firms as the first workplace on subsequent job transition (Section 6) and the likelihood of being barred by FINRA (Section 6).

6.1 Job transition

First, I examines the re-employment prospects of financial advisers by focusing on how long it takes them to secure new jobs after leaving a firm. I compare advisers who began their careers at high-misconduct firms to those who started at lower-misconduct firms.

Using cross-sectional data of 605,719 unique advisers, I apply survival analysis and the Cox proportional hazards model to assess how initial workplace ethics and compliance norms influence future job transitions and employability.

To analyze re-employment duration, I use Kaplan-Meier survival curves and Cox proportional hazards models. The Kaplan-Meier charts show the probability of remaining unemployed over time, allowing comparison between advisers who began their careers at high-versus low-misconduct firms. The Cox model quantifies this difference, controlling for other variables. I estimate the following Cox model.

$$\lambda_i(\tau) = \lambda_0(\tau)\exp(\gamma \times \text{Top misconduct firm}_i + \beta \times X_i) \tag{2}$$

$\lambda_0(\tau)$ is the baseline hazard of re-employment at time (τ) . $\lambda_i(\tau)$ is the hazard for individual i, conditional on being unemployed for τ months. The key coefficient, γ, captures the effect of starting at a high-misconduct firm. A hazard ratio, e^{γ}, less than one implies longer unemployment duration (slower re-employment), while a value greater than one indicates quicker re-employment. This framework allows us to assess how the first employer's misconduct environment influences future job mobility.

Insert Figure 1 here

Figure 1 and Table 8 highlight the re-employment disadvantages faced by advisers commencing their careers at top misconduct firms. Their higher survival curves and a hazard ratio of 0.748 suggest they are 25.2% less likely to secure new employment at any given time compared to peers from lower-misconduct firms. This slower re-employment may stem from the negative signaling effect of early exposure to unethical practices, which can raise employer concerns or limit transferable skills. Conversely, advisers who started in more reputable firms appear better positioned for quicker job transitions.

Insert Table 8 here

6.2 Barred Brokers

Finally, I examine whether starting a career at a top misconduct firm increases the likelihood of being barred by FINRA—the most severe disciplinary sanction in the industry. Being barred by FINRA means a financial adviser is permanently prohibited from associating with any FINRA member firm, effectively ending their career in the regulated securities industry.

Insert Table 9 here

Table 9 presents the results of our regression analysis. We report the findings progressively: Column (1) does not include any fixed effects, Column (2) includes year fixed effecrs, Column (3) introduces city fixed effects, Column (4) has both year and city fixed effects, and Column (5) incorporates year $\times$ city fixed effects for our most stringent specification. The coefficients on the indicator for advisers who began their careers at top misconduct firms are positive and statistically significant across all specifications. This suggests that early exposure to a high-misconduct environment increases the likelihood of receiving the industry's harshest penalty: permanent removal from the profession.

7 Conclusion

This study investigates how early exposure to unethical corporate cultures influences financial misconduct and long-term career outcomes among U.S. financial advisers. As the financial advisory industry grows in importance—with over half of U.S. households relying on financial professionals—understanding the origins of adviser behavior is critical. Using a comprehensive adviser-year panel dataset from 2012 to 2022, this study provides evidence that early employment at top misconduct firms leaves lasting career imprints on financial advisers.

The analysis reveals that advisers who start their careers at high-misconduct firms are more likely to commit future misconduct, experience longer unemployment after leaving their first job, and face a higher risk of permanent industry exclusion. These patterns align with the theory of career imprinting, which suggests that early professional environments shape long-term behavior and ethical standards, especially during formative career stages.

To address self-selection concerns, an instrumental variable approach using historical state unemployment rates confirms a causal link between starting at a top misconduct firm and future misconduct. This effect is not present for advisers who join such firms later in their careers, underscoring the unique influence of early exposure.

