From Conflict to Trust: Fiduciary Duty and Financial Adviser Misconduct

by

Yuwen Yuan

A dissertation accepted and approved in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

in Finance

Dissertation Committee:

Youchang Wu, Chair

John Chalmers, Core Member

Diane Del Guercio, Core Member

Benjamin Hansen, Institutional Representative

University of Oregon

Spring 2025

© 2025 Yuwen Yuan

DISSERTATION ABSTRACT

Yuwen Yuan

Doctor of Philosophy in Finance

Title: From Conflict to Trust: Fiduciary Duty and Financial Adviser Misconduct

Commission-based brokers often face criticism for providing biased advice. This study investigates whether imposing fiduciary duty on brokers can mitigate such biases and reduce misconduct. Utilizing variations in state-level fiduciary regulations on brokers prior to 2016 and the issuance of the 2016 federal fiduciary rule from the Department of Labor, I employ a difference-in-differences test and find that imposing fiduciary duty significantly reduces brokers' misconduct. Specifically, counties where brokers were newly subject to fiduciary duty saw a 20% to 40% greater decrease in misconduct after 2016 compared with control counties. This effect translates into approximately a $300,000 reduction in misconduct-related losses per county per year. The policy is more effective in areas with weakened investor discipline and labor market discipline, suggesting that fiduciary duty can compensate for the shortcomings of other disciplinary mechanisms. Further analysis of municipal bond mutual funds shows that brokers under fiduciary status are more likely to adopt asset-based service models and move away from commission-based products. Broker-sold funds in treated states exhibit greater increases in returns and larger reductions in expenses.

CURRICULUM VITAE

NAME OF AUTHOR: Yuwen Yuan

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene
Medical School of Shanghai Jiao Tong University, Shanghai, China

DEGREES AWARDED:

Doctor of Philosophy in Finance, 2025, University of Oregon
Master of Business Administration/Master of Science in Finance, 2020, University of Oregon
Bachelor of Science/Doctor of Medicine, 2014, Medical School of Shanghai Jiao Tong University

AREAS OF SPECIAL INTEREST:

Financial Intermediation
Financial Advisers
Household Finance
Private Equity
Intersection between Law and Finance

WORKING PAPERS:

From Conflict to Trust: Fiduciary Duty and Financial Adviser Misconduct, 2024

Asset Prices and Ordinary Consumption, 2023, Joint with John Chalmers (University of Oregon) and Aditya Kaul (University of Alberta)

Private Equity and Financial Adviser Misconduct, 2022, Joint with Albert Sheen (U.S. Securities and Exchange Commission) and Youchang Wu (University of Oregon)

GRANTS, AWARDS, AND HONORS:

Robin & Roger Best Research Award, University of Oregon, 2022-2025

Consumer Protection Research Grant from School of Law, University of Oregon, 2023-2024

Hopewell-Racette Research Scholarship, University of Oregon, 2021

ACKNOWLEDGMENTS

I first wish to express my sincere appreciation to my advisor Youchang Wu for his guidance throughout my Ph.D. journey. You are a true role model as both a researcher and an educator. Your dedication to your work, intellectual curiosity, and pursuit of excellence have deeply influenced the way I approach both teaching and research. I would also like to thank Diane Del Guercio. Your feedback has always been constructive, detailed, and thought-provoking. As a female professor, you also offered me tremendous emotional support and helped me build confidence in my academic path. I am deeply grateful to John Chalmers. You consistently provided practical and insightful suggestions, and every meeting with you gave me something new to reflect on. I would like to thank Ben Hansen. Your perspective continues to inspire me to think broadly and deeply about economic questions.

I want to thank all the past and present faculty members in the Department of Finance at the University of Oregon who supported me throughout this journey. In alphabetical order: Ioannis Branikas, Gabriel Buchbinder, Maria Chaderina, Brandon Julio, Roberto Gutierrez, Robert Ready, Albert Sheen, Jay Wang, Yuchi Yao, Calvin Zhang, and Jane Zhang. Thank you for your encouragement, thoughtful feedback, and for creating a supportive environment.

I am also incredibly grateful to the wonderful staff at the Lundquist College of Business. Your help, whether with logistics, scheduling, or tech issues, made the everyday challenges of the Ph.D. program much easier to manage.

To my fellow Ph.D. students, thank you for the friendship, shared struggles, and all the laughs along the way. A special thanks to Wensong Zhong! Your help with research and, more importantly, your friendship and emotional support over the past five years meant more than I can express.

DEDICATION

I dedicate this dissertation to my beloved husband, Leilei Guo, and our daughter, Anne Guo. Leilei, thank you for encouraging me to pursue this path and for taking care of our family while I focused on my research. Your selflessness, patience, and constant support mean the world to me. You always put our needs ahead of your own, and I am deeply grateful to have you by my side. Anne, you are such a sweet and warm-hearted girl. Your joy, hugs, and endless encouragement brought me so much happiness and emotional strength. Thank you for being my little cheerleader through it all.

I also dedicate this work and the entire Ph.D. journey to my parents, Hong Fan and Qun Yuan. You have always encouraged me to follow my dreams without judgment and shown incredible patience with my stubbornness. Your support has been my greatest source of strength in overcoming every obstacle along the way.

Finally, I dedicate this to my sister, Yujian Fan. Thank you for taking care of our parents and supporting the entire family while I was thousands of miles away. Thank you for allowing me to be the “spoiled and relentless” little sister while you held everything together back home.

Thank you all, from the bottom of my heart.

TABLE OF CONTENTS

Chapter	Page
I. INTRODUCTION	12
II. RELATED LITERATURE	21
III. INSTITUTIONAL BACKGROUND	24
Financial Advisory Industry and Fiduciary Duty	24
2016 DOL Fiduciary Rule and Industry Response	26
Potential Effects of 2016 DOL Fiduciary Rule on Brokers	28
Differentiating State Laws	28
Legal Forums for Broker Misconduct	30
IV. DATA AND DESCRIPTIVE STATISTICS	32
Data	32
Summary Statistics	36
Individual Brokers Summary Statistics	36
County-Level Summary Statistics	37
Municipal Bond Mutual Fund Summary Statistics	37
V. STATE BORDER DISCONTINUITY OF FIDUCIARY DUTY	39
Empirical Design	39
Covariate Balance	40
Model Specification	40
Impact of Fiduciary Duty on Broker Misconduct	41
VI. 2016 DOL FIDUCIARY RULE EFFECT ON BROKERS' MISCONDUCT	43
Empirical Design	43

Model Specification 44
Results 45
Baseline Results 45
Pre-trends and Treatment Effect Dynamics 46
Effect of SEC RegBI on Brokers' Misconduct 47
VII. DISCIPLINE MECHANISMS AND THE IMPACT OF FIDUCIARY DUTY . 49
Investor Discipline 49
Labor Market Discipline 49
VIII. POLICY EFFECT ON BROKERS' ADVISING BEHAVIOR 51
Dual-registered Ratio 51
Advice on Municipal Bond Mutual Funds 52
Model Specification 54
Fund Flow Rate 55
Effect on the Distribution Channel of MBMFs 56
Effect on the Performance of Broker-Sold MBMFs 56
Effect on the Flow-Fee Sensitivity of Broker-sold MBMFs 57
Broker Entry and Exit 58
IX. ROBUSTNESS TESTS 60
X. CONCLUSION 63
TABLES 64
FIGURES 82
APPENDIX 92
REFERENCES CITED 94

LIST OF TABLES

Table Page

1. Individual Adviser-Level Summary Statistics 64

2. County-Level Summary Statistics 65

3. MBMF Share Class-Year Summary Statistics 66

4. Fiduciary Duty Effect on Broker Misconduct: Regression Discontinuity 67

5. Fiduciary Duty Effect on Broker Misconduct: Difference-in-differences 68

6. Fiduciary Duty Effect on Broker Disaggregated Misconduct 69

7. Effect of SEC RegBI On Broker Misconduct 70

8. Fiduciary Duty and Investor Discipline 71

9. Fiduciary Duty and Labor Market Discipline 72

10. Fiduciary Duty Effect on Dual Registration Ratio 73

11. Fiduciary Duty Effect on MBMFs 74

12. Fiduciary Duty Effect on Broker Entry and Exit 75

13. Robustness: Individual Broker-Level Analysis 76

14. Robustness: All-County Sample 77

15. Robustness: Placebo Test Using Registered Investment Adviser Data 78

16. Robustness: Alternative Misconduct Measure 79

17. Robustness: Five-Year Event Window 80

18. Robustness: Dual-Registered Advisers Before 2016 81

LIST OF FIGURES

Figure Page

1. Geographical Variation in Misconduct 82

2. Time Series of Misconduct 83

3. Total Net Assets of MBMFs Across States 84

4. GSS Trust Score Across States 85

5. State Regulatory Regimes of Fiduciary Duty on Brokers 86

6. Balance of Covariates 87

7. Average Misconduct Counts Around 2016 DOL Fiduciary Rule 88

8. DiD Analysis: Coefficient Plot 89

9. Fiduciary Rule Effect on Dual-Registered Ratio 90

10. Monthly Flow Rate of MBMFs Around the 2016 DOL Fiduciary Rule 91

Chapter 1

Introduction

The financial advisory market has become increasingly important in recent years. Shifts in the pension landscape have led many retail investors, who are often unprepared for financial decision-making (Lusardi and Mitchell (2014)), to seek advice from financial advisers on the investment of their lifetime savings.[1] Despite this increasing reliance, financial advisers often face criticism for potential conflicts of interest (COI) between themselves and their clients. Misaligned incentives can result in suboptimal investment advice that benefits advisers at the expense of clients, particularly when clients are less capable of assessing the quality of the advice. The growing demand for financial advisers, coupled with persistent COI, has contributed to the prevalence of misconduct in the financial advisory industry (Egan et al. (2019)).

In response, regulators around the world have tightened the regulatory frameworks governing financial advisers. One approach has been to prohibit commission-based compensation entirely.[2] However, the shift to fee-only advisory models has led to unintended consequences. One major potential issue is the emergence of an "advice gap." Advice is expensive and often not cost-effective. Investors with limited assets often cannot afford fee-based advice and are consequently left without professional guidance—a concern anticipated by earlier theoretical studies (Inderst and Ottaviani (2012a), Inderst and Ottaviani (2012b), Thiel (2022)).

Instead of banning commission-based compensation, U.S. regulators have adopted an alternative

[1] According to the Investment Company Institute (Holden and Schrass (2024)), in mid-2023, more than four in ten US households owned individual retirement accounts (IRAs). The growth in IRAs has been significantly driven by rollovers from employer-sponsored retirement plans. Notably, more than half of IRA-owning households with rollovers relied heavily on professional financial advisers to guide their investment decisions during the rollover process.

[2] Examples include the United Kingdom, Australia, and the Netherlands.

approach. In 2016, the U.S. Department of Labor (DOL) introduced a rule to impose fiduciary duty (FD) on brokers who manage retirement accounts. While FD and commission-based compensation are inherently in conflict, the rule provided exemptions that allowed certain commission-based products to remain available, subject to enhanced disclosure requirements. By doing so, the rule sought to strengthen investor protections by increasing legal discipline without overhauling brokers' commission-based compensation model. The intent was to strike a balance between the quality of advice and its accessibility. This rule faced substantial opposition from both Congress and the industry and was ultimately vacated by a 2018 Fifth Circuit Court ruling. Despite this, the debate continues. Various regulators and states have sought to enforce FD or similar legal threats on brokers, including the SEC's Regulation Best Interest (RegBI) in 2019 and the DOL's recent attempt of FD rule in 2024.[3,4] Critics argue that the FD rule was redundant given existing oversight and unlikely to meaningfully alter broker behavior. Advisers could still adjust their practices to prioritize their own interests over clients', rendering the rule ineffective despite significant compliance and legal costs.[5] At the heart of this policy debate lies a fundamental question: Can imposing FD, without banning commission-based compensation, effectively discipline brokers and reduce their misconduct? As such, an empirical examination of this question is essential to determine the necessity of such regulatory interventions.

To address this question, this paper presents two main empirical findings. First, I find a significant reduction in misconduct among brokers after they were subjected to FD. Further analysis suggests that the reduction in misconduct is particularly effective in contexts where investor discipline and labor market discipline are weak, indicating that the legal discipline introduced by FD can substitute for other disciplinary mechanisms when they fail. Second, I investigate how brokers' advising behavior changed following the DOL rule, with a focus on municipal bond mutual funds (MBMFs). The analysis reveals that brokers became more likely to register as dual-registered

[3] The SEC's Regulation Best Interest under the Securities Exchange Act of 1934 establishes a "best interest" standard of conduct for brokers and associated persons when they make a recommendation to a retail customer of any transaction or investment strategy involving securities, including recommendations of types of accounts.

[4] On April 23, 2024, the U.S. Department of Labor (DOL) released a final rule, titled the "Retirement Security Rule." It redefines who qualifies as a fiduciary under the Employee Retirement Income Security Act. The DOL also released a set of amendments to Prohibited Transaction Exemptions (PTEs), which are specific requirements for fiduciaries engaging in transactions that could create a conflict of interest. Although the rule was originally scheduled to take effect on September 23, 2024, it has since been suspended due to legal challenges. As of May 2025, the implementation remains on hold pending further judicial review and regulatory reassessment.

[5] A case of Edward Jones

advisers, thereby enabling them to offer both commission- and fee-based services. Brokers also increasingly avoided commission-based products. MBMFs that remained under commission-based compensation exhibited higher returns, lower expenses, and a stronger negative relationship between fund flows and distribution fees after the 2016 DOL fiduciary rule. These results suggest an improvement in the quality of service provided by brokers after they were subjected to FD.

To empirically examine the impact of FD imposition on brokers, I leverage two variations in FD policy: First, states in the U.S. differ on whether to impose FD on brokers, as documented by Finke and Langdon (2012). In this study, I categorize the states into two groups: the fourteen states that do not impose FD on brokers, referred to as No-FD states, and the rest, classified as Quasi-FD states, which impose either strict or partial FD requirements. To better control for differences across counties, I restrict the sample in my main analysis to the counties along the state borders. I argue that the counties along the state borders are similar but have a discontinuity in the FD legal framework. Second, to further alleviate selection bias and get closer to the causal interpretation of the relationship between imposing FD and misconduct by brokers, I exploit a temporal variation—the 2016 DOL fiduciary rule—and conduct a difference-in-differences (DiD) analysis. Cross-border counties in No-FD states prior to 2016 are considered the treated group, while counties that already had at least some level of FD imposition serve as the control group.

If the 2016 DOL fiduciary rule was vacated and never implemented, why does it still matter? Several factors justify the consideration of this policy event. First, the 2016 DOL fiduciary rule marked the beginning of a series of policy changes and growing awareness among both brokers and investors regarding the potential imposition of FD on brokers. The policy debate persisted after the 2016 DOL fiduciary rule was vacated in 2018. Just one year later, the SEC introduced the RegBI rule for brokers in 2019. Moreover, the DOL never ceased proposing revised versions of the FD rule. Second, according to a survey by Deloitte, industry companies reportedly adapted quickly to the 2016 DOL fiduciary rule, actively preparing to meet its requirements.[6] Third, as documented by Egan et al. (2022), the rule elicited a tangible response from both investors and insurance/brokerage firms. This is evidenced by a marked increase in FD-related customer complaints reported on the FINRA BrokerCheck website, along with frequent references to "DOL" in the 10-K filings of these companies.

[6]Report by Deloitte

In this study, the primary outcome variable is misconduct by brokers. "Misconduct" refers to the misconduct events documented in brokers' files on the BrokerCheck website, following Egan et al. (2019). I collect records of individual brokers and Registered Investment Advisers (RIAs) from FINRA's BrokerCheck website and the SEC Investment Adviser Public Disclosure (IAPD) website, respectively. My dataset comprises 1.5 million financial advisers from 2005 to 2022, over 90% of whom are either brokers only or dual-registered. Brokers (including dual-registered advisers) form my analysis sample because only brokers are subject to changes in FD imposition, whereas RIAs consistently adhere to FD.[7] I construct an adviser-year panel dataset that includes each financial adviser's employment history, branch location, qualification exams, and incidents of misconduct. Then, based on the geographical information of branch locations, I aggregate individual financial advisers' records into a county-year panel dataset and link to county-level data. The final county-level panel data includes information about the incidence of misconduct, density of financial advisers, and dual-registered ratio, as well as variables about demographic, trust, and ethical environment.[8] In total, the dataset covers approximately 2,900 counties, among which 475 counties make up the cross-border sample for my main analysis.