Overall, this study emphasizes the critical role of first jobs in shaping long-term ethical behavior. The findings carry important implications for policy, firm hiring practices, and industry regulation. Regulators and firms may benefit from closely monitoring the cultural environments of entry-level positions, as these early experiences can profoundly shape advisers' career trajectories.

Table 1: **Summary statistics**

This table reports summary statistics for the variables used in the analysis for the sample period from 2012-2022. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix A.

Variable	N	Mean	SD	P25	P50	P75
	(1)	(2)	(3)	(4)	(5)	(6)
Financial misconduct (%)	6,636,350	0.467	6.817	0.00	0.00	0.00
Total misconduct	6,636,350	0.008	0.072	0.00	0.00	0.00
Stock of misconduct	6,636,350	0.055	0.228	0.00	0.00	0.00
Cummulative misconduct	6,636,350	0.076	0.376	0.00	0.00	0.00
Barred broker (%)	6,636,350	0.184	4.291	0.00	0.00	0.00
Top misconduct firm	6,636,350	0.001	0.032	0.00	0.00	0.00
Experience	6,636,350	1.743	0.913	1.10	1.79	2.48
Male adviser	6,636,350	0.717	0.450	0.00	1.00	1.00
Investment Company Representative (Series 6)	6,636,350	0.018	0.133	0.00	0.00	0.00
General Securities Representative (Series 7)	6,636,350	0.033	0.180	0.00	0.00	0.00
General Securities Principal Qualification Exam (Series 24)	6,636,350	0.007	0.085	0.00	0.00	0.00
Uniform Securities State Law Examination (Series 63)	6,636,350	0.048	0.214	0.00	0.00	0.00
Investment Advisers Law Examination (Series 65)	6,636,350	0.019	0.136	0.00	0.00	0.00
Uniform Combined State Law Examination (Series 66)	6,636,350	0.025	0.157	0.00	0.00	0.00

Table 2: **Top- and Non-top misconduct firms - Comparison**

This table presents the comparison of the average firm characteristics between multi- and single-branch firms for the period from 2012-2022. Additional variables are defined as in Appendix A.

Variable	Top misconduct firm (1)	Non-top misconduct firm (2)	Difference (3)	t-statistic (4)
Financial misconduct (%)	1.945	0.465	1.48***	-17.873
Total misconduct	0.022	0.008	0.014***	-16.501
Stock of misconduct	0.166	0.055	0.111***	-40.145
Cummulative misconduct	0.265	0.076	0.189***	-41.401
Barred broker (%)	0.914	0.184	0.73***	-14.005
Experience	1.519	1.743	-0.224***	20.193
Male adviser	0.836	0.717	0.119***	-21.751
Investment Company Representative (Series 6)	0.006	0.018	-0.012***	7.289
General Securities Representative (Series 7)	0.065	0.033	0.032***	-14.704
General Securities Principal Qualification Exam (Series 24)	0.012	0.007	0.005***	-4.443
Uniform Securities State Law Examination (Series 63)	0.066	0.048	0.018***	-6.736
Investment Advisers Law Examination (Series 65)	0.044	0.019	0.025***	-15.247
Uniform Combined State Law Examination (Series 66)	0.026	0.025	0.001	-0.455

Table 3: **Financial misconduct and Top misconduct firm**: This table presents estimates from the regressions of adviser misconduct on first workplace for the period from 2012-2022. The dependent variable is the flow of financial misconduct, which is the indicator variable equals to 1 if there is the report of financial misconduct in a given year and zero otherwise. *Top misconduct firm* is a binary variable equals to one if a financial adviser commences a career in top misconduct firms, and zero otherwise. Further variable definitions can be found in the Appendix. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	1.454***	1.448***	0.879**	0.874**	0.849**
	(7.09)	(7.07)	(2.34)	(2.34)	(2.19)
Adviser experience	-0.010	-0.004	-0.031**	-0.025*	-0.023
	(-0.55)	(-0.26)	(-2.04)	(-1.70)	(-1.56)
Male adviser	0.298***	0.296***	0.297***	0.295***	0.294***
	(17.59)	(17.39)	(19.33)	(19.15)	(19.07)
Investment Company Representative (Series 6)	0.005	-0.084**	-0.128***	-0.200***	-0.191***
	(0.10)	(-2.03)	(-3.56)	(-6.00)	(-5.20)
General Securities Representative (Series 7)	-0.138***	-0.221***	-0.149***	-0.219***	-0.214***
	(-6.83)	(-8.85)	(-7.76)	(-9.90)	(-10.03)
General Securities Principal Qualification Exam (Series 24)	-0.168***	-0.162***	-0.108***	-0.104***	-0.104***
	(-5.82)	(-5.61)	(-4.10)	(-3.92)	(-3.98)
Uniform Securities State Law Examination (Series 63)	-0.268***	-0.214***	-0.214***	-0.169***	-0.166***
	(-10.71)	(-9.97)	(-7.77)	(-6.90)	(-7.39)
Investment Advisers Law Examination (Series 65)	-0.093***	-0.068***	-0.142***	-0.121***	-0.130***
	(-4.54)	(-3.40)	(-6.43)	(-5.53)	(-5.96)
Uniform Combined State Law Examination (Series 66)	-0.220***	-0.172***	-0.267***	-0.226***	-0.225***
	(-6.86)	(-5.88)	(-8.59)	(-7.89)	(-7.74)
Constant	0.295***	0.287***	0.334***	0.325***	0.322***
	(6.25)	(6.23)	(8.55)	(8.53)	(8.62)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
Adj. R-squared	0.001	0.001	0.009	0.009	0.029

Table 4: **Alternative financial misconduct**: This table presents estimates from the regressions of alternative measures of misconduct on first workplace for the period from 2012-2022. Panel A reports the total financial misconduct, which is the natural logarithm of one plus total count of financial misconduct incidents in a given year. Panel B reports stock of financial misconduct, which is the binary variable equals to one if the financial adviser has the previous records of financial misconduct and zero otherwise. Panel C shows the accumulative financial misconduct, which is the cumulative sum of financial misconduct incident overtime. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Total financial misconduct

	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	0.014***	0.014***	0.010***	0.010***	0.010***
	(7.47)	(7.43)	(3.17)	(3.16)	(3.08)
Experience	-0.000*	-0.000	-0.001***	-0.001***	-0.001***
	(-1.89)	(-1.54)	(-4.87)	(-4.40)	(-4.12)
Male adviser	0.003***	0.003***	0.003***	0.003***	0.003***
	(12.93)	(12.71)	(15.26)	(15.05)	(14.94)
Investment Company Representative (Series 6)	0.002***	0.001**	0.000	-0.001**	-0.001**
	(4.49)	(2.23)	(0.18)	(-2.46)	(-2.46)
General Securities Representative (Series 7)	-0.002***	-0.003***	-0.002***	-0.003***	-0.003***
	(-6.79)	(-9.98)	(-8.36)	(-11.91)	(-11.68)
General Securities Principal Qualification Exam (Series 24)	-0.003***	-0.003***	-0.002***	-0.002***	-0.002***
	(-9.93)	(-9.60)	(-7.71)	(-7.43)	(-7.39)
Uniform Securities State Law Examination (Series 63)	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***
	(-7.39)	(-5.50)	(-5.92)	(-4.29)	(-4.58)
Investment Advisers Law Examination (Series 65)	-0.002***	-0.002***	-0.003***	-0.002***	-0.003***
	(-7.60)	(-6.33)	(-10.95)	(-9.89)	(-10.08)
Uniform Combined State Law Examination (Series 66)	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***
	(-4.30)	(-3.20)	(-6.44)	(-5.41)	(-5.32)
Constant	0.006***	0.006***	0.007***	0.007***	0.007***
	(14.29)	(14.43)	(23.73)	(23.99)	(24.02)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
Adj. R-squared	0.001	0.001	0.009	0.009	0.028