The first finding documented in this paper is a negative relationship between the imposition of FD on brokers and their incidence of misconduct. This finding is supported by results from both regression discontinuity test and DiD test.

By using a regression discontinuity design within the cross-border counties from 2005 to 2015, I find that the imposition of FD is associated with a statistically and economically significant reduction in broker misconduct. The estimates suggest that brokers in counties with FD imposition experienced, on average, a 0.158% lower likelihood of committing misconduct and 0.002 fewer counts of misconduct incidents in a given year compared with brokers in counties without FD imposition. Based on the unconditional mean, this represents a 32% reduction in average likelihood of a broker committing misconduct and 23% reduction in average number of misconduct incident counts within a county in a given year if the county imposed FD on brokers. This estimate is robust across different

[7] "Brokers only" refers to FINRA-registered representatives. "Dual-registered" refers to FINRA-registered representatives who are also registered as investment adviser representatives. "RIA only" refers to individuals who are registered only as investment adviser representatives and are overseen by the SEC or state regulators.

[8] If the brokers simultaneously work for multiple counties, I assign their records to all the counties they work for. If brokers work for multiple firms in the same county, I retain the record with the longest employment period to avoid multi-counting.

misconduct measures and after controlling for county demographic, financial advisory labor market, local trust level and ethical environment.

Then, I test the impact of the 2016 DOL fiduciary rule on brokers' misconduct using a DiD analysis within cross-border counties. I consider the years after 2016 (starting from 2017) as post and use four years before and after as the event window. Counties without FD imposition on brokers before 2016 are considered treated by the policy, and counties that already have at least some level of FD imposition on brokers are considered the control group. By using border-year fixed effects, I restrict the comparison to the counties along the same borders but on opposite sides within the same year, which helps identify the cross-sectional variation in outcome attributable solely to whether the counties are treated or not. I also include county fixed effects, which ensures that I capture only within-county variation so that the estimates are not affected by time-invariant unobservable differences between the treated and control counties. I find that treated counties experience a significant reduction in misconduct after 2016 compared with control counties. Specifically, my estimates suggest that the 2016 DOL fiduciary rule leads to a 20% decrease in the percentage of the treated counties' brokers committing misconduct and a 40% decrease in the average per brokers misconduct incident count. The estimated dollar amount effect is equivalent to a reduction in losses of approximately \$300,000 per county per year. I interpret these results as suggesting that imposing FD on brokers would reduce their misconduct level. Since the magnitude of $\overline{D}(Misconduct)$ is smaller than $\overline{N}(Misconduct)$, this suggests that imposing FD on brokers has a more pronounced impact on reducing misconduct among existing offenders, rather than converting those who commit misconduct into non-offenders. The misconduct types that drive the results most are regulatory misconduct and customer disputes.

These findings suggest that imposing FD on brokers effectively reduces their incidences of misconduct. With the imposition of FD, brokers face increased legal costs as risks of class-action lawsuits, liabilities, and civil penalties increase. As outlined by traditional economic models of crime (Becker (1968)), the decision to engage in misconduct can be viewed as an economic choice that involves cost-benefit trade-offs. The imposition of FD significantly raises the costs associated with committing misconduct. Therefore, if the benefits of misconduct remain unchanged, the likelihood of an average broker engaging in such behavior should decrease as the associated costs increase.

Next, I turn to the cross-sectional heterogeneity in the impact of FD imposition on broker misconduct across counties. Previous literature (Parsons et al. (2018)) as well as my own analysis demonstrate that the likelihood of misconduct is shaped by both demand-side and supply-side factors, exhibiting substantial geographic variation. Understanding the economic mechanisms through which FD reduces misconduct is essential for evaluating the effectiveness of such regulatory interventions and identifying the areas where such policies are most needed to mitigate disparities in misconduct incidence.

I first document that the reduction in brokers' misconduct following the 2016 DOL fiduciary rule is more pronounced in counties with higher levels of trust, measured by higher General Social Survey (GSS) social trust score, greater religious adherence, and broader social tolerance for unethical behavior. The role of trust in financial advisory relationships is nuanced: while trust is foundational to establishing and maintaining such relationships (Gurun et al. (2018)), it can also reduce investors' monitoring, creating room for misconduct (Hayes et al. (2021)). In this context, the strengthened legal discipline from FD can help offset weaker investor discipline in high-trust environments.

Then, I examine the interplay between labor market discipline and the FD imposition. The results show that the reduction in misconduct is primarily driven by counties that have higher adviser density (higher probability of reemployment) and a lower likelihood of termination following misconduct. As these factors are indicative of weakened labor market discipline (Egan et al. (2019), Gurun et al. (2021)), the findings suggest that the imposition of FD may serve as a substitute to compensate for impaired labor market discipline in reducing broker misconduct.

Lastly, I investigate the impact from the 2016 DOL fiduciary rule on brokers' advising behavior, focusing on a specific type of financial product, MBMFs. There are several caveats to consider when relating misconduct to advising behavior. First, most of the misconduct is initiated by customers, which depends on not only brokers' advising behavior but also customers' willingness and ability to initiate a complaint. In contrast, the performance of a financial product is independent of customers' complaint behavior, helping to disentangle the brokers' advising behavior from the demand-side monitoring and reporting behavior. Second, misconduct captures only extreme cases, not fully representing the more routine services that brokers provide to investors. By analyzing MBMFs, as a representative financial product sold by brokers on a daily basis, I am able to assess more typical advising behavior that affects a wider population of investors.

The choice of MBMFs is based on two reasons: First, due to the tax exemption, MBMFs issued by a particular state are primarily sold to the residents of that state. The brokers handling these transactions are typically also registered in the same state.[9] As a result, changes in the flow or performance of the MBMFs issued in a given state are likely to reflect state-specific regulatory changes. Second, MBMFs purchasers are predominantly retail investors, who are generally less financially sophisticated. Compared to other types of mutual funds, MBMFs also tend to be more illiquid and opaque, which exacerbates the potential COI between brokers and investors. These features make MBMFs a particularly informative setting for examining how state-level FD changes influence brokers' advising behavior and product selection.

I begin by applying the same DiD analysis to examine changes in the dual-registration ratio across cross-border counties. I find that brokers in treated counties were significantly more likely to become dual-registered following the 2016 DOL fiduciary rule, relative to those in control counties. Next, I analyze the changes in MBMFs' distribution channel and find that funds issued in treated states experienced a larger decrease in the Total Net Asset (TNA)-weighted broker-sold ratio, implying that brokers tend to move away from commission-based products when they are subjected to FD. Lastly, I investigate changes in the returns, expenses, and flows of broker-sold funds. I find that after the 2016 DOL fiduciary rule, broker-sold MBMFs issued in treated states exhibit greater increases in returns, larger reductions in expenses, and a stronger negative relationship between distribution fees and fund flows. These findings highlight that one of the most direct effects of the 2016 FD rule was to incentivize brokers to become dual-registered and reduce reliance on commission-based products. More importantly, the results suggest that imposing FD on brokers may not only reduce extremely harmful behaviors such as misconduct, but also potentially enhance the quality of more frequent financial services, as evidenced by the improved performance of broker-sold MBMFs following the rule.

One concern with the regulatory interventions such as the 2016 DOL fiduciary rule is the potential for unintended consequences that may harm investor welfare. Theoretical models (Inderst and Ottaviani (2012b), Inderst and Ottaviani (2012a), Thiel (2022), Chang and Szydlowski (2020)) predict that the regulatory interventions such as increased commission disclosure, stricter penalties for biased advice, or outright caps and bans on commissions may result in regulatory "backfire."

[9] Brokers must register in their state of residence. They must also register in any state where they sell or offer to sell securities, or where they advertise. In most states, if a financial adviser serves more than a threshold number of clients—typically five—they are required to register in that state.

In such cases, the cost of doing business increases. The incentive to offer low-cost or "free" advice diminishes, and advisers or firms may exit the market. This can create an "advice gap," where many investors lose access to professional guidance.[10] To evaluate whether similar effects followed the 2016 DOL fiduciary rule, I compare the changes in broker and firm counts, as well as adviser entry and exit, in treated versus control counties. While there is no evidence of declines in the overall number of brokers or firms, treated counties experienced a larger drop in broker entry. This may indicate early signs of reduced entry, though the long-term effects on market structure have yet to materialize.

My paper makes several contributions to the literature. First, unlike other studies that utilize financial products' flow or performance as the outcome variable—such as the flow or return of variable annuities or mutual funds—my study focuses on financial advisers' misconduct as the primary outcome measure. One advantage of using this measure is its direct and positive association with investors' welfare.[11] Second, the misconduct I analyze spans a range of financial products, including equities, bonds, mutual funds, and variable annuities. Unlike studies that focus on a specific type of financial product, my results offer broader generalizations that are applicable to all types of brokers. Third, by employing a regression discontinuity design within cross-border counties and a DiD approach utilizing the 2016 DOL fiduciary policy change, my rigorous empirical design is more likely to provide a causal interpretation of the relationship between the imposition of FD and brokers' misconduct. Finally, the analysis of MBMFs offers a unique empirical advantage in uncovering the effects of state-specific changes in the FD regulatory framework. It allows me to examine how FD imposition influences brokers' product recommendations and the quality of advice in a context where conflicted incentives and investor vulnerability are both salient. Together, this study contributes new empirical evidence on the effects of imposing FD on brokers' misconduct, potentially informing ongoing policy discussions and future regulatory decisions.

The rest of the paper is organized as follows: Section 2 reviews the related literature. Section 3 provides the institutional background on the financial advisory industry and fiduciary duty. Section

[10]For example, adviser numbers in the U.K. fell by 25% following a commission ban (Financial Conduct Authority 2016, 18).

[11]A limitation is that misconduct is also tied to enforcement levels or customers' likelihood to initiate complaints, which may increase following the regulatory changes. Nevertheless, given that my findings indicate a decrease in brokers' misconduct levels after the implementation of the 2016 DOL fiduciary rule, any increase in local enforcement post-rule would only lead to an underestimation of the potential effect. Also, the analysis on MBMFs can help distinguish the supply-side behavioral change from the demand-side changes.

4 describes the data sources and presents summary statistics. Section 5 examines the impact of FD imposition on brokers' misconduct by regression discontinuity design. Section 6 presents my main analysis, focusing on the effects of the 2016 DOL fiduciary rule on brokers' misconduct. Section 7 explores the cross-sectional variations in the effects of the 2016 FD rule and discusses potential channels. Section 8 illustrates the policy's impact on brokers' advising behavior. Section 9 offers robustness tests for the main analysis. Section 10 concludes the paper and discusses policy implications.

Chapter 2

Related Literature

My study relates to the literature on the COI in financial advisory services. Studies based on both data and field experiments have documented the existence of COI in different financial products. Earlier studies of COI focused on the U.S. mutual fund industry (Bergstresser et al. (2009), Christoffersen et al. (2013), Del Guercio and Reuter (2014)). For example, Christoffersen et al. (2013) find that fund-level inflows increase with load payments to brokers, especially when those brokers are unaffiliated with the fund. They further note that inflows spurred by load payments tend to be linked with subsequent underperformance. Later studies expand the investigation into different financial products, such as insurance (Anagol et al. (2017), Egan et al. (2022)), mortgages (Guiso et al. (2022), Robles-Garcia (2019)) and structured financial products (Egan (2019), Vokata (2021)).

Another strand of literature points out that the COI between financial advisers and clients varies due to factors from both the supply side and demand side. From the demand side, studies have linked clients' financial literacy and sophistication to their likelihood of being exploited by financial advisers. Theoretically, Stoughton et al. (2011) show how kickbacks distort the incentive of financial advisers, especially when customers are unsophisticated. They also suggest that increased competition among active portfolio managers can reduce kickbacks and enhance the independence of advisory services. Inderst and Ottaviani (2012b) show how the effectiveness of commission-based incentives varies with customer awareness. They argue that when customers are aware of an adviser's incentives, contingent commissions can effectively motivate advisers to identify which specialized products best meet the specific needs of their clients. Conversely, when customers naively assume they are receiving unbiased advice, high product prices and corresponding high commissions can become tools for exploitation. Empirically, the previous literature finds that the quality of financial advice is related to clients' financial literacy (Kim et al. (2021), their trust in financial advisers (Reiter et al. (2022), Hayes et al. (2021)), the social ethical environment (Parsons et al. (2018)) and gender (Bhattacharya et al. (2023)). From the supply side, Bollen and Pool (2012) and Dimmock and Gerken (2012) point out that there are some supply-side predictors, such as past violations and aggressive operations, that are able to detect and predict investment adviser frauds. Gurun et al. (2018) find that financial advisers' ability to maintain client relationships after job changes weakens their employers' willingness to fire advisers for misconduct, which leads to an increase in the level of misconduct. Egan et al. (2019) show that roughly one-third of advisers with misconduct are repeat offenders and that the labor market partially undoes firm-level discipline by rehiring such advisers who are fired because of misconduct. A paper by Patel (2019) directly links commission-based compensation to adviser misconduct, but emphasizes that this relationship is mediated by market competition. While the opportunity to earn sales commissions generally increases the likelihood of misconduct, in regions with greater competition, commissions are associated with fewer misconduct claims. Dimmock et al. (2021) find that when a financial adviser has a negative personal financial shock due to real estate price changes, the adviser is more likely to commit misconduct. Sheen et al. (2021) find that the level of misconduct increases after the transition of the advisory firm's ownership to private equity. Their results highlight the tension between advisory firms' profit motive and ethical business practices, especially when customers are financially unsophisticated.

My study is also related to the strand of literature discussing the compensation structure in the financial advisory market and how the regulatory intervention may lead to unintended consequences. Theoretically, a series of papers by Inderst and Ottaviani (Inderst and Ottaviani (2012a), Inderst and Ottaviani (2012b)) highlight the role of commissions in making the advisor responsive to supply-side incentives. They also emphasize that commonly adopted policies such as mandatory disclosure and caps on commissions may have unintended welfare consequences and decrease the advisory efficiency. Chang and Szydlowski (2020) present an equilibrium model and conclude that although conflicted fees lead to distorted information, they are irrelevant for customers' welfare: banning conflicted fees improves only the information quality, not customers' welfare. Thiel (2022) builds on the work by Inderst and Ottaviani (2012a) and develops a model of price competition in advice markets with endogenous entry of advisers. While commission bans increase consumer surplus in the short run, they hurt the profitability of advisers. In the long run, advisers exit the market, advice becomes inaccessible, and consumer surplus decreases.

Among this body of work, my paper is most closely related to several empirical studies that examine the effect of imposing FD on brokers in the U.S. market. Bhattacharya et al. (2019) leverage a transaction-level dataset of deferred annuities and cross-state variation in common law fiduciary duty. They find that the imposition of FD on brokers increases risk-adjusted returns of annuities by 25 bps. It also leads to a 16% decline in the entry of affected firms. Egan et al. (2022) also use the 2016 DOL fiduciary rule to investigate how the rule impacts the annuity variable market. They show that after this rule, sales of high-expense variable annuities dropped by over 50% and became more sensitive to expenses. Using structural model estimates, they conclude that overall investor welfare improved after the rule. Kasten (2023) analyzes the impact of the 2016 DOL fiduciary rule on mutual funds. He finds that flows to mutual funds with conflicted broker compensation arrangements decreased after the policy relative to those without such arrangements.

Chapter 3

Institutional Background

3.1 Financial Advisory Industry and Fiduciary Duty

In the United States, the retail financial advisory business operates under two regulatory regimes: fee-based RIAs and commission-based brokers. At the federal level, RIAs are subject to the Investment Advisers Act of 1940 (or "Advisers Act"), and regulators consistently impose fiduciary standards on them. On the other hand, for brokers, there is an ongoing regulatory debate about whether FD should be imposed on them. Before the 2016 DOL fiduciary duty rule, regulators imposed a "suitability" standard on brokers, which is less stringent than the fiduciary standard. With the growing awareness of COI between brokers and investors, regulators have made various attempts to address the COI by imposing more stringent legal duties on brokers.

The regulatory debate on brokers began with the controversial "Merrill Lynch Rule". During the early 1990s, firms like Merrill Lynch began charging annual asset-based fees instead of transaction-based commissions in some brokerage accounts. The SEC, in 1999, suggested a regulation that would allow brokers' fee-based accounts to bypass the fiduciary obligations suggested by the Act, as long as the advice provided was merely incidental to their brokerage services. Officially titled "Certain brokers Deemed Not to Be Investment Advisers", this regulation, informally known as the Merrill Lynch Rule, was enacted in 2005, legitimizing a practice that had been ongoing for fifteen years. However, in 2007, the Financial Planning Association successfully challenged the SEC in court, claiming that the rule obscured the distinction between brokers and fiduciaries. As a consequence of the court's decision, brokers desiring to charge asset-based fees were required to register as fiduciary RIAs with the SEC. This unexpected victory once again drew a clear line between commission-based brokers and asset-based RIAs, clarifying the regulatory regimes they should follow.

Afterwards, the SEC and the DOL, two regulatory forces, have been continuously discussing the new regulatory regime for brokers. In 2009, the Treasury Department urged the SEC to establish FD for brokers, and in 2010, the Dodd-Frank Act permitted the SEC to pursue this proposal. In 2013, the SEC issued a request for comment on the concept of a fiduciary rule. Finally, on June 5, 2019 the SEC passed RegBI, which imposes a more stringent standard on brokers but falls short of a full fiduciary rule. The effective date for RegBI is June 30, 2020. Despite its successful implementation in 2020, RegBI has faced a lot of criticism after implementation. The main critique is that the RegBI is principle-based and therefore too subjective, leaving too much room for interpretation when it comes to implementation and compliance. The other loophole is that RegBI does not apply to commodities or to insurance products that are not registered as securities, such as annuities, which have been documented as highly-problematic products (Egan et al. (2019)).

Separately, the DOL has pushed hard to impose more stringent FD on brokers advising clients with retirement accounts. Near the end of 2010, the DOL released an initial fiduciary rule attempting to reduce COI from brokers in retirement accounts, but withdrew the rule quickly in the face of industry complaints. In 2015, President Obama endorsed a major overhaul of the initial DOL fiduciary rule. The DOL re-proposed the rule in 2015, with a final version in 2016, and an implementation date of January 2018. In February 2017, President Trump ordered the DOL to review the rule, pushing the implementation date to January 2019. In March 2018, the Fifth Circuit Court of Appeals vacated the rule, confirming this ruling on June 21, 2018. In May 2019, the DOL announced reconsideration of the fiduciary rule for retirement accounts. In April 2024, the DOL released a final version of its reconsidered fiduciary rule, titled the "Retirement Security Rule," which redefined who qualifies as a fiduciary under the Employee Retirement Income Security Act (ERISA) and amended several Prohibited Transaction Exemptions (PTEs). The rule was scheduled to take effect in September 2024, with some provisions delayed until 2025. However, implementation has since been suspended due to legal challenges and remains on hold as of May 2025.

3.2 2016 DOL fiduciary Rule and Industry Response

The fiduciary standard of care for retirement plans is governed by the ERISA. It typically mandates that brokers offering advice on employer-sponsored retirement plans act as fiduciaries. For other retirement accounts such as individual retirement accounts (IRAs), under the ERISA's current Five-Part Test, a broker is considered an Investment Advice Fiduciary if the person: (1) provides investment advice for a fee; (2) on a regular basis; (3) pursuant to a mutual understanding with the plan fiduciary; (4) that the advice will serve as a primary basis for investment decisions regarding the plan's assets; and (5) the advice is individualized based on the specific needs of the plan. Under this Five-Part test, it is easy for brokers to avoid fiduciary status because one of the components requires that advice is provided on a regular basis. This means that if investment professionals make one-time recommendations, they are not considered fiduciaries. For example, when workers roll over their savings from 401(k)s into an IRA upon leaving a job or retiring, the brokers who provide advice are likely not adhering to fiduciary standards since they make one-time recommendations even if the advice was to roll over someone's entire lifetime savings.

Amid growing concerns over conflicted advice in retirement accounts, the federal government moved to expand the fiduciary standard to a broader set of financial professionals. In February 2015, U.S. President Barack Obama directed the DOL to proceed with a proposal aimed at broadening the investment-advice standards for brokers and advisers managing retirement accounts. The DOL officially released the regulation, known as the "Fiduciary Rule", in April 2016, setting an initial compliance deadline of April 10, 2017. This rule intended to impose FD on brokers within the retirement sector. Most consequentially, the expansion of the FD defined in ERISA would now include IRAs in addition to traditional employer-sponsored retirement plans.

Receiving commission payments for products sold is usually incompatible with fiduciary responsibility. Under this expansion of FD, brokers over retirement accounts would no longer be able to make recommendations that can directly affect the level of their compensation without committing a prohibited transaction. These prohibited transactions include investment recommendations that create compensation from commissions, 12b-1 fees, revenue sharing, trailing commissions, and forms of non-monetary compensation such as gifts and trips. However, the proposed rule offered an exemption to allow brokers to receive commissions if the brokers and financial institutions satisfied a list of conditions described in the Best Interest Contract Exemption (BICE) rule. These conditions included acknowledging FD to the investor, adhering to standards of impartial conduct, disclosing information about COI, as well as adopting and publicly disclosing policies and procedures that mitigate COI.

The fiduciary rule was met with significant resistance from various stakeholders in the financial industry, leading to legal challenges. In March 2018, the Fifth Circuit Court of Appeals vacated the rule, arguing that the DOL had overstepped its authority by broadening the definition of fiduciary. The court's decision effectively nullified the rule, meaning it did not go into full effect as planned. The DOL subsequently did not appeal the court's decision. The vacating of the fiduciary rule returned the regulatory environment to its prior state, where brokers are not fiduciaries. However, the concern about regulatory changes over brokers' responsibility has remained as other regulators, including the SEC and state governments, sought to implement their own versions of the fiduciary rule. For example, In February 2020, Massachusetts released its own fiduciary standard for brokers and agents that is more stringent than the SEC's Regulation Best Interest.[1]

Despite the vacating of 2016 DOL fiduciary rule, considering the increased scrutiny over brokers and regulatory uncertainty, firms took actions to avoid or increase the transparency of their COI practices. Many firms transitioned away from traditional forms of compensation and switched to fee-based advisory service. Under this circumstance, brokers have to become dual-registered if they want to continue to provide service in these firms. By becoming dual-registered, they voluntarily take on the fiduciary responsibility despite the regulatory uncertainty. In addition to changing the service model, many firms also reduced access to or choice within the products offered to retirement investors, as reported by a survey study by Deloitte. Products affected included, but were not limited to, mutual funds, annuities, structured products, fixed income products, and private offerings, many of which are cited as the controversial products related to financial advisers' misconduct (Egan et al. (2019)). For example, 86% of firms participating in the survey reported a reduction in the number and types of mutual funds available to retirement investors, and 48% of study participants made reductions to their annuity offerings to retirement investors.

[1] https://www.sec.state.ma.us/divisions/securities/enforcement/adopting-release.htm

3.3 Potential Effects of 2016 DOL fiduciary Rule on Brokers

While the commission-based compensation structure is still allowed under BICE, the disclosure burden to prove that these prohibited transactions met the criteria laid out in BICE would be significantly heavier than before. Moreover, the brokers who are involved in these prohibited transactions would be at greater risk of class-action lawsuits, liabilities, and civil penalties.

Brokers have three choices after the Fiduciary Rule: they could stop selling commission-based product, or move to an alternative compensation structure like flat-fee advisory model, or continue engaging in commission-based transactions while meeting the increased disclosure requirements.

Choosing the fee-based model required becoming dual-registered, meaning the services provided would fall under the fiduciary standard. This imposed a stricter legal duty of care and heightened the likelihood of litigation and legal losses, thereby increasing legal costs and reducing the incentive to commit misconduct.

On the other hand, brokers who continued to recommend commission-based products were required to disclose more detailed information about the COI. This increased transparency helped reduce the information asymmetry that gives rise to the conflicted advice. As a result, advisers may have been discouraged from engaging in conflicted compensation arrangements, knowing such practices had to be disclosed and could raise concerns among clients.

In conclusion, the tighter regulatory environment introduced by the 2016 FD rule had the potential to influence brokers' professional behavior, particularly in practices involving COI. Consequently, broker misconduct, which is largely driven by such conflicts (Patel (2019)), was likely mitigated by the rule.

3.4 Differentiating State Laws

The debate about whether FD should be imposed on brokers is about federal level policy. At the state level, the FD standards for brokers vary widely.

My categorization of state brokers common law standards of care follows Finke and Langdon (2012). States are divided into three groups: (1) states that unambiguously apply a fiduciary standard to brokers in that state, (2) states that unambiguously apply no fiduciary standards to brokers, and (3) states where there is evidence of a limited fiduciary standard applied to brokers.

In my later analysis, I further aggregate groups (1) and (3) and call them the "Quasi-FD States" and name group (2) as "No-FD states".

Four states have unambiguous fiduciary standard on brokers where courts explicitly impose FD on brokers: California, Missouri, South Dakota, and South Carolina. California courts, for example, have held that a broker's FD requires that he or she act in the highest good faith toward the customer (Hobbs v. Bateman Eichler, Hill Richards Inc. 1985). While South Carolina courts have not expressly stated that brokers must live up to a fiduciary standard, the courts have imposed duties commensurate with those required when a FD applies, including a duty to refrain from acting contrary to a customer's best interest, avoid fraud, and communicate information to the customer that would be to the customer's advantage (Cowburn v. Leventis 2005).

States that do not impose FD on brokers are Arizona, Arkansas, Colorado, Hawaii, Massachusetts, Minnesota, Mississippi, Montana, New York, North Carolina, North Dakota, Oregon, Washington, and Wisconsin. The courts in these states have expressly stated that, under state law, a FD does not exist between a client and a broker, or over non-discretionary accounts.

The remaining states (Alabama, Alaska, Connecticut, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Michigan, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, Ohio, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Texas, Utah, Vermont, Virginia, West Virginia, and Wyoming) impose either a limited fiduciary standard, or the courts have interpreted state law to impose duties that appear to be fiduciary in nature. These states impose standards that exceed the suitability standard set forth under FINRA rules, but do not expressly classify brokers as fiduciaries. For example, Louisiana does not expressly impose a standard of conduct higher than the suitability standard, but does require a court to consider a variety of circumstances when determining whether a higher standard should exist. The items that Louisiana courts must consider include the relationship between the brokers and client, the nature of the account, and the sophistication of the customer (Beckstrom v. Parnell 1998).

It is worth noting that after the vacating of 2016 DOL Fiduciary Rule, several states began to consider or strengthen their own fiduciary rules to fill the regulatory gap left at the federal level, including Massachusetts, Nevada, Maryland, and New Jersey. These state-level initiatives potentially lead to a complex regulatory environment for financial service providers who operate across multiple jurisdictions. But these state-level regulatory changes do not impact my empirical design since I consider the 2016 DOL fiduciary rule as the start of a series of regulatory changes, not only state-level initiatives, but also SEC's RegBI and DOL's third attempt of FD rule. In my robustness test, I delete these four states and the results still hold.

3.5 Legal Forums for Broker Misconduct

Financial advisory misconduct cases are typically resolved through FINRA arbitration, where clients seek monetary compensation for alleged harm. This prevalence is largely due to mandatory arbitration clauses in brokerage agreements, which require clients to resolve disputes through FINRA's arbitration process. These proceedings are binding, with limited grounds for appeal. In 2024, approximately 84% of customer arbitration cases were resolved through either a monetary award or settlement (FINRA Dispute Resolution Statistics, 2024). Some cases proceed to state court when they involve breaches of fiduciary duty under state common law or violations of state securities statutes, or to federal court when federal securities laws are at issue or when diversity jurisdiction applies. In addition to private dispute resolution, regulatory bodies such as the SEC, FINRA's enforcement division, or state securities regulators may initiate disciplinary actions, which can lead to fines, suspensions, or permanent industry bans, particularly in cases involving fraud or repeat misconduct.

Even when cases are resolved through FINRA arbitration or in federal court, state-level fiduciary duty laws remain highly relevant. In 2024, breach of fiduciary duty was the most frequently cited claim in FINRA customer arbitration cases, with 1,252 filings (FINRA Dispute Resolution Statistics, 2024). Claimants' attorneys often invoke state fiduciary standards in FINRA proceedings to frame the adviser-client relationship, particularly in jurisdictions with robust investor protection laws like California and Missouri. These arguments can influence arbitrators' assessments of adviser conduct, even though FINRA arbitration does not formally apply state law. Similarly, when cases proceed to state court, plaintiffs frequently rely on state fiduciary duty statutes or common law to establish liability, especially in the absence of explicit federal fiduciary standards for brokers. Importantly, federal securities law and FINRA regulations generally do not preempt state fiduciary duties, which often apply concurrently and can significantly influence legal outcomes—particularly where federal law is silent or complementary.

In conclusion, the legal environment at the state level significantly shapes both the strategy and potential outcomes of financial misconduct claims across different forums (Black (2010)).

Chapter 4

Data and Descriptive Statistics

4.1 Data

Individual Financial Advisers Data. I construct an adviser-year dataset containing all the financial advisers in the U.S. from 2005 to 2022. The financial advisers in my dataset include both RIAs and brokers, whose data are collected from the SEC Investment Adviser Public Disclosure (IAPD) website and FINRA BrokerCheck website, respectively.[1,2] For dual-registered financial advisers, whose records could be found on both websites, I use the information on BrokerCheck website. Records on BrokerCheck and IAPD are both based on Form U4 and contain the same information in slightly different formats.[3]

Each financial adviser is identified by a unique CRD number, which remains the same for the financial adviser's entire employment history, whether as an RIA or a broker. There is a PDF-formatted report for each CRD. I download all the reports and construct adviser-year panel data by parsing through the reports. The extracted information includes employment history (registered employment exclusively), branch location, work type, qualification exams, and misconduct disclosures.[4] In total, the dataset has 1.5 million financial advisers.

Each adviser-year record provides the branch location of the employer, either as the city and state name, or the zip-code. According to the branch location information, I link each adviser-year

[1] https://adviserinfo.sec.gov/

[2] https://brokercheck.finra.org/

[3] The registration of a broker or RIA is done by the submission of an initial Form U4 to the state regulator through the advisory firm's IARD/CRD account. When there is a material change to information that should be disclosed on the Form U4, the adviser has an obligation to update the Form U4 promptly.

[4] The work type here refers to broker, investment adviser representative, or both broker and investment adviser.

record to county FIPS. The city-state name to FIPS conversion is based on the name matching using the city name and FIPS linking table from the Census. Zip code to FIPS conversion is based on the HUD-USPS ZIP Code Crosswalk file.[5] I aggregate the individual adviser records into county-level data, which includes information about average brokers' experience, dual-registered ratio, financial adviser density (number of financial advisers per capita) and misconduct-related measures.

Misconduct Measures. FINRA BrokerCheck and SEC IAPD requires that "all individuals registered to sell securities or provide investment advice are required to disclose customer complaints and arbitration, regulatory actions, employment terminations, bankruptcy filings, and criminal or judicial proceedings". By retrieving the universe of financial advisers' reports, I collect all the information about these disclosures.

There are nine types of disclosed events, which are further divided into 23 sub-categories on BrokerCheck disclosures.[6] Considering the relevance to financial advisory services, I follow Egan et al. (2019) and Sheen et al. (2021) and keep five types of disclosed events: civil event, criminal event, regulatory event, customer dispute, and termination (Employment Separation After Allegations).[7] To be conservative, I keep only the confirmed cases that clearly indicate the wrongdoing of financial advisers. All pending, dismissed, denied cases are excluded. I parse through each financial adviser's event disclosures and assign each event record to the year the disclosed event was initiated. After this step, I construct an adviser-year misconduct record and then link it back to adviser-year employment-related records.

For individual-level data, I construct a dummy variable, $D(Misconduct)$, for each adviser-year observation, which equals one if the adviser commits any type of misconduct in the year. I construct a dummy variable for each type of misconduct, which equals one if the adviser has one or more incidents of this type of misconduct in the year. I also count the total number of misconduct incidents for each adviser in each year, denoted as $N(Misconduct)$. Some of the events disclosed the alleged amount and settle/granted-damages amount. For each adviser-year observation, I also collect and construct $Dollar(Misconduct)$ as the total non-missing dollar amount of settlement or

[5] https://www.huduser.gov/portal/datasets/usps_crosswalk.html

[6] The format and categorization of misconduct are slightly different on IAPD website. But the content is the same. I convert the format of IAPD to make it consistent with BrokerCheck.

[7] The other four types of events are Bond, Judgment/Lien, Financial, and Investigation.

granted-damages from all misconduct incidents for each adviser in each year.