Panel B - Stock of financial misconduct

	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	0.112***	0.112***	0.092***	0.092***	0.091***
	(8.74)	(8.73)	(6.36)	(6.36)	(6.13)
Experience	0.020***	0.020***	0.018***	0.018***	0.018***
	(7.27)	(7.22)	(6.83)	(6.76)	(6.70)
Male adviser	0.042***	0.041***	0.041***	0.041***	0.041***
	(12.13)	(12.12)	(11.29)	(11.29)	(11.20)
Investment Company Representative (Series 6)	-0.002	-0.005**	-0.011***	-0.014***	-0.014***
	(-0.82)	(-2.56)	(-4.65)	(-6.18)	(-5.93)
General Securities Representative (Series 7)	-0.006***	-0.009***	-0.007***	-0.010***	-0.010***
	(-4.03)	(-5.45)	(-4.71)	(-6.35)	(-6.38)
General Securities Principal Qualification Exam (Series 24)	-0.021***	-0.021***	-0.015***	-0.015***	-0.015***
	(-6.75)	(-6.70)	(-6.10)	(-6.05)	(-6.01)
Uniform Securities State Law Examination (Series 63)	-0.015***	-0.013***	-0.008***	-0.006**	-0.006**
	(-5.82)	(-4.80)	(-3.13)	(-2.26)	(-2.22)
Investment Advisers Law Examination (Series 65)	-0.016***	-0.015***	-0.025***	-0.024***	-0.024***
	(-6.90)	(-6.73)	(-10.57)	(-10.42)	(-10.39)
Uniform Combined State Law Examination (Series 66)	-0.017***	-0.015***	-0.023***	-0.021***	-0.021***
	(-7.61)	(-6.64)	(-9.16)	(-8.21)	(-8.28)
Constant	-0.008*	-0.008*	-0.003	-0.004	-0.004
	(-1.84)	(-1.90)	(-0.72)	(-0.80)	(-0.83)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
Adj. R-squared	0.016	0.016	0.048	0.048	0.053

Panel C - Accumulative financial misconduct

	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	0.189***	0.189***	0.140***	0.140***	0.133***
	(7.69)	(7.68)	(4.24)	(4.24)	(3.60)
Experience	0.028***	0.028***	0.025***	0.025***	0.025***
	(6.59)	(6.55)	(6.40)	(6.35)	(6.30)
Male adviser	0.062***	0.062***	0.062***	0.061***	0.061***
	(11.90)	(11.89)	(11.09)	(11.09)	(10.99)
Investment Company Representative (Series 6)	-0.005	-0.009***	-0.017***	-0.021***	-0.021***
	(-1.51)	(-3.15)	(-4.84)	(-6.17)	(-6.03)
General Securities Representative (Series 7)	-0.011***	-0.015***	-0.012***	-0.016***	-0.016***
	(-4.69)	(-6.01)	(-5.12)	(-6.65)	(-6.68)
General Securities Principal Qualification Exam (Series 24)	-0.031***	-0.031***	-0.023***	-0.023***	-0.023***
	(-6.79)	(-6.74)	(-6.26)	(-6.21)	(-6.15)
Uniform Securities State Law Examination (Series 63)	-0.022***	-0.019***	-0.011***	-0.009**	-0.008**
	(-5.60)	(-4.68)	(-2.81)	(-2.10)	(-2.06)
Investment Advisers Law Examination (Series 65)	-0.023***	-0.022***	-0.035***	-0.034***	-0.034***
	(-7.08)	(-6.90)	(-10.48)	(-10.29)	(-10.24)
Uniform Combined State Law Examination (Series 66)	-0.025***	-0.022***	-0.032***	-0.030***	-0.030***
	(-7.49)	(-6.56)	(-8.46)	(-7.61)	(-7.66)
Constant	-0.014**	-0.014**	-0.008	-0.008	-0.009
	(-2.07)	(-2.11)	(-1.07)	(-1.12)	(-1.14)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
Adj. R-squared	0.012	0.012	0.048	0.048	0.055