For aggregated county-level data, following Sheen et al. (2021), I construct $\overline{D}(Misconduct)_{i,t}$, as the percentage of advisers working at county i committing any misconduct during year t:

$$\overline{D}(Misconduct)_{i,t} = \frac{\sum_{j=1}^{Nadv_{i,t}} D(Misconduct_{j,i,t})}{Nadv_{i,t}} \tag{4.1}$$

where $D(Misconduct)_{j,i,t}$ is dummy variable D (Misconduct) for adviser j working at county i during time t and $Nadv_{i,t}$ is the total number of advisers at county i during year t. Similarly, I construct the county-level misconduct rate for each misconduct type, $\overline{D}(Civil)_{i,t}$, $\overline{D}(Criminal)_{i,t}$, $\overline{D}(Regulatory)_{i,t}$, and $\overline{D}(Customer)_{i,t}$

I also construct the average misconduct incident count at the county level $\overline{N}(Misconduct)_{i,t}$, as the average number of misconducts committed by an adviser working at county i during year t:

$$\overline{N}(Misconduct)_{i,t} = \frac{\sum_{j=1}^{Nadv_{i}} N(Misconduct)_{j,i,t}}{Nadv_{i,t}}. \tag{4.2}$$

Finally, I take the average of non-zero $Dollar(Misconduct)$ and construct $\overline{Dollar}(Misconduct)_{i,t}$ as the average non-missing alleged and settlement amounts of the misconduct incidents within a county i in a given year t.

County-level Demographic and Economics Data. I obtain annual demographics such as education, race ratio, workforce ratio from the Census and the American Community Survey, economic variables such as income per capita and population from the Bureau of Economic Analysis (BEA), and local unemployment rate from the Local Area Unemployment Statistics (LAUS).

Local Trust and Ethics Data. To measure the local trust and ethical environment, I construct four variables using multiple data sources.

The first is a state-level measure of social trust (*SocialTrust*), following Hayes et al. (2021). It is derived from the General Social Survey (GSS), a biennial personal interview survey of social attitudes. I use responses to the question "Generally speaking, would you say that most people can be trusted?" Answers are coded as "can trust" (3), "depends" (2), and "cannot trust" (1). I then average these responses at the state level for each survey wave from 2000 to 2022.

The second measure is the county-level religion participation (*ReligionAdherenceRate*). Religion participation has been documented to be closely related to financial fraud (Dyreng et al.

(2012), McGuire et al. (2012)). I measure a county's religion participation rate using the total religion adherence rate from the Association of Religion Data Archives (ARDA).

The third measure is local political corruption data ($PoliticalCorruption$) which is a proxy for social tolerance for unethical and illegal activities. Following Parsons et al. (2018), I collect data on federal convictions for corruption-related crimes by elected officials from the "Report to Congress on the Activities and Operations of Public Integrity Section" published by the DOJ. For each county, I find the geographically closest district headquarters and use its conviction number as a proxy for local unethical and illegal activity. As argued by Glaeser and Saks (2006), a significant advantage of using political corruption is that it is enforced at the federal level by the DOJ. The federal judicial system's relative isolation from local corruption "should treat people similarly across space" (p. 1054). So the regional differences of this measure are mainly due to the local ethical culture instead of legal enforcement.

The last measure is local Physicians Rent-seeking Data ($PhysicianRentSeeking$), which is a proxy for local ethical culture, specifically unethical and not illegal activities following Parsons et al. (2018). I obtain data on monetary transfers from major pharmaceutical firms to prescribing physicians during 2015 from the Centers for Medicare & Medicaid Services (CMS)'s "OpenPaymentsData" website.[8] Payments are listed by firm, doctor, date, amount in dollars, and activity (if any), such as a speaking engagement, consulting arrangement, dinner, or gift. I merge these payment data with Medicare (Part D) prescriptions in year 2015 for each physician using CMS's Prescriber Look-up Tool.[9] Then, for each county, I regress sensitivities between drug company payments and prescriptions using physicians' individual records, following Engelberg et al. (2014). Larger numbers indicate higher responsiveness by a county's physicians from the pharmaceutical firms' payment. Although such practices have raised ethical questions, currently no federal, state, or local statutes forbid such financial relationships.

Municipal Bond-Based Mutual Fund Data. Data for open-end MBMFs in this study are drawn from Morningstar Direct. The initial dataset is a survivor-bias-free sample of 5,350 U.S. open-end MBMF share classes, representing 1,602 funds labeled as "U.S. municipal fixed income" that existed at any point after January 2000. I exclude 1910 national fund share classes and

[8] https://openpaymentsdata.cms.gov/

[9] https://data.cms.gov/tools/medicare-part-d-prescriber-look-up-tool

focus only on 3422 MBMF share classes that have a clear single-state issuer. The performance measures I draw from Morningstar include $TrueNoLoad$, monthly/yearly total net asset (TNA), monthly/yearly net flow, yearly distribution fee, yearly net expense ratio, yearly gross return and yearly Morningstar return.[10] I define share classes with $TrueNoLoad$ equal to "No" as broker-sold MBMFs.

4.2 Summary Statistics

4.2.1 Individual Brokers Summary Statistics

Table 1 reports the summary statistics for the individual financial adviser data. After combining the BrokerCheck and IAPD data, there are approximately 1.5 million financial advisers, constituting 12 million adviser-year records from 2005 to 2022. As of 2022, 45% of the universe financial advisers remains in the sample. Among all adviser-year records, 67% are from pure brokers, 31% are from dual-registered advisers, and the remaining 2% are from pure RIAs. Since RIAs are always under FD and only brokers are subject to cross-state variation and policy changes regarding FD imposition, my main analysis includes only the records of pure brokers or dual-registered advisers. The pure RIA records are used for placebo and robustness tests.

In Panel A of Table 1, I divide the financial advisers into two groups: brokers (including dual-registered) and pure RIAs. For brokers (including dual-registered), who constitute my main analysis sample, 33% are dual-registered as both brokers and RIAs. On average, these advisers have 13 years of experience, defined as the number of years since the adviser first registered. Based on my definition of misconduct, which includes five types of confirmed cases, the unconditional probability of a financial adviser committing any type of misconduct in a given year is 0.499%, and the average misconduct incident count for a broker in a given year is 0.006. Among the five types of misconduct, customer disputes are the most common, occurring with an unconditional probability of 0.261%.

As demonstrated by the panel, brokers (including dual-registered) differ significantly from pure RIAs in various dimensions. Compared with brokers and dual-registered, RIAs typically have more experience and a higher unconditional probability of committing misconduct. This is consistent

[10] A true no-load fund is defined as any fund with the following characteristics: Front Load equal to zero, Deferred Load equal to zero and 12b-1 Fee less than or equal to 0.25.

with previous literature (Finke et al. (2022), Egan et al. (2019)), which documented that RIAs tend to have a higher misconduct rate than brokers, and independent RIAs differ significantly from brokers and dual-registered financial advisers.

In Panel B of Table 1, I delve deeper into the dollar amounts involved in misconduct cases and show the summary statistics for non-zero dollar amounts. Eighty percent of the customer dispute cases, fifty percent of regulatory cases, and twenty percent of civil cases disclose the dollar amounts involved as settlement amounts or granted amounts. Among the different types of misconduct, as expected, civil cases are the most severe and involve the largest dollar amounts. The average dollar amount for a civil case is approximately three million, while the average for a regulatory case is $41,000. The average alleged and settlement amounts for a customer dispute event are $1.45 million and $437,000, respectively, indicating that most settled customer dispute events are severe and result in significant losses to investors. The median settlement ratio, which is the settlement amount divided by the alleged amount, is 41%. However, this number is also highly right-skewed, as the 99th percentile of settlement ratios is 48.

4.2.2 County-Level Summary Statistics

Table 2 presents the county-year summary statistics for the 499 border counties and 2,498 non-border counties. Panel A of the table illustrates demographic measures. Generally, border counties tend to be larger in terms of population and have higher incomes, older and more educated populations, lower minority ratios, and higher unemployment rates compared to non-border counties.

Panel B of Table 2 provides insights into the county-year financial advisory labor market and misconduct measures. On average, there is one adviser per 1,000 capita across counties. Border counties exhibit higher adviser density and fewer dual-registered advisers than non-border counties. The average experience of brokers in a given county is 15 years, with no significant differences between border and non-border counties. In border counties, the average rate of misconduct ($\overline{D}(misconduct)$) is 0.49%, and the number of incidents ($\overline{N}(misconduct)$) is 0.006 per year per 1,000 advisers. The average disclosed dollar amount for misconduct per county per year is $188,000, with no significant differences in misconduct measures between border and non-border counties. It is worth noting that $\overline{Dollar}(misconduct)$ is the average of non-missing and non-zero observations.

Figures 1 and 2 illustrate the cross-sectional and time-series variations in financial misconduct.

Figure 1 provides a snapshot of the misconduct count per 1,000 capita in 2019 across all U.S. counties. The significant variation observed across the map underpins the empirical analysis in this study. Figure 2 depicts the time-series patterns of county-level financial misconduct levels for three groups of counties, categorized by their average misconduct rate over the sample period into high, medium, and low. Both panel A and B reveal similar patterns, showing considerable fluctuations in misconduct levels over time. Notably, there is an increase in financial misconduct around the time of the financial crisis. Additionally, there is also an immediate and sharp increase in misconduct around 2016, suggesting a change in enforcement resulting from the policy change. However, overall misconduct levels declined rapidly after 2016.

Panel C of Table 2 explores the political, cultural, and ethical environment measures, which are closely related to social culture and financial misconduct. Compared to non-border counties, border counties typically have lower social trust score, a lower religious adherence rate, and more unethical activities represented by political corruption and physicians' rent-seeking activities. Figure 4 shows the trust level across the states as a snapshot in 2016.

4.2.3 Municipal Bond Mutual Fund Summary Statistics

In Table 3, I report summary statistics for MBMFs included in my analysis. The data are structured at the share class–year level and are disaggregated by broker-sold and direct-sold funds for comparison. Figure 3 displays the distribution of MBMF issuance across states, with California and New York accounting for the highest total TNA. As shown in Table 3, broker-sold funds, relative to direct-sold funds, generally exhibit lower TNA, greater outflows, and weaker performance, as evidenced by lower returns and higher expenses. Because broker-sold funds are directly influenced by brokers' behavior, particularly in response to FD regulation, this paper focuses on this segment. Among broker-sold funds, the average TNA at the share class level is $132 million, with a median Morningstar annual flow rate of –8%, indicating net outflows. I report two return measures obtained from Morningstar: the average gross return is 4.11%, and the Morningstar return (net return) is 2.92%. To assess the impact of FD imposition on fund costs, I analyze three expense measures: the gross expense ratio, net expense ratio, and distribution fee, which average 1.32%, 1.19%, and 0.56%, respectively.

Chapter 5

State Border Discontinuity of Fiduciary Duty

5.1 Empirical Design

To assess the impact of FD imposition on financial advisers' misconduct, it is essential to recognize that FD is not assigned randomly. Both the characteristics of investors and financial advisers could be significantly correlated with the likelihood of FD imposition as well as the propensity to commit misconduct. For instance, as documented by Parsons et al. (2018), financial misconduct is closely linked to local social tolerance for unethical behavior, which are also key factors influencing legislation and law enforcement, including FD imposition. To address the endogeneity concerns, I first utilize the natural discontinuity of FD imposition across counties located on either side of state borders that differ in FD regulations. This identification strategy is based on two empirical observations: First, as shown in Table 2, border counties generally differ significantly from central counties in various dimensions, making comparisons between rural and central areas in different states unreasonable. Second, counties on either side of a border tend to be economically and demographically similar, especially in terms of social norms and ethical environments, due to their geographical proximity.

To visually illustrate the border counties in my sample, Figure 5 presents the map of U.S. counties. The darker-blue represents the counties with strict or some level of FD imposition on brokers. The lighter-blue represents the counties without FD imposition on brokers, and the red represents the cross-border counties that are included in my main analysis. As seen from the figure, the counties along the same borders tend to be geographically close to each other, suggesting a low probability of dramatic variation in demographic features, economic activities, and social culture.

5.2 Covariate Balance

A foundational assumption of the regression discontinuity identification approach is that both treated and untreated groups should be comparable based on observable characteristics. Therefore, it is essential to confirm that counties on either side of a state border are similar in demographic, economic, political, and cultural aspects. Any notable differences in these variables might represent omitted variables, potentially skewing the results. To that end, Figure 6 shows the balance of covariates across the border counties with or without FD imposition on brokers. The comparison is within the counties along the same border within the same year. Figure 6A displays the comparison of demographic and economic variables, including income, population, age, minority ratio, education, workforce ratio, unemployment ratio, and stock market participation. None of these variables show significant differences across the counties with or without FD imposition. In Figure 6B, I report the results of the variables related to politics, religion, and ethical culture. No significant differences are observed. The main takeaway from this test is that the counties located on opposite sides of the same borders generally share similar demographic, economic, and cultural environments.

5.3 Model Specification

The first key regression in this paper examines the effect of FD imposition on brokers' misconduct using a regression discontinuity approach. For this analysis, I limit the sample to the period starting from 2005 because all legal cases that inform the states' fiduciary statuses occurred before that year. The sample ends in 2015, coinciding with the proposal of the DOL FD rule by the Obama administration. The formal regression equation is written as:

$$y_{i,b,t} = \alpha_{b,t} + \beta \times DummyFD_i + \gamma \times X_{i,b,t} + \varepsilon_{i,b,t} \tag{5.1}$$

where $y_{i,b,t}$ is the misconduct measure for county i located at border b during time t. I use both $\overline{D}(Misconduct)$ and $\overline{N}(Misconduct)$ as the dependent variable[1]. $DummyFD_i$ is a dummy variable indicating whether brokers in county i is under FD imposition or not. β is the coefficient of interest, which captures the effect from FD imposition treatment. $\alpha_{b,t}$ is the crucial border-year fixed effects, which controls the effect of unobservable local economic and culture forces on the brokers' misconduct likelihood. The control variables in $X_{i,b,t}$ include the year-varying demographic, economic and cultural controls at the county level. Since the misconduct rate and average misconduct incident count are measured more accurately when the number of advisers is larger, I weight each observation in the analysis by the number of brokers in the county. I cluster standard errors at the county level.

5.4 Impact of Fiduciary Duty on Broker Misconduct

Table 4 presents the results from estimating equation 5.1 with different dependent and control variables. In columns (1) and (3), I control only for the border-year fixed effects, without including any other control variables. In columns (2) and (4), I introduce observable year-varying control variables to investigate the effect of cross-sectional variation among counties within the same border-year. Notably, the main estimate of interest, β, is statistically significant across all specifications. After including local economic and cultural environment-related variables in columns (2) and (4), the estimates of both $\overline{D}(Misconduct)$ and $\overline{N}(Misconduct)$ are significant at the one percent level. In column (2), the coefficient of -0.158% suggests that counties with FD imposition on brokers have, on average, 0.158% fewer brokers committing misconduct each year. Given that the unconditional average $\overline{D}(Misconduct)$ is 0.49%, this translates to an approximate 30% reduction in the likelihood of brokers committing misconduct annually in these counties. In column (4), the estimate of $\overline{N}(Misconduct)$ is -0.00151. Given that the unconditional average $\overline{N}(Misconduct)$ is 0.0065, this translates to an approximate 23% reduction in the average count of misconduct conducted by a broker annually in these counties.

Interestingly, by analyzing the cross-sectional variation of observable variables, I have identified several economic and cultural determinants of brokers' misconduct level within counties. These findings are detailed in columns 2 and 4 of Table 4. Demographically and economically, larger population counties with lower income levels, older populations, and more workforce tend to have higher

[1]All of the misconduct-related measures are multiplied by 100 for ease of interpretation.

rates of misconduct. The positive correlations between age and workforce ratio with misconduct are expected due to higher client rates in these areas, which naturally lead to a higher incidence of misconduct. The impact of these economic variables can also be linked to the profit-maximizing behaviors of brokers. For instance, the negative correlation between income and misconduct, though counter-intuitive, might be attributed to the lower financial sophistication of populations with lower incomes. This lack of financial sophistication could decrease the likelihood of detecting misconduct, thereby increasing the vulnerability of these populations to such behaviors. Culturally, counties with a greater religious adherence also exhibit higher misconduct rates, aligning with findings from previous studies (Hutton et al. (2015), Dyreng et al. (2012)). Additionally, in the financial advisory labor market, counties with more experienced brokers tend to report higher misconduct levels, a finding consistent with the evidence presented in Egan et al. (2019).

In summary, by analyzing the 2005-2015 sample and the border-discontinuity in FD imposition on brokers, I find that such imposition is associated with lower levels of misconduct. Counties on the fiduciary side of the border show an approximate 30% lower misconduct rates compared with the counties on the other side, as demonstrated by both $\overline{D}(Misconduct)$ and $\overline{N}(Misconduct)$. Additionally, I have identified several economic and cultural variables that correlate with higher rates of misconduct, which helps to pinpoint financially vulnerable counties.

Chapter 6

2016 DOL Fiduciary Rule Effect on Brokers' Misconduct

6.1 Empirical Design

By utilizing the state border-discontinuity in FD imposition on brokers, I find that the imposition of FD is associated with lower brokers' misconduct levels. This design effectively controls for investor-side omitted variables by comparing similar investors on two sides of the same border. However, one concern that may hinder the causal interpretation of this empirical design is that it does not fully mitigate the potential selection bias from brokers.

In April 2016, the DOL redefined "investment advice" within pension and retirement plans through the fiduciary rule, which resulted in brokers working with retirement accounts being newly classified as investment advisers and thus placed under FD. Given that the majority of brokers are involved in the retirement accounts business, this rule effectively imposed FD on most brokers at the federal level. Despite facing legal challenges and being vacated in 2018, I still regard the 2016 DOL fiduciary rule as the beginning of a series of regulatory threats on brokers and utilize it as a temporal policy shock.

To test the effect of the 2016 DOL fiduciary rule on brokers' misconduct, I will employ a DiD strategy. Counties that were not subject to FD impositions before 2016 are considered the treated group, as they experienced a change in fiduciary status due to the rule. Conversely, counties where FD was already imposed on brokers serve as the control group. In these areas, brokers' practices have consistently been required to adhere to at least some level of fiduciary duty, resulting in a significantly lesser policy shock.

In Figure 7, I plot the average $\overline{N}$(misconduct) for treated and control counties around 2016. As shown in the figure, misconduct declines sharply in both groups following 2016, with a more pronounced decline in treated counties.

6.2 Model Specification

To implement the DiD strategy, I use 2016 as the base year and choose an event window of eight years, from 2013 to 2020. The formal regression equation is written as:

$$y_{i,b,t} = \beta \times Treated_i \times DummyPost2016_t + \gamma \times X_{i,t} + \delta_{b,t} + \theta_i + \varepsilon_{i,b,t} \tag{6.1}$$

where $y_{i,b,t}$ is the misconduct measure for county i located at border b during time t. $\overline{D}(Misconduct)$, $\overline{N}(Misconduct)$ and the disaggregated misconduct rate for each type of misconduct are the dependent variables. $Treated_i$ is a dummy variable which equals to 1 if the county is not under FD imposition before 2016. $DummyPost2016_t$ is a dummy indicating whether the year is after 2016. β is the coefficient of interest, which captures the effect from the 2016 DOL fiduciary rule. The control variables in $X_{i,b,t}$ include the year-varying demographic, economic, cultural, and financial advisory labor market related controls at the county level. $\delta_{b,t}$ is the border-year fixed effects, which removes the border-specific time fixed effects. The county fixed effects term θ_i removes the time-invariant county-specific fixed effects. By using these fixed effects, I detect the within-county and within-border-year treatment effect. I weight each observation in the analysis by the number of advisers in the county since the counties with more brokers would provide more accurate estimates of the annual misconduct rate. I cluster standard errors at the county level. And the results are robust by clustering standard errors at different levels.

One important assumption for DiD strategy is the parallel trends assumption, which posits that the treated and control groups would have followed similar trends in the absence of the treatment. To validate this assumption and examine the dynamics of the treatment effect, I also test the time-varying treatment effect. The specification is as follows:

$$y_{i,b,t} = \sum_{t=2013}^{t=2020} \beta_t \times Treated_i \times DummyT_t + \gamma \times X_{i,t} + \delta_{b,t} + \theta_i + \varepsilon_{i,b,t} \tag{6.2}$$

where DummyT is a dummy variable indicating whether the year is the event time t, where t = 2013, 2014, ..., 2019, 2020, and the coefficient β_t captures the difference between the treated counties and control counties in the year t. The baseline is $t = 2016$. As with Eq. 6.1, I estimate this model using weighted regressions, in which each observation is weighted by the number of brokers within the county and cluster the standard error at the county level.

6.3 Results

6.3.1 Baseline Results

I begin by assessing the similarity between treated and control counties prior to the treatment for two primary reasons. First, the underlying identification assumption of the DiD design is that the parallel trends assumption — the premise that treated and control groups would have followed similar trends in the absence of the treatment — is more likely to hold if the treated and control counties are inherently similar. Second, examining pre-treatment summary statistics helps interpret the economic magnitude of the treatment effect. Table A.1, which compares the treated-county-year and control-county-year observations using the pre-2016 sample, reveals that treated counties typically have slightly lower incomes, less experienced brokers, more Republican voters, and a higher incidence of political corruption. However, in other dimensions, especially in relation to misconduct-related measures, the counties are very similar.

Table 5 presents my estimates of the effect of 2016 FD rule on brokers' misconduct, based on Eq.6.1. I use $\overline{D}(misconduct)$ and $\overline{N}(misconduct)$ as the dependent variables in columns 1-3 and 4-6, respectively. Within each column, I incrementally add control variables. In columns 2 and 5, I include time-varying demographic and economic variables, while columns 3 and 6 incorporate control variables related to the financial advisory labor market. These variables are included to control for the potential shifts in employers' behavior and labor market dynamics following the policy change, and their subsequent influence on brokers' misconduct levels. The coefficient β, indicating the impact of the FD rule on brokers' misconduct, is statistically significant at at least the 5 percent level across all specifications, with very similar magnitude of estimates regardless of the controls used.

Column 3 shows that post-2016, the imposition of FD on brokers in treated counties is associated with a decrease in brokers' misconduct rate by an additional 0.126% points compared to control counties. Similarly, column 6 indicates a decrease in the average number of misconduct incidents per broker by 0.003 units more in treated counties than in the control counties. Compared to the pre-treatment levels of $\overline{D}(misconduct)$ (0.71%) and $\overline{N}(misconduct)$ (0.008 incidents per adviser) in the treated group, these estimates suggest that treated counties are experiencing a 20% reduction in misconduct rates and a 40% reduction in the average number of misconduct incidents.

To assess the equivalent dollar amount effect of the policy, I extrapolate these estimates to all counties in the U.S. Assuming the average county has 250 brokers, with an average loss per misconduct incident as $400,000, the decrease in the number of misconduct incidents ($\overline{N}(misconduct)$ effect of 0.003) translates to a reduction in dollar amount losses of approximately $300,000 per county per year post-2016 DOL fiduciary rule.

I also dive deeper into the policy effects on specific types of misconduct, with detailed results presented in Table 6. The findings indicate that the reduction in misconduct following the 2016 policy is primarily driven by decreases in customer disputes and terminations. Both types of misconduct, as shown in the summary statistics from Table 2, are the most common and generally less severe misconduct. For other types of misconduct, such as civil, regulatory, and criminal cases, a longer time may be necessary to observe the policy's impact.

6.3.2 Pre-trends and Treatment Effect Dynamics

To strengthen the validity claim of parallel trend assumption for treated and control counties in the absence of treatment, Figure 8 plots the coefficients β_t from Eq.6.2, with Panel A and B showing results for $\overline{D}(misconduct)$ and $\overline{N}(misconduct)$ as dependent variables, respectively. The graphs illustrate that there are no significant trends prior to 2016, alleviating concerns about non-parallel pre-trends. Post-2016 coefficients shed light on the dynamic impacts of the DOL fiduciary rule. A noticeable decrease in misconduct begins in 2018, likely due to the lag between the occurrence of misconduct and its reporting. Interestingly, as shown in Figure 8B, misconduct levels slightly rebound in 2020. After the 2016 DOL fiduciary rule was vacated, the industry anticipated the introduction of similar regulations. In 2019, the SEC issued the RegBI rule, which is imposed on brokers but is unexpectedly less stringent than the fiduciary duty. The resurgence in misconduct levels may reflect a mixed effect from both the repeal of the 2016 fiduciary rule and the introduction of RegBI.

6.3.3 Effect of SEC RegBI on Brokers' Misconduct

To understand the dynamics of policy effects on brokers' misconduct, particularly in light of a resurgence in misconduct levels, I employ the same DiD strategy to test the effects of RegBI, issued by the SEC. The year following 2019 is defined as the event year, and due to data constraints, I analyze the three years preceding and following this period. As indicated in Table 7, the coefficients across all specifications are positive, but show only marginal significance in columns (5) and (6). This pattern suggests a notable, albeit unexpected, outcome following the introduction of RegBI. It appears that the regulatory changes on brokers, which is originally expected to be FD, may have inadvertently led to reduced compliance pressures on brokers. This unexpected reduction in compliance stress among brokers seems to have precipitated a resurgence in misconduct levels.

It is important to highlight that, due to ongoing concerns about COI between brokers and retirement account customers, along with the perceived vagueness of RegBI, the DOL has reissued a new version of the fiduciary rule, set for implementation in September 2024. This development underscores concerns that RegBI may not have fully met its original objectives of enhancing compliance, oversight, and the professional integrity of brokers.

Chapter 7

Discipline Mechanisms and the Impact of Fiduciary Duty

As illustrated in Figures 1 and 2, the level of misconduct across counties demonstrated considerable time-series and cross-sectional variation. Prior studies have suggested that this variability can be attributed to a range of factors, including investors' demographics and financial literacy, economic conditions, political leanings, religious adherence, and prevailing social norms or ethical cultures (Parsons et al. (2018), Stoughton et al. (2011), Inderst and Ottaviani (2012b), Kim et al. (2021), Reiter et al. (2022), Bhattacharya et al. (2023)).

One channel is that these factors weaken the demand- and supply-side discipline that normally constrains adviser behavior. For example, in communities where investors place high trust in financial advisers, especially when the trust stems from personal relationships rather than professional performance, trust may dampen the discipline. That is, excessive trust can reduce scrutiny and lower the likelihood that misconduct is detected or penalized, thereby weakening the discipline (Hayes et al. (2021)). Similarly, a fully employment labor market may have higher tolerance for misconduct. Advisers face fewer reputational or employment consequences. As a result, the expected cost of biased behavior is lower. This increases the incentive to act opportunistically (Egan et al. (2019); Gurun et al. (2021)).

In these contexts, legal interventions such as the imposition of FD act as a substitute for weak local disciplinary forces by imposing a uniform legal standard of conduct, thereby raising advisers' cost of misconduct. This implies that the effectiveness of the 2016 FD rule is likely to be heterogeneous: its impact should be strongest where investor or labor market disciplines are least effective. The results of the sub-sample analysis in this section support this hypothesis.

7.1 Investor Discipline

COI between financial advisers and investors arise from agency problems and information asymmetry (Egan (2019)). As described in the model by Prendergast (2002), consumers play a critical monitoring role in mitigating these agency problems. However, the precision of consumer monitoring depends on the customers' willingness and ability to monitor advisers effectively. In this study, I focus on variables related to local trust and ethics, which are key determinants of investors' monitoring precision. When consumers place high trust in brokers or exhibit greater tolerance for unethical behavior, they tend to have lower expectations of exploitation and weaker incentives for self-protection. This, in turn, leads to diminished investor discipline. In such settings, the legal discipline introduced by FD may play a particularly important role in curbing adviser misconduct.

In the sub-sample analysis, I find that the effect of the fiduciary duty rule is more pronounced in areas with higher levels of social trust, stronger religious affiliation, and greater tolerance for unethical conduct (Table 8). This pattern suggests that the rule has a greater impact in settings where investor discipline is weaker. These results are consistent with my hypothesis that legal discipline can serve as a substitute for weak investor discipline. In environments where investors are less inclined or less able to monitor financial advisers, the imposition of fiduciary standards plays a more substantial role in curbing adviser misconduct.

7.2 Labor Market Discipline

This section investigates how labor market discipline moderates the impact of the 2016 DOL fiduciary rule on broker misconduct. Local labor market conditions shape the expected career consequences of misconduct. In markets where labor discipline is weak, advisers are less likely to face reputational or employment penalties. As a result, the expected cost of misconduct is lower. This reduced cost increases the incentive to engage in biased behavior. If FD substitutes for market discipline, its impact should be greater in these areas. I test this hypothesis by comparing changes in misconduct across regions with varying levels of labor market discipline.

The level of labor market discipline is likely to be correlated with both the average experience of brokers and the size of the local advisory market. For example, more experienced brokers managing more clients have a lower risk of dismissal following misconduct, as discussed in Gurun et al. (2021). Additionally, a labor market might undermine firm-level discipline if it is sufficiently large, allowing brokers dismissed for misconduct to easily secure employment elsewhere.

I use the measures of average broker experience and broker density per capita as proxies of local labor market discipline to investigate how labor market discipline interacts with the policy effect. The findings, presented in Panels A and B of Table 9, suggest that the policy impacts are more pronounced in larger and more experienced markets. This supports the notion that the imposition of FD on brokers, following the 2016 DOL fiduciary rule, may help to partially restore weakened labor discipline.

To further assess this potential mechanism, I estimate a more direct proxy for labor discipline based on the likelihood of a broker being dismissed after committing misconduct, using data from the universal financial adviser records and conduct subsample analysis based on this estimate.[1] The findings presented in Panel C of Table 9 align with earlier results, demonstrating that the impact of FD imposition on brokers is more pronounced in markets with lower labor discipline. This indicates that the FD serves a supplemental role in reinforcing labor discipline.

[1]In this context, labor discipline refers to the overall discipline imposed by both the firm and the labor market. I define "being fired" as 1 whenever a broker changes jobs, regardless of whether he or she leaves the industry or move to a new firm.

Chapter 8

Policy Effect on Brokers' Advising Behavior

So far, I have shown that the 2016 DOL fiduciary rule significantly reduced broker misconduct, particularly in markets with weaker investor and labor market discipline. In the next step of the analysis, I examine whether the rule also affected brokers' broader advising behavior.

While misconduct reflects the most severe violations, shifts in business models and product choices may capture more subtle yet meaningful changes in how brokers provide services under increased legal obligations. These measures also help disentangle brokers' advising behavior from investors' complaint behavior, as they more directly reflect the advising behavior rather than clients' responses to it.

This section explores three dimensions of brokers' response. First, I analyze changes in the share of dual-registered advisers. Second, I examine whether the composition and performance of MBMFs sold by brokers changed following the rule. Third, I investigate whether the rule induced brokers or firms to exit the market, preliminarily addressing the concern about "advice gap". Together, these analyses provide a more complete picture of how FD reshapes adviser behavior beyond misconduct.

8.1 Dual-registered Ratio

The 2016 DOL fiduciary rule introduced two major changes affecting brokers who serve retirement accounts. First, it expanded the FD to include brokers advising on retirement assets, placing them under the same legal obligations as RIAs. As a result, the regulatory advantage of operating solely as a broker diminished. Second, brokers who wished to continue selling commission-based products were required to provide enhanced disclosures and comply with additional compliance requirements. This increased burden reduced the attractiveness and availability of commission-based offerings. If brokers seek to expand their business and collect asset-based fee compensation, they had to register as RIAs. Under both provisions, one would expect brokers to increasingly become dual-registered. In this section, I test this prediction by examining whether the rule led to a rise in dual-registered advisers.

I employ the same DiD approach as in the misconduct analysis, but change the dependent variable to the county-level dual-registered ratio ($DualRegis$). This measure is defined as the number of advisers registered as both brokers and RIAs divided by the total number of advisers in the county (including pure brokers, pure RIAs, and dual-registered advisers). The results, presented in Table 10, consistently show that counties newly subject to the FD rule experienced a greater increase in the dual-registered ratio after 2016 compared to control counties. The estimated effect is economically meaningful, corresponding to an average increase of 1.7 percentage points.

Figure 9 plots the dynamic treatment effects and pre-trends in dual registration across counties. The figure shows no significant differences between treated and control counties prior to 2016, alleviating concerns about violations of the parallel trends assumption.