Table 5: **Removing misconduct coworkers**: This table presents estimates from the regressions after removing for the period from 2012-2022 under different restricted samples. Panel A excludes the first year of each financial adviser . Panel B remove the observations in the first workplace. Panel C shows remove financial adviser commiting financial misconduct in the first workplace. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	1.347***	1.342***	0.869***	0.866***	0.857***
	(7.23)	(7.21)	(2.91)	(2.90)	(2.83)
Experience	-0.027**	-0.022*	-0.040***	-0.035***	-0.033***
	(-2.36)	(-1.94)	(-4.26)	(-3.68)	(-3.41)
Male adviser	0.257***	0.255***	0.253***	0.251***	0.250***
	(14.55)	(14.37)	(14.95)	(14.79)	(14.77)
Investment Company Representative (Series 6)	-0.110***	-0.181***	-0.195***	-0.254***	-0.249***
	(-4.81)	(-8.35)	(-10.65)	(-11.70)	(-9.42)
General Securities Representative (Series 7)	-0.115***	-0.181***	-0.126***	-0.182***	-0.177***
	(-8.29)	(-10.53)	(-8.28)	(-11.24)	(-10.65)
General Securities Principal Qualification Exam (Series 24)	-0.111***	-0.107***	-0.071***	-0.068***	-0.069***
	(-4.43)	(-4.24)	(-3.06)	(-2.92)	(-3.05)
Uniform Securities State Law Examination (Series 63)	-0.260***	-0.215***	-0.210***	-0.172***	-0.171***
	(-14.34)	(-14.12)	(-10.80)	(-10.15)	(-10.61)
Investment Advisers Law Examination (Series 65)	-0.033*	-0.013	-0.079***	-0.061***	-0.065***
	(-1.80)	(-0.70)	(-3.98)	(-3.06)	(-3.27)
Uniform Combined State Law Examination (Series 66)	-0.208***	-0.168***	-0.238***	-0.203***	-0.202***
	(-8.96)	(-7.97)	(-10.75)	(-10.20)	(-10.04)
Constant	0.241***	0.234***	0.268***	0.260***	0.256***
	(9.04)	(9.08)	(12.58)	(12.58)	(12.67)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City $\times$ Year FE	No	No	No	No	Yes
Observation	6,590,010	6,590,010	6,590,010	6,590,010	6,590,010
Adj. R-squared	0.001	0.001	0.009	0.009	0.028

Table 6: **Endogeneity test: Historical state unemployment**: This table presents estimates from the 2-stage least squared regressions of adviser misconduct for the period from 2012-2022. In Column 1, the dependent variable in the first stage is *Top misconduct firm*, equals to one if financial advisers start their career in top misconduct firms and zero otherwise, scaled by 100. The instrument variable is *State unemployment rate* which is the historical state unemployment rate at the entry year of each financial adviser. In Column 2, the dependent variable in the second stage is the flow of financial misconduct, which is equals to one if there is the record of financial misconduct in a given year and and zero otherwise. *Fitted value (Instrumented Top misconduct firm)* is the fitted value of Top misconduct firm, obtained in the first-stage regression. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) First stage	(2) Second stage
Dependent variable	Top misconduct firm	Financial misconduct (%)
IV: State unemployment rate	0.163***	
	(6,878)	
Fitted value (Instrumented Top misconduct firm)		1.393***
		(15.76)
Experience	0.006***	-0.004
	(12.15)	(-1.106)
Male adviser	0.009***	0.296***
	(9.519)	(50.27)
Investment Company Representative (Series 6)	-0.025***	-0.064***
	(-6.853)	(-2.874)
General Securities Representative (Series 7)	-0.004	-0.202***
	(-1.215)	(-11.45)
General Securities Principal Qualification Exam (Series 24)	0.005	-0.165***
	(0.988)	(-5.264)
Uniform Securities State Law Examination (Series 63)	0.018***	-0.221***
	(7.218)	(-14.64)
Investment Advisers Law Examination (Series 65)	0.016***	-0.072***
	(4.695)	(-3.572)
Uniform Combined State Law Examination (Series 66)	0.006*	-0.178***
	(1.866)	(-9.467)
Constant	-0.001	0.471***
	(-0.719)	(46.19)
Observations	6,636,350	6,636,350
Adj. R-squared	0.877	0.001
Year FE	Yes	Yes
City FE	Yes	Yes