8.2 Advice on Municipal Bond Mutual Funds

The main findings presented in Sections 6 and 7 suggest that the imposition of FD can significantly reduce misconduct among brokers, suggesting an association with improved financial service quality provided by brokers. However, there are concerns about using misconduct as the sole measure of financial service quality. First, misconduct outcomes are influenced not only by the quality of services but also by investors' likelihood of filing complaints, which may confound the results. Additionally, as misconduct reflects only the most severe cases, the broader impact from FD on the quality of brokers' more common financial service remains unclear. To address these concerns, I examine the effect of the 2016 DOL fiduciary rule on the performance of financial products sold by brokers. First, changes in these financial products are unlikely to be directly influenced by investors' complaint behavior. Second, assuming customers follow brokers' recommendations, the performance of these products can serve as a proxy for the quality of brokers' services. This approach enables a more comprehensive assessment of routine advising practices and helps disentangle changes in brokers' behavior from the confounding effects of variations in customer complaint behavior.

In this part of study, I focus on MBMFs for two reasons: First, my analysis focuses solely on MBMFs issued by a single state. This choice is informed by the fact that state-tax exemptions generally mean that MBMFs issued by one state are predominantly sold and purchased by local brokers and investors. Therefore, variations in fund flow or performance of these single-state issued MBMFs can be attributed to state-specific differences, such as whether the state is affected by the 2016 DOL rule by my DiD analysis, assuming all other variables remain constant. Second, retail investors represent a significant portion of the municipal bond market, accounting for approximately 70% of participants (Municipal Securities Rulemaking Board). These investors frequently choose MBMFs due to their lower trading costs and the benefit of professional management. The inherent illiquidity and opacity of the municipal securities market underscore the critical importance of financial advisers/brokers. So, MBMFs could be a useful example to examine the COI between brokers and customers.

One might question that MBMFs represent a narrow category and whether the findings are generalizable. In response, I argue that fund families and brokers typically adopt uniform marketing, disclosure, and compensation practices across fund types. When compliance departments adjust practices in response to FD changes, these adjustments are unlikely to be limited to a single product category. Thus, although the empirical focus is on one segment of the market, the MBMF sample provides a meaningful and policy-relevant lens into broader behavioral shifts among brokers in response to evolving legal standards.

In the U.S., mutual funds are generally categorized as either broker-sold or direct-sold. Broker-sold funds involve transactions mediated by brokers, who are typically compensated through commissions or distribution fees. These funds are directly affected by the legal responsibilities imposed on brokers. A natural response to FD regulation is a decline in the broker-sold ratio within mutual funds, as continued commission-based compensation under the rule triggers higher disclosure and compliance costs. Additionally, enhanced disclosure requirements improve transaction transparency, and the strengthened legal discipline under FD can improve the quality of advice. These factors may incentivize funds to retain only higher-quality broker-sold share classes. Taken together, the imposition of FD on brokers should lead to a shift away from broker-sold products and toward direct-sold, and within broker-sold MBMFs, a shift toward those with better quality, such as higher return and lower costs.

In Figure 10, I present a graph of the average $NetFlow/TNA$ ratio for the months surrounding the implementation of the 2016 DOL fiduciary rule in April 2016. The Net Flow is directly draw from Morningstar direct. The graph shows a noticeable decline in the net flow of broker-sold MBMFs, following the introduction of the rule. This decline is expected, as the new fiduciary rule requires brokers who wish to receive commissions from sales of MBMFs to undertake more paperwork to meet disclosure compliance. After the regulation change, brokers have three options: if dual-registered, they can transition these clients to an investment adviser account and sell different share classes of MBMFs; they can cease selling MBMFs altogether; or they can continue selling these products despite the heightened disclosure requirements. Each of these choices likely contributes to a stagnation or reduction in commission-based MBMF net flows, as evidenced by the clear decrease post-April 2016.

8.2.1 Model Specification

To assess the impact of the 2016 DOL fiduciary rule on state-specific MBMFs, I employ a DiD analysis similar to the strategy used in Section 7. This analysis is conducted at both the fund-year level and share-class-year level. At the fund level, I examine changes in the broker-sold TNA ratio within each fund. At the share class level, I focus on key product characteristics, including annual return and expense ratio. Funds and Share classes from states that had not imposed FD on brokers before 2016 are designated as treated, while those from states with pre-existing FD impositions on brokers serve as controls. The analysis covers the period from 2013 to 2020, including four years before and four years after the implementation of the 2016 rule.

The formal regression equation at the fund level is as follows:

$$y_{f,t} = \beta \times Treated_f \times DummyPost2016_t + \gamma \times X_{f,t} + FEs + \varepsilon_{f,t} \tag{8.1}$$

where $y_{f,t}$ is the broker-sold TNA ratio of fund f during year t. $Treated_f$ is a dummy variable which equals to 1 if the MBMF is issued by a state that is not under FD imposition before 2016 and vice versa. $DummyPost2016_t$ is a dummy indicating whether the year is after 2016. β is the coefficient of interest, which captures the effect from the 2016 DOL fiduciary rule. The control variables in $X_{f,t}$ include the year-varying fund average return, expense, log of TNA and TNA growth. The fixed effects I include are: *year fixed effects* to account for year-specific variations, *Fund fixed effects* to control for time-invariant influences attributable to fund management. I cluster two way standard errors at fund, year level.

The formal regression equation at the share class level is as follows:

$$y_{i,f,t} = \beta \times Treated_i \times DummyPost2016_t + \gamma \times X_{i,t} + FEs + \varepsilon_{i,f,t} \tag{8.2}$$

where $y_{i,f,t}$ is the performance of share class i from fund group f during year t. Return and expense measures have been used as the dependent variable. $Treated_i$ is a dummy variable which equals to 1 if the MBMF is issued by a state that is not under FD imposition before 2016 and vice versa. $DummyPost2016_t$ is a dummy indicating whether the year is after 2016. β is the coefficient of interest, which captures the effect from the 2016 DOL fiduciary rule. The control variables in $X_{i,b,t}$ include the year-varying TNA. The fixed effects I included are: *year fixed effects* to account for region-year-specific variations, *Share class fixed effects* to control for time-invariant characteristics specific to each share class, *Fund family fixed effects* to control for influences attributable to fund management, and *Share class type fixed effects* to address variations specific to the type of share class. I cluster two way standard errors at share class, year level.

8.2.2 Fund Flow Rate

In contrast with the monthly data depicted in Figure 10, I use yearly net flow to better mitigate the noise from seasonal patterns in fund net flows. I employ two specific measures of net flow in this paper. These measures are at the share classes level:

$$Est.FlowRate = \frac{TNA_{i,f,t} - TNA_{i,f,t-1} * GrossReturn_{i,f,t}}{TNA_{i,f,t-1}} \tag{8.3}$$

$$MorningStarFlowRate = \frac{Est.NetFlow_{i,f,t}}{TNA_{i,f,t-1}} \tag{8.4}$$

where $Est.NetFlow$ directly comes from MorningStar Dataset.

8.2.3 Effect on the Distribution Channel of MBMFs

I begin by examining how the 2016 DOL fiduciary rule affected the selling strategies of MBMF providers, or specifically, how the broker-sold ratio within a fund changed after brokers were subjected to fiduciary standards. This analysis uses the annual broker-sold ratio (*BrokerSoldRatio*), defined as the year-end ratio of the TNA of broker-sold share classes to the fund's total TNA. The results are presented in Panel A of Table 11. Both columns show that, relative to MBMFs issued in control states, funds issued in states newly subject to the FD rule experienced a larger decline in the broker-sold ratio. This finding is consistent with the prediction that imposing FD on brokers reduces the incentive to sell commission-based products. Faced with higher disclosure and compliance costs, brokers/firms may become more reluctant to distribute such products, leading fund providers to shift away from broker-sold share classes.

8.2.4 Effect on the Performance of Broker-Sold MBMFs

After examining the broker-sold ratio in MBMFs following the implementation of the 2016 DOL fiduciary rule, I now turn to share class level analysis. Here, I focus on the broker-sold MBMF share classes due to the fact that they are directly influenced by the brokers' behavior resulted from FD status changes. To investigate how the new rule might impact the performance of these funds. I focus primarily on two performance metrics: returns and expenses.

I use two return measures provided by Morningstar. *Net Return*, this is directly draw from Morningstar, which is calculated by taking the change in yearly net asset value, reinvesting all income and capital-gains distributions during that year, and dividing by the starting TNA. This return does not include sale charge but account for management, administrative, 12b-1 fees, and other costs taken out of fund assets. *Gross return*, which is calculated by taking the Total Return and backing out the most recent expense ratio. For expenses, I also consider two different measures: *Net expense* is the percentage of fund assets, net of reimbursements, used to pay for operating expenses and management fees. *Gross expense* represents the total gross expenses (net expenses with waivers added back in) divided by the fund's average net assets. The difference is that the gross expense ratio does not reflect any fee waivers in effect during the time period.

Column 1 and 2 in Panel B of Table 11 reports the results using return measures as dependent variables. Both of them consistently show that after 2016, the MBMFs in treated states have significantly higher return compared with those in control states with an economic magnitude as 14-16 basis points. Compared with the pre-treatment average estimates in Table **??**, the coefficients indicates that there is a 5% -7% greater increase of returns for the MBMFs in treated states compared with the effect on MBMFs from control states after the imposition of FD on brokers.

Column 3, 4 and 5 in Panel B of Table 11 displays the results for expense-related measures. The coefficient on both measures are negative and statistically significant. The coefficients indicate that after 2016, the expense ratio of MBMFs from treated states decreased by approximately 1 basis point compared to those from control states. The absence of significant results for the distribution fee is not surprising, considering that nearly half of the MBMFs have missing data for this measure, and there is little variation, as many funds report only up to the allowable ceiling for distribution fees.

8.2.5 Effect on the Flow-Fee Sensitivity of Broker-sold MBMFs

Earlier literature finds that fund flows tend to respond positively to distribution fees, and that inflows spurred by commission-based incentives are often associated with subsequent underperformance (Sirri and Tufano (1998); Christoffersen et al. (2013)). These findings suggest that the commission paid by mutual funds, and the responsiveness of fund inflows to these payments, reflect potential COI in the mutual fund industry.

Under the 2016 DOL fiduciary rule, brokers who receive 12b-1 fees are subject to heightened disclosure requirements and must demonstrate that their recommendations are in the client's best interest. This regulatory shift increases transparency and legal exposure, potentially weakening brokers' incentives to prioritize high-commission products. In fact, high distribution fees may even serve as red flags that attract regulatory scrutiny. As a result, the hypothesis here is that the policy would reduce, or even change the direction of the sensitivity of fund flows to commission.

To test this hypothesis, I use the distribution fee as a proxy for broker commissions and conduct a triple-difference analysis to examine how the sensitivity of fund flows to distribution fees changes following the 2016 DOL fiduciary rule. The results are presented in Panel C of Table 11. In the first row, somewhat surprisingly, there is no significant relationship between distribution fees and fund flows—contrary to findings in prior literature. One possible explanation is that the sample begins in 2013, by which time investor and regulatory awareness of commission-based compensation may have already reduced the effectiveness of commission-driven distribution strategies. In the second row, consistent with the hypothesis, I find a significantly stronger negative relationship between distribution fees and fund flows after the 2016 rule. This pattern holds across both flow measures: the Morningstar Flow Rate and the Estimated Flow Rate. These findings suggest that increased regulatory scrutiny and disclosure requirements may have reduced brokers' responsiveness to commission incentives in fund selection, or even led brokers to avoid commission-based products to minimize scrutiny from regulators or investors.

In conclusion, the results suggest that the 2016 DOL fiduciary rule led to meaningful changes in mutual fund distribution, broker behavior, and product quality. Funds in treated states experienced a larger decline in TNA ratio of broker-sold share classes. Among the broker-sold funds that remained, I find evidence of improved performance. These funds show higher returns and lower expense ratios. I also find a stronger negative relationship between distribution fees and fund flows after the rule. This suggests that brokers became less responsive to commission incentives, or brokers may have actively avoided high-fee products to reduce the risk of scrutiny from regulators or investors. Together, these findings suggest that fiduciary duty regulation not only reduces misconduct. It also encourages a shift toward better-quality products and more transparent advising practices.

8.3 Broker Entry and Exit

When countries have implemented a complete ban on commission-based compensation, one documented unintended consequence has been the exit of financial advisers from the market. As argued in Thiel (2022), a shift to fee-based advice causes a tension between consumers, who think advice fees are too high, and advisers, who report downward pressure on fees and exit the market. To address the concern that the 2016 DOL fiduciary rule may have produced similar exit patterns among the U.S. brokers, this section examines the entry and exit dynamics of brokers following the rule's implementation.

I use the same DiD design to examine changes in the (log of) number of brokers and brokerage firms at the county level. As shown in Panel A of Table 12, the results indicate no statistically or economically significant change in the total number of brokers or firms following the rule. However, when I focus on brokers' entry and exit behavior, the results in Panel B show a larger decline in broker entry in treated counties compared to control counties. I conclude that while the overall size of the brokerage industry remained stable, the rule may have discouraged new brokers from entering the market, suggesting early signs of reduced market entry in response to increased regulatory burden.

Chapter 9

Robustness Tests

To ensure the robustness of my findings, I have conducted several robustness tests by modifying the sample and adjusting the empirical strategy. In most cases, these alternative tests yield results that are consistent with those of the main analysis, reinforcing the reliability of my conclusions.

Individual brokers Analysis. I start the robustness check by repeating the DiD test using individual brokers' employment and misconduct-related data. The results are reported in Panel A of Table 13 using both $D(misconduct)$ and $N(misconduct)$ as dependent variables. While the results are generally consistent with the main analysis, they show a smaller economic magnitude, which is expected given that the county-level regression is weighted by the number of brokers in each county. Specifically, the results for $D(misconduct)$ display marginal significance and a smaller economic magnitude, suggesting that the policy change may have a more pronounced effect on reducing the frequency of misconduct among existing offenders rather than converting offenders to non-offenders. Additionally, the positive and significant coefficient on dual registration suggests that brokers are more likely to become dual-registered in response to regulatory pressures.

In Panel B of Table 13, I employ a Poisson regression for $N(misconduct)$, addressing the issues associated with rare event count data, which can lead to biased results if analyzed using ordinary least squares (OLS) regression, as documented by Cohn et al. (2022). In my main county-level analysis, scaling these counts by the number of brokers within each county also mitigates this issue, following the method documented by Boulton and Williford (2018). The Poisson regression results are robust and even stronger, which addresses the concerns about the potential problems of using count data in the analysis.

All state counties instead of only cross-border counties. Table 14 presents the results when including all counties in the analysis, as opposed to limiting it to just cross-border counties. Although the results generally align with the main findings in terms of direction, they exhibit a smaller economic magnitude and weaker statistical significance. This pattern indicates a stronger endogeneity issue when including all counties across neighboring states, which likely biases the estimates.

Placebo test using RIAs' data. As previously noted, there are three types of financial advisers: brokers, dual-registered financial advisers, and RIAs. RIAs, regulated by the SEC, are consistently subject to FD and thus should not be impacted by the 2016 DOL fiduciary rule. In contrast, both pure brokers and dual-registered financial advisers are expected to be affected by this regulation.[1] In Table 15, I conduct a placebo test using data from RIAs to validate the specificity of the rule's impact. Given that RIAs were already under FD, they should be just exposed to the policy shock but theoretically show no response to the 2016 changes. The results across all specifications confirm this assumption, as they are statistically insignificant, indicating that the impact of the new fiduciary rule is specifically applying to brokers and dual-registered advisers, with no detected spillover effects.

Alternative misconduct measure. In my main analysis, I focus exclusively on confirmed misconduct cases, excluding all pending, dismissed, and denied cases, as well as cases resolved in favor of brokers. To test the robustness of these findings, I conducted a supplementary analysis using an alternative misconduct measure that includes all filed cases, regardless of their resolution. The results of this analysis are presented in Table 16. The findings using this broader measure of misconduct are consistent with those from the main analysis in terms of both the point estimates of the coefficients and their statistical significance. Quantitatively, the estimated treatment effects appear even stronger when using this alternative measure. Specifically, the β estimate is -0.409 in column (6) of Table 16, compared to -0.314 in column (6) of Table 5. This suggests that the inclusion of all filed cases does not alter the fundamental conclusions drawn from the confirmed cases and reinforces the robustness of the results.

Different event window. In my benchmark DiD analysis, I examine an event window of four

[1] Dual-registered financial advisers serve in dual capacities. In their role as brokers, they adhere to a "suitability" standard, while as investment advisers, they are subject to fiduciary duty. Therefore, the 2016 DOL fiduciary duty rule impacts their brokers activities.

years before and after the 2016 DOL fiduciary rule. To further test the robustness of my findings, I expanded the event window to include five years before and after the event, spanning from 2012 to 2021. The results of this extended analysis are presented in Table 17. These findings are highly consistent with those reported in Table 5, both in terms of economic magnitude and statistical significance.

Policy effect on dual-registered advisers. One potential concern is whether the observed decrease in misconduct following the imposition of FD is truly driven by the policy itself, or instead reflects changes in business practices resulting from brokers being forced to become dual-registered advisers. To address this concern, I restrict the sample to advisers who were already dual-registered prior to 2016. This approach ensures that the policy only affected the activities of these advisers, without altering their registration status or business activities. The results from this restricted sample are consistent with the main findings and slightly stronger (Table 18), supporting the interpretation that the decline in misconduct is attributable to the FD policy rather than shifts in business. Since dual-registered financial advisers are more likely to engage in controversial or higher-risk business activities, the legal discipline imposed by the FD policy may be particularly effective in mitigating such behaviors among this group.

Chapter 10

Conclusion

This paper examines the impact of imposing FD on brokers, focusing on both adviser misconduct and broader advising behavior. Using county-level misconduct data and leveraging regulatory variation from the 2016 Department of Labor FD rule and pre-existing state fiduciary regulations, I find that FD significantly reduces broker misconduct. The effect is especially pronounced in areas with weaker investor protection and labor market discipline, suggesting that FD serves as a substitute for informal monitoring mechanisms.

In response to the rule, brokers tend to shift away from commission-based compensation structures and increasingly adopt dual registration. Analysis of the municipal bond mutual fund (MBMF) market reveals that broker-sold funds exhibit higher returns, lower expenses, and a stronger negative flow-fee relationship after the FD imposition, indicating a shift toward higher-quality, less conflicted financial products.

Preliminary evidence on market structure reveals a decline in new broker entry in treated areas, raising questions about potential access gaps. Further research is needed to understand the long-term implications of these shifts, especially regarding adviser availability, investor access, and overall market efficiency.

Overall, these findings provide empirical support for extending fiduciary standards to brokers. They suggest that FD improves adviser conduct, enhances product quality, and helps protect investors in markets with limited disciplinary mechanisms.

Table 1: Individual Adviser-Level Summary Statistics

This table reports summary statistics of 1.5 million individual financial advisers and their misconduct records from 2005 to 2022 in the sample. Panel A reports the adviser-year summary statistics. The sample is divided as brokers (including Dual), which construct my sample in main analysis, and Pure RIA, which are used in some of my robustness tests. *Experience* is defined as the number of years since an adviser first registered. *DualRegistered* is a dummy variable indicating whether an adviser is also registered as RIA. $D(Misconduct)$ is a dummy variable indicating whether an adviser commits any misconduct in the year. $N(Misconduct)$ is the total number of misconduct incidents committed by an adviser in a year. $D(Civil)$ is a dummy variable indicating whether an adviser commits regulatory misconduct in the year. Dummy variables for other specific misconduct types are defined accordingly. Panel B reports dollar amount information of financial advisers' misconduct. $Dollar(misconduct)$ is the non-missing and non-zero dollar amount reported for a misconduct event. Dollar variables for other specific misconduct types are defined accordingly. *SettleRatio* is ratio using $Dollar(CustSettle)$ divided by $Dollar(CustAlleged)$.
Source: BrokerCheck and IAPD website

Panel A. Summary Statistics at the Adviser-Year Level

	Broker(including Dual)			Pure IA			Diff.(Broker - Pure IA)
	mean	sd	p50	mean	sd	p50	b
Dual Registered	0.318	0.466	0.000				
Broker Experience	13	10	11	20	10	19	-7***
D(misconduct)*100	0.499	7.049	0.000	0.963	9.768	0.000	-0.464***
D(cust)*100	0.261	5.102	0.000	0.282	5.300	0.000	-0.021
D(reg)*100	0.094	3.061	0.000	0.617	7.828	0.000	-0.523***
D(civil)*100	0.003	0.550	0.000	0.035	1.870	0.000	-0.032***
D(criminal)*100	0.021	1.432	0.000	0.025	1.573	0.000	-0.004
D(termi)*100	0.147	3.826	0.000	0.068	2.610	0.000	0.078***
N(misconduct)*100	0.600	11.265	0.000	1.202	15.513	0.000	-0.602***
N(cust)*100	0.326	9.399	0.000	0.410	11.342	0.000	-0.083**
N(reg)*100	0.100	3.412	0.000	0.662	8.742	0.000	-0.562***
N(civil)*100	0.003	0.563	0.000	0.035	1.870	0.000	-0.032***
N(criminal)*100	0.021	1.479	0.000	0.025	1.629	0.000	-0.004
N(termi)*100	0.149	3.930	0.000	0.070	2.712	0.000	0.079***
Observations	10,661,836			165,765			10,827,601

Panel B: Misconduct-Related Dollar Amount

	mean	sd	min	p50	p99	max	count
Dollar(misconduct)	386,114	9,868,670	0	29,000	4,250,000	1.42e+09	30,567
Dollar(Civil)	3,127,735	11,108,606	500	491,274	99,101,352	99,101,352	196
Dollar(Regulatory)	40,703	337,795	10	5,000	625,000	15,810,000	5,135
Dollar(CustSettle)	442,589	10,731,340	0	40,000	4,698,500	1.42e+09	25,791
Dollar(CustAlleged)	1,495,685	60,680,856	0	77,117	13,000,000	9.22e+09	26,655
SettleRatio	6.72	392.06	0	0.41	48	55,000	20,182

Table 2: County-Level Summary Statistics

This table reports summary statistics of county-year observations from 2005 to 2022 in the sample. The sample is divided into Border counties, which comprise my main sample and Non-Border counties, which are used in robustness tests. Panel A shows the local demographic and economic variables. Panel B shows the financial advisory market-related variables, which are aggregated from individual data in Table 1. $\overline{D}(Misconduct)$ is the percentage of advisers that commit any misconduct in a year. $\overline{N}(Misconduct)$ is the average number of misconduct incidents across advisers in each year. The county-level misconduct for each type, for example, $\overline{D}(Civil)$, is the average of corresponding dummy variable across advisers in each year. $\overline{Dollar}(misconduct)$ is the average of non-zero dollar amount in each year. Panel C is the local ethical culture-related variables.

Panel A. County Demographic

	Border			Non Border			Diff.(NonBorder - Border)
	mean	sd	p50	mean	sd	p50	b
Income per capita	42,046	16,635	38,832	40,161	11,966	37,983	-1885***
Population	137,093	306,489	33,087	102,407	318,092	32,857	-34686***
Minority Ratio	0.17	0.17	0.10	0.18	0.18	0.11	0.02***
MoreThanCollege Ratio	0.23	0.10	0.20	0.21	0.09	0.19	-0.02***
Workforce Ratio	0.63	0.04	0.64	0.64	0.04	0.64	0.00***
Median Age	40.68	5.23	40.00	39.51	4.96	40.00	-1.17***
Unemployment Rate	6.08	2.97	5.40	5.96	2.71	5.40	-0.11**
Observations	7,631			38,297			45,928

Panel B: County-Level Financial Advisory Market

	Border			Non Border			Diff.(NonBorder - Border)
	mean	sd	p50	mean	sd	p50	b
Broker Density per 1,000 capita	0.96	1.17	0.62	0.87	1.07	0.55	-0.09***
Dual-Registered Ratio	0.36	0.24	0.38	0.38	0.23	0.39	0.02***
Broker Experience	15.28	5.30	15.02	15.16	5.15	15.03	-0.12
$\overline{D}(misconduct) * 100$	0.49	3.32	0.00	0.48	3.01	0.00	-0.01
$\overline{D}(cust) * 100$	0.10	2.63	0.00	0.07	1.86	0.00	-0.03
$\overline{D}(reg) * 100$	0.09	1.42	0.00	0.09	1.52	0.00	0.00
$\overline{D}(civil) * 100$	0.01	0.38	0.00	0.00	0.16	0.00	-0.00
$\overline{D}(criminal) * 100$	0.02	0.68	0.00	0.01	0.47	0.00	-0.01
$\overline{D}(termi) * 100$	0.17	2.05	0.00	0.16	1.74	0.00	-0.00
$\overline{N}(misconduct) * 100$	0.65	8.59	0.00	0.55	3.96	0.00	-0.10
$\overline{N}(cust) * 100$	0.36	8.10	0.00	0.27	2.98	0.00	-0.09
$\overline{N}(reg) * 100$	0.09	1.43	0.00	0.09	1.54	0.00	-0.00
$\overline{N}(civil) * 100$	0.01	0.38	0.00	0.00	0.16	0.00	-0.00
$\overline{N}(criminal) * 100$	0.02	0.68	0.00	0.01	0.47	0.00	-0.01
$\overline{N}(termi) * 100$	0.17	2.08	0.00	0.17	1.77	0.00	-0.00
Observations	7,631			38,297			45,928

Panel C: County-Level Culture and Ethical Related

	Border			Non Border			Diff.(NonBorder - Border)
	mean	sd	p50	mean	sd	p50	b
GSS Trust Score	1.73	0.24	1.73	1.68	0.22	1.65	-0.05***
Religion Adherence Rate	0.44	0.24	0.47	0.44	0.24	0.45	-0.01**
Number of Political Corruption	7.42	9.06	5.00	9.28	10.81	6.00	1.86***
Physician Rent-Seeking	2.35	0.58	2.37	2.52	0.77	2.45	0.18***
Observations	7631			38297			45928

Table 3: MBMF Share Class-Year Summary Statistics

This table shows the summary stats of the sample of domestic open-end municipal bond mutual fund share classes from 2005 to 2022. The observation is at share-class-year level.
Source: MorningStar Mutual Fund Database

	Broker Sold			Direct Sold			Diff.(BrokerSold - DirectSold)
	mean	sd	p50	mean	sd	p50	b
Total Net Assets (Million)	132.06	548.69	23.94	224.84	671.30	53.83	-92.79***
Est. Net Flow	-4.05	55.16	-0.91	7.19	98.70	0.40	-11.24***
MorningStar FlowRate	0.03	0.97	-0.08	0.49	2.03	0.03	-0.46***
Est. FlowRate	0.03	1.15	-0.10	0.54	2.37	0.01	-0.50***
Gross Return(%)	4.11	6.92	4.04	4.00	6.24	3.93	0.11
Net Return(%)	2.92	6.79	2.80	3.40	6.40	3.23	-0.48***
Gross Expense Ratio(%)	1.32	0.56	1.33	1.06	22.28	0.73	0.26
Net Expense Ratio(%)	1.19	0.38	1.20	0.65	0.20	0.64	0.54***
Distribution Fee(%)	0.56	0.35	0.51	0.07	0.11	0.00	0.49***
Observations	15390			14683			30073

Table 4: Fiduciary Duty Effect on Broker Misconduct: Regression Discontinuity

This table reports the results from estimating equation 5.1, which measures how imposing FD impacts the misconduct by brokers using sample from 2005 to 2015. In columns 1 and 2, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In columns 3 and 4, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct across a county's advisers in a given year. w/FD is a dummy variable indicating whether the county has FD imposition on brokers at the state-level regulatory regime. In column 2 and column 4, we control the county demographic, economic, financial advisory market-related, and culture-related variables. I control for $border \times year$ fixed effects in all models. Observations are at the county-year level and are weighted by the number of advisers in the county. Standard errors are clustered by county and t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) $\overline{D}(misconduct)$	(2) $\overline{D}(misconduct)$	(3) $\overline{N}(misconduct)$	(4) $\overline{N}(misconduct)$
w/ FD	-0.327**	-0.158***	-0.370*	-0.151**
	(-1.98)	(-2.71)	(-1.92)	(-2.03)
Demographic and Economic				
Income per capita(log)		-0.758***		-1.000***
		(-3.15)		(-3.55)
Population(log)		0.156***		0.180***
		(2.85)		(2.90)
Median Age		1.507**		2.273***
		(2.09)		(2.65)
MoreThanCollage Ratio		0.848		1.059
		(1.14)		(1.14)
Workforce Ratio		1.287		4.580
		(0.46)		(1.43)
Trust Culture				
GSS Trust Score		-0.270		-0.296
		(-1.29)		(-1.23)
Religion Adherence Rate		0.865**		1.020**
		(2.28)		(2.27)
Financial Advisory Labor Market				
Broker Density		-0.017		0.080
		(-0.09)		(0.42)
Broker Experience		0.065***		0.087***
		(3.46)		(3.67)
Dual-Registered Ratio		0.366		0.186
		(1.09)		(0.45)
Observations	6718	2868	6718	2868
R^2	0.432	0.419	0.341	0.401
Border-Year FE	Yes	Yes	Yes	Yes

Table 5: Fiduciary Duty Effect on Broker Misconduct: Difference-in-differences

This table reports the results from estimating equation 6.1, which estimate the effect from the 2016 DOL fiduciary rule on brokers' misconduct. The dummy variable $Post$ is one if the year is after 2016. $Treated$ is equal to one if the adviser is at the states without FD before 2016 and vice versa. In columns 1, 2, and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and $county$ fixed effects in all models. Columns (1)- (3) and Columns (3)- (6) incrementally include controls. The independent variable I am interested in is $Post \times Treated$, indicating the 2016 FD policy effect on misconduct. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$
Treated $\times Post$	-0.134**	-0.118**	-0.126***	-0.270**	-0.249***	-0.314***
	(-2.24)	(-2.42)	(-2.72)	(-2.54)	(-2.88)	(-2.73)
Broker Density			0.872*			1.289
			(1.81)			(1.28)
Dual-Registered Ratio			0.615			3.405
			(1.28)			(1.19)
Broker Experience			-0.063***			-0.041
			(-2.87)			(-1.14)
Observations	3961	3925	3859	3961	3925	3859
R^2	0.509	0.513	0.515	0.316	0.317	0.318
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Fiduciary Duty Effect on Broker Disaggregated Misconduct

This table displays the regression results from DiD analysis measuring the 2016 DOL fiduciary rule on different types of misconduct, respectively. In Panel A, the dependent variables are the percentage of a county's advisers that commit any misconduct of this specific type in a given year. In Panel B, the dependent variables are the average number of misconduct incidents of this specific type across a county's advisers in a given year. I control for *border* × *year* and *county* fixed effects in all models. Observations are at the county-year level and are weighted by the number of advisers in the county. Standard errors are clustered by county, and t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Effect on Disaggregated Broker Misconduct Rate

	(1)	(2)	(3)	(4)	(5)	(6)
	$\overline{D}(misconduct)$	$\overline{D}(cust)$	$\overline{D}(reg)$	$\overline{D}(civil)$	$\overline{D}(criminal)$	$\overline{D}(termi)$
Treated $\times Post$	-0.126***	-0.001	-0.018	-0.005	-0.005	-0.065**
	(-2.72)	(-0.55)	(-1.09)	(-0.76)	(-0.97)	(-2.50)
Broker Density	0.872*	-0.021	0.553***	0.008	0.101	0.179
	(1.81)	(-0.69)	(2.81)	(0.21)	(1.55)	(1.06)
Dual-Registered Ratio	0.615	0.064	0.080	0.056	-0.106**	0.383
	(1.28)	(0.90)	(0.53)	(1.00)	(-1.98)	(1.21)
Broker Experience	-0.063***	-0.012	-0.018**	-0.002	0.004	-0.025*
	(-2.87)	(-1.64)	(-2.41)	(-0.78)	(1.11)	(-1.81)
Observations	3859	3859	3859	3859	3859	3859
R^2	0.515	0.145	0.385	0.189	0.261	0.329
DemographicControls	Yes	Yes	Yes	Yes	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect on Disaggregated Broker Average Misconduct Incident Count

	(1)	(2)	(3)	(4)	(5)	(6)
	$\overline{N}(misconduct)$	$\overline{N}(cust)$	$\overline{N}(reg)$	$\overline{N}(civil)$	$\overline{N}(criminal)$	$\overline{N}(termi)$
Treated $\times Post$	-0.314***	-0.231**	-0.014	-0.005	-0.005	-0.060**
	(-2.73)	(-2.34)	(-0.72)	(-0.76)	(-0.80)	(-2.11)
Broker Density	1.289	0.472	0.535**	0.008	0.105	0.170
	(1.28)	(0.52)	(2.44)	(0.21)	(1.57)	(0.89)
Dual-Registered Ratio	3.405	2.888	0.088	0.056	-0.110**	0.483
	(1.19)	(1.03)	(0.54)	(1.00)	(-2.02)	(1.34)
Broker Experience	-0.041	-0.002	-0.018**	-0.002	0.004	-0.023
	(-1.14)	(-0.09)	(-2.34)	(-0.78)	(1.15)	(-1.56)
Observations	3859	3859	3859	3859	3859	3859
R^2	0.318	0.299	0.412	0.189	0.264	0.315
DemographicControls	Yes	Yes	Yes	Yes	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Effect of SEC RegBI On Broker Misconduct