Table 7: **Top misconduct firm vs. Second joined top misconduct firm**:This table presents estimates from the regressions of adviser misconduct on first workplace and second workplace for the period from 2012-2022. The dependent variable is the flow of financial misconduct, which is the indicator variable equals to one if there is the report of financial misconduct in a given year and zero otherwise. *Top misconduct firm* is a binary variable equals to one if a financial adviser commences a career in top misconduct firms, and zero otherwise. *Second joined top misconduct firm* is a binary variable equals to one if a financial adviser commences a career in top misconduct firms only in the second workplace, and zero otherwise. Further variable definitions can be found in the Appendix. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Financial misconduct (%)	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	1.456***	1.450***	0.879**	0.875**	0.849**
	(7.04)	(7.02)	(2.36)	(2.35)	(2.21)
Second joined top misconduct firm	0.073**	0.079***	0.030	0.034	0.034
	(2.51)	(2.79)	(1.20)	(1.40)	(1.40)
Experience	-0.010	-0.005	-0.031**	-0.025*	-0.023
	(-0.57)	(-0.27)	(-2.08)	(-1.73)	(-1.59)
Male adviser	0.299***	0.297***	0.297***	0.295***	0.294***
	(17.82)	(17.61)	(19.49)	(19.30)	(19.26)
Investment Company Representative (Series 6)	0.008	-0.080**	-0.126***	-0.198***	-0.189***
	(0.18)	(-2.04)	(-3.60)	(-6.33)	(-5.48)
General Securities Representative (Series 7)	-0.135***	-0.218***	-0.148***	-0.217***	-0.213***
	(-7.51)	(-9.40)	(-8.13)	(-10.04)	(-10.34)
General Securities Principal Qualification Exam (Series 24)	-0.166***	-0.160***	-0.108***	-0.104***	-0.104***
	(-5.77)	(-5.56)	(-4.03)	(-3.86)	(-3.91)
Uniform Securities State Law Examination (Series 63)	-0.261***	-0.206***	-0.211***	-0.166***	-0.163***
	(-11.24)	(-9.88)	(-8.04)	(-6.83)	(-7.28)
Investment Advisers Law Examination (Series 65)	-0.089***	-0.064***	-0.140***	-0.119***	-0.128***
	(-4.19)	(-3.16)	(-5.70)	(-5.04)	(-5.38)
Uniform Combined State Law Examination (Series 66)	-0.216***	-0.168***	-0.265***	-0.224***	-0.222***
	(-7.00)	(-5.94)	(-8.67)	(-7.99)	(-7.80)
Constant	0.282***	0.274***	0.329***	0.319***	0.317***
	(6.62)	(6.54)	(8.86)	(8.80)	(8.89)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
Adj. R-squared	0.001	0.001	0.009	0.009	0.029

Table 8: **Employment duration**: The table estimates the relationship between the *first workplace* effect and a financial adviser's duration out of the financial advisory industry, corresponding to a Cox proportional hazard model (Equation 2). Observations are cross-sectional. The total number of observations is restricted to 554,124 unique financial advisers, who switch firms over the course of their careers. Coefficients are reported in terms of proportional hazards, with standard errors in parentheses.
***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Unemployment spells	Model 1	Model 2
Top misconduct firm	0.830***	0.748***
	(0.0280)	(0.0253)
Experience		0.962***
		(0.000162)
Male adviser		0.939***
		(0.00296)
Investment Company Representative (Series 6)		0.922***
		(0.00308)
General Securities Representative (Series 7)		0.882***
		(0.00299)
General Securities Principal Qualification Exam (Series 24)		0.946***
		(0.00351)
Uniform Securities State Law Examination (Series 63)		0.872***
		(0.00301)
Investment Advisers Law Examination (Series 65)		1.055***
		(0.00356)
Uniform Combined State Law Examination (Series 66)		0.910***
		(0.00322)
Observations	554,124	554,124

Table 9: **Barred brokers**: This table presents estimates from the regressions of Barred broker on first workplace for the period from 2012-2022. *Barred broker* equals to one if the financial adviser is permanently removed from the industry and zero otherwise. 1^{st} *workplace adviser* is a binary variable equal to one if a financial adviser commences a career in top misconduct firms and zero otherwise. t-statistics are provided in parentheses. Robust standard errors are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Barred broker	(1)	(2)	(3)	(4)	(5)
Top misconduct firm	0.713***	0.709***	0.562**	0.560**	0.569**
	(3.23)	(3.23)	(2.40)	(2.39)	(2.48)
Experience	-0.050***	-0.042***	-0.057***	-0.048***	-0.046***
	(-7.39)	(-6.78)	(-9.52)	(-8.61)	(-8.36)
Male adviser	0.122***	0.119***	0.120***	0.117***	0.116***
	(12.99)	(12.60)	(13.96)	(13.50)	(13.26)
Investment Company Representative (Series 6)	0.085*	0.002	0.028	-0.043	-0.050
	(1.78)	(0.04)	(0.67)	(-1.20)	(-1.53)
General Securities Representative (Series 7)	-0.057***	-0.135***	-0.062***	-0.130***	-0.126***
	(-5.81)	(-10.23)	(-6.82)	(-11.57)	(-10.94)
General Securities Principal Qualification Exam (Series 24)	-0.086***	-0.084***	-0.061***	-0.060***	-0.061***
	(-6.91)	(-6.54)	(-4.94)	(-4.70)	(-4.81)
Uniform Securities State Law Examination (Series 63)	-0.129***	-0.072***	-0.111***	-0.059***	-0.059***
	(-13.68)	(-7.34)	(-12.36)	(-6.68)	(-6.29)
Investment Advisers Law Examination (Series 65)	-0.113***	-0.087***	-0.131***	-0.108***	-0.107***
	(-8.14)	(-6.83)	(-9.48)	(-8.37)	(-8.12)
Uniform Combined State Law Examination (Series 66)	-0.127***	-0.075***	-0.138***	-0.090***	-0.088***
	(-9.88)	(-6.45)	(-11.33)	(-7.86)	(-7.66)
Constant	0.195***	0.183***	0.211***	0.196***	0.194***
	(11.66)	(11.74)	(15.48)	(16.01)	(16.13)
Year FE	No	Yes	No	Yes	No
City FE	No	No	Yes	Yes	No
City × Year FE	No	No	No	No	Yes
Observation	6,636,350	6,636,350	6,636,350	6,636,350	6,636,350
R-squared	0.000	0.001	0.016	0.017	0.027