This table reports the results estimating the effect from 2019 SEC RegBI rule on brokers' misconduct using the county-year sample from 2017 to 2022. The dummy variable $Post$ is one if the year is after 2019. $Treated$ is one if the adviser is at the states without FD before 2019 and vice versa. In columns 1, 2 and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and $county$ fixed effects in all models. Columns (1)- (3) and Columns (3)- (6) incrementally include controls. The regressions are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$
Treated $\times Post$	0.035	0.052	0.061	0.164	0.225*	0.233*
	(0.55)	(0.82)	(0.96)	(1.50)	(1.84)	(1.87)
Broker Density			0.180			0.258
			(0.64)			(0.68)
Dual-Registered Ratio			0.038			0.211
			(0.14)			(0.52)
Broker Experience			-0.036*			-0.058**
			(-1.96)			(-2.28)
Observations	2913	2887	2816	2913	2887	2816
R^2	0.531	0.535	0.537	0.504	0.509	0.510
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Fiduciary Duty and Investor Discipline

This table displays the DiD regression results on sub-samples, splitting based on $SocialTrust$ (Panel A), $ReligionAdherenceRate$ (Panel B), and $PoliticalCorruption$ (Panel C). The dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and *county* fixed effects in all models. The p-values for F-test of equal coefficients in subsamples are displayed in the last row. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Social Trust Score

	(1) Low-Trust $\overline{N}(misconduct)$	(2) High-Trust $\overline{N}(misconduct)$
Treated $\times Post$	0.071	-0.280**
	(0.25)	(-2.15)
Broker Density	-1.144	1.937**
	(-0.97)	(2.08)
Dual-Registered Ratio	-0.163	0.779
	(-0.22)	(0.75)
Broker Experience	0.002	-0.020
	(0.07)	(-0.43)
Observations	1619	2152
R^2	0.426	0.649
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.022	

Panel B: Religion Adherence Rate

	(1) Low-ReligonAdh $\overline{N}(misconduct)$	(2) High-ReligonAdh $\overline{N}(misconduct)$
Treated $\times Post$	0.018	-0.288**
	(0.13)	(-2.02)
Broker Density	0.646	0.794
	(0.79)	(1.10)
Dual-Registered Ratio	0.500	-0.551
	(0.61)	(-0.83)
Broker Experience	-0.000	-0.026
	(-0.00)	(-0.60)
Observations	1883	1831
R^2	0.448	0.710
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.192	

Panel C: Number of Political Corruption

	(1) Low-PoliticalCorruption $\overline{N}(misconduct)$	(2) High-PoliticalCorruption $\overline{N}(misconduct)$
Treated $\times Post$	0.052	-0.287**
	(0.58)	(-2.23)
Broker Density	1.667***	0.187
	(3.20)	(0.24)
Dual-Registered Ratio	0.053	0.037
	(0.11)	(0.04)
Broker Experience	-0.021	-0.011
	(-0.87)	(-0.26)
Observations	1943	1814
R^2	0.512	0.704
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.047	

Table 9: Fiduciary Duty and Labor Market Discipline

This table displays the DiD regression results on sub-samples, splitting based on financial advisory labor market size (Panel A), brokers' experience (Panel B), and financial advisory labor market discipline (Panel C). The dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for *border* $\times$ *year* and *county* fixed effects in all models. The p-values for F-test of equal coefficients in subsamples are displayed in the last row. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Labor Market Size

	(1) Low-AdvDensity $\overline{N}(misconduct)$	(2) High-AdvDensity $\overline{N}(misconduct)$
Treated $\times Post$	0.147	-0.233**
	(0.90)	(-2.58)
Broker Density	9.489	-0.157
	(1.28)	(-0.20)
Dual-Registered Ratio	0.306	0.315
	(0.85)	(0.43)
Broker Experience	0.003	-0.035
	(0.21)	(-0.69)
Observations	1876	1911
R^2	0.444	0.664
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.005	

Panel B: Labor Market Maturity

	(1) Low-AdvExperience $\overline{N}(misconduct)$	(2) High-AdvExperience $\overline{N}(misconduct)$
Treated $\times Post$	-0.058	-0.338*
	(-1.28)	(-1.92)
Broker Density	-1.377**	-0.299
	(-1.98)	(-0.10)
Dual-Registered Ratio	-0.564	1.298
	(-1.47)	(1.32)
Broker Experience	-0.024	0.005
	(-0.95)	(0.13)
Observations	1916	1820
R^2	0.551	0.658
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.364	

Panel C: Labor Market Discipline

	(1) Low-LaborDis $\overline{N}(misconduct)$	(2) High-LaborDis $\overline{N}(misconduct)$
Treated $\times Post$	-0.289**	0.007
	(-2.57)	(0.02)
Broker Density	1.209	-0.760
	(1.43)	(-0.89)
Dual-Registered Ratio	0.121	0.700
	(0.12)	(1.01)
Broker Experience	-0.048	-0.017
	(-0.94)	(-0.53)
Observations	2077	1712
R^2	0.689	0.382
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.115	

Table 10: Fiduciary Duty Effect on Dual Registration Ratio

This table shows the effect of the 2016 DOL fiduciary rule on dual registration ratio within the county. The dummy variable *Post* is one if the year is after 2016. *Treated* is equal to one if the adviser is at the states without FD before 2016 and vice versa. The dependent variables *DualRegis* which is the number of dual-registered financial advisers divided by total number of advisers. I control for *border* $\times$ *year* and *county* fixed effects in all models. The F-test of coefficients from subsample analysis are displayed in the last row. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) DualRegis Ratio	(2) DualRegis Ratio	(3) DualRegis Ratio
Treated $\times Post$	0.022***	0.018***	0.017***
	(3.39)	(2.76)	(2.91)
Broker Density			-0.064
			(-1.15)
Broker Experience			0.012***
			(6.42)
Observations	3961	3925	3859
R^2	0.961	0.963	0.966
DemographicControls	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Table 11: Fiduciary Duty Effect on MBMFs

This table shows the effect of the 2016 DOL fiduciary rule on MBMFs' broker-sold ratio and performance using DiD analysis illustrated on Equation 8.1 and 8.2. The dummy variable *Post* is one if the year is after 2016. *Treated* is one if the MBMF is issued by the states without FD before 2016 and vice versa. In Panel A, the dependent variables is *BrokerSoldRatio*. I control for *Year*, and *Fund* fixed effects in all models. In Column 1, no control is added and in Column 2, I add TNA_t, $TNAGrowth_t$, $Return_t$, $Expense_t$ as the controls. In Panel B, I restrict the sample as broker-sold MBMF. I use two return- and three expense-related variables. I control for *ShareClass* and *Year* fixed effects in all models. In Panel C, I estimate the effect of policy on flow-fee sensitivity by adding *DistriFee* as interaction. Observations are at the share-class-year level from 2013 to 2020. Standard errors are clustered two way at the share class and year level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Policy Effect on MBMFs' Distribution

	(1) Broker Sold Ratio	(2) Broker Sold Ratio
Treated $\times Post$	-0.020*	-0.018*
	(-1.71)	(-1.70)
Observations	3355	2986
R^2	0.974	0.977
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes

Panel B: Policy Effect on Performance of Broker-Sold MBMFs

	(1) Net Return	(2) Gross Return	(3) Net Expense	(4) Gross Expense	(5) Distribution Fee
Treated $\times Post$	0.168**	0.143**	-0.010*	-0.014**	-0.001
	(2.48)	(2.10)	(-1.96)	(-1.99)	(-0.17)
Net Asset Value	-0.035	-0.004	-0.007	-0.029***	0.012*
	(-0.66)	(-0.07)	(-1.25)	(-3.33)	(1.81)
Observations	5445	5389	5503	5499	5241
R^2	0.866	0.864	0.974	0.954	0.895
Year FE	Yes	Yes	Yes	Yes	Yes
ShareClass FE	Yes	Yes	Yes	Yes	Yes

Panel C: Policy Effect on Flow-Fee Sensitivity of Broker-Sold MBMFs

	(1) MorningStar FlowRate	(2) Est. FlowRate
Distri Fee	0.014	0.012
	(0.34)	(0.29)
Treated $\times Post = 1\times$ Distri Fee	-0.093**	-0.096**
	(-3.16)	(-3.14)
Net Aseet Value_{t-1}	-0.013	-0.014
	(-0.57)	(-0.59)
Net Return_{t-1}	0.001*	0.001*
	(2.06)	(2.13)
Net Return_t	0.005	0.004
	(1.09)	(0.97)
Observations	4269	4269
R^2	0.606	0.601
Year FE	Yes	Yes
ShareClass FE	Yes	Yes

Table 12: Fiduciary Duty Effect on Broker Entry and Exit

This table shows the effect of the 2016 DOL fiduciary rule on the number of broker and brokerage firms. The dummy variable *Post* is one if the year is after 2016. *Treated* is equal to one if the adviser is at the states without FD before 2016 and vice versa. In Panel A, the dependent variables are the log of the brokers' or brokerage branches' number within the county. In Panel B, the dependent variables are the entry or exit ratio within a county. I control for *border* $\times$ *year* and *county* fixed effects in all models. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Change of Firm (Branch) Numbers and Adviser Numbers

	(1)	(2)
	ln(Total Firm)	ln(Total Adv)
Treated $\times Post$	-0.016	-0.019
	(-0.86)	(-0.85)
Observations	3925	3925
R^2	0.992	0.995
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes

Panel B: Entry and Exit of Advisers

	(1)	(2)
	Adv Entry	Adv Exit
Treated $\times Post$	-0.025***	-0.011
	(-4.04)	(-1.44)
Observations	3919	3925
R^2	0.238	0.296
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes

Table 13: Robustness: Individual Broker-Level Analysis

This table shows the effect of the 2016 DOL fiduciary rule on brokers' individual level misconduct. For panel A, in columns 1 and 2, the dependent variable $D(Misconduct)$ is an indicator variable equal to 100 if an adviser commits any misconduct in a given year and zero otherwise, and $N(Misconduct)$ is the number of misconduct incidents multiplied by 100 reported by an adviser in a given year. The dummy variable *Post* is equal to one if the year is after 2016 and and zero for the 2013 to 2016. $Treated$ is equal to one if the adviser is in the states without FD before 2016. I control for *border* $\times$ *year* and *county* fixed effects in all models. In panel B, I re-run the DiD analysis using Poisson model for count variable $N(Misconduct)$. Observations are at the adviser-year level from 2013 to 2020. Standard errors are clustered by county, and t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Individual-Level DiD Analysis

	(1)	(2)	(3)	(4)
	D(misconduct)	D(misconduct)	N(misconduct)	N(misconduct)
Treated $\times Post$	-0.056*	-0.056	-0.145***	-0.160**
	(-1.92)	(-1.64)	(-2.68)	(-2.52)
Broker Experience		0.010***		0.014***
		(14.59)		(12.78)
Dual Registered		0.172***		0.228***
		(8.95)		(6.93)
Observations	1809753	1634625	1809753	1634625
R^2	0.002	0.003	0.004	0.005
Border-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adviser FE	No	No	No	No

Panel B: Individual-Level DiD Analysis Poisson Regression

	(1)	(2)
	N(misconduct)	N(misconduct)
Treated $\times Post$	-0.318***	-0.312***
	(-3.07)	(-3.01)
Broker Experience		0.025***
		(15.18)
Dual Registered		0.352***
		(7.20)
Observations	1782119	1612528
Border-Year FE	Yes	Yes
County FE	Yes	Yes
Adviser FE	No	No

Table 14: Robustness: All-County Sample

This table reports the results from DiD analysis using all the counties instead of just cross-border counties. The dummy variable *Post* equal to one if the year is after 2016. *Treated* is equal to one if the adviser is at the states without FD before 2016 and vice versa. In columns 1 and 2, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In columns 3 and 4, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct across a county's advisers in a given year. I control for $border \times year$ and *county* fixed effects in all models. In Columns (2) and Columns (4), I include controls. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$
Treated $\times Post$	-0.028	-0.035	-0.077*	-0.096**
	(-1.09)	(-1.53)	(-1.75)	(-2.13)
Broker Density		0.341**		0.326*
		(2.48)		(1.73)
Dual-Registered Ratio		0.336*		0.883*
		(1.72)		(1.85)
Broker Experience		-0.005		0.003
		(-0.58)		(0.26)
Observations	27549	26840	27549	26840
R^2	0.269	0.271	0.241	0.242
DemographicControls	No	Yes	No	Yes
Region-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Table 15: Robustness: Placebo Test Using Registered Investment Adviser Data

This table reports the results from DiD analysis using pure RIAs' aggregated data instead of brokers' (including Dual-registered) data. The dummy variable *Post* is one if the year is after 2016. *Treated* is one if the adviser is at the states without FD before 2016 and vice versa. In Columns 1, 2 and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In Columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for *border* $\times$ *year* and *county* fixed effects in all models. Columns (1)- (3) and Columns (3)- (6) incrementally include controls. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	D(misconduct)	D(misconduct)	D(misconduct)	N(misconduct)	N(misconduct)	N(misconduct)
Treated $\times Post$	-0.113	-0.160	-0.190	-0.116	-0.201	-0.245
	(-0.34)	(-0.42)	(-0.49)	(-0.33)	(-0.48)	(-0.58)
Broker Density			-14.312			-21.365**
			(-1.62)			(-2.22)
Broker Experience			-0.001			-0.002
			(-0.01)			(-0.04)
Observations	1343	1331	1331	1343	1331	1331
R^2	0.371	0.376	0.376	0.408	0.417	0.418
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 16: Robustness: Alternative Misconduct Measure

This table reports the results from DiD analysis using alternative misconduct measure, using the filed case instead of the confirmed cases as in the main analysis. The dummy variable *Post* equal to one if the year is after 2016. *Treated* is equal to one if the adviser is at the states without FD before 2016 and vice versa. In Columns 1, 2 and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In Columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and *county* fixed effects in all models. Columns (1) - (3) and Columns (3) - (6) incrementally include controls. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{D}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$	$\overline{N}(misconduct)$
Treated $\times Post$	-0.152*	-0.135*	-0.150**	-0.368**	-0.339***	-0.409***
	(-1.76)	(-1.95)	(-2.30)	(-2.55)	(-2.94)	(-3.03)
Broker Density			1.518**			2.159*
			(2.12)			(1.77)
Dual-Registered Ratio			0.629			3.565
			(1.03)			(1.21)
Broker Experience			-0.041			-0.015
			(-1.60)			(-0.35)
Observations	3961	3925	3859	3961	3925	3859
R^2	0.559	0.563	0.565	0.342	0.342	0.343
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 17: Robustness: Five-Year Event Window

This table reports the results from DiD analysis using 5 years before and after event windows instead of 4 years event window as in main analysis. The dummy variable $Post$ equal to one if the year is after 2016. $Treated$ is equal to one if the adviser is at the states without FD before 2016 and vice versa. In Columns 1, 2 ,and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In Columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and $county$ fixed effects in all models. Columns (1)- (3) and Columns (3)- (6) incrementally include controls. Observations are at the county-year level from 2012 to 2021 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) D(misconduct)	(2) D(misconduct)	(3) D(misconduct)	(4) N(misconduct)	(5) N(misconduct)	(6) N(misconduct)
Treated $\times Post$	-0.114**	-0.108**	-0.119***	-0.209**	-0.221***	-0.279***
	(-2.08)	(-2.44)	(-2.80)	(-2.30)	(-2.80)	(-2.90)
Broker Density			0.338			0.310
			(0.98)			(0.43)
Dual-Registered Ratio			0.884**			3.212
			(2.08)			(1.37)
Broker Experience			-0.066***			-0.050*
			(-3.34)			(-1.65)
Observations	4948	4425	4349	4948	4425	4349
R^2	0.503	0.501	0.502	0.284	0.287	0.288
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 18: Robustness: Dual-Registered Advisers Before 2016

This table reports the results from DiD analysis restricted on the advisers that were already dual-registered before 2016. The dummy variable *Post* equal to one if the year is after 2016. $Treated$ is equal