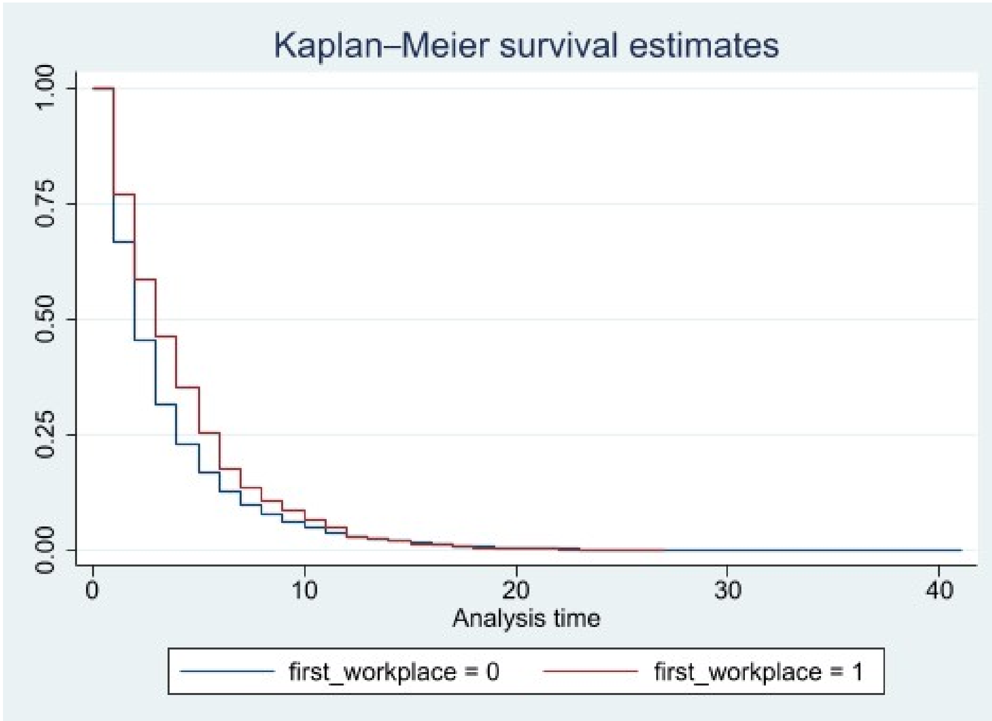

Figure 1: **Duration until finding a new workplace**: This figure presents Kaplan–Meier survival estimates of the time financial advisers remain unemployed following job separation. The survival curves compare advisers who began their careers at top misconduct firms (first_workplace = 1) with those who started at other firms (first_workplace = 0). The results indicate that advisers from top misconduct firms experience significantly longer durations before securing new employment.

Table 10: **Appendix A - Variable definitions**

Variable	Description
Top misconduct firm (%)	An indicator variable that is equal to one if the adviser started the job in one of the top 20% of high misconduct firms and zero otherwise.
Total misconduct	The natural logarithm of one plus the raw misconduct incidents reported for each adviser in a given year
Stock of financial misconduct (%)	An indicator equal to one when a financial adviser has a past record of misconduct and zero otherwise
Accumulative financial misconduct (%)	An accumulative sum of the stock of financial misconduct over time
Male adviser	An indicator equal to one if a financial adviser is male and zero otherwise
Experience	The natural logarithm of the advisor's total years of work experience
Investment company representative (Series 6)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This license authorizes financial professionals to sell mutual funds, variable annuities, and other investment products
General securities representative (Series 7)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This license allows financial professionals to trade a wide range of securities, including stocks, bonds, options, and mutual funds.
General securities principal qualification exam (Series 24)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA-administered exam qualifies individuals to supervise and manage a firm's general securities business.
Uniform securities state law examination (Series 63)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to solicit orders for securities and provide investment advice within a specific state.
Investment advisers law examination (Series 65)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to act as an investment advisor.
Uniform combined state law examination (Series 66)	An indicator variable equal to one if a financial adviser holds this license and zero otherwise. This FINRA exam qualifies individuals to act as both securities agents and investment adviser representatives.
Historical state unemployment rate	The state unemployment rate during the time that each financial adviser commenced their career.
Second joined top misconduct firm	An indicator variable equals to one if financial advisers start their second employment in the top 20% of high misconduct firm and zero otherwise.

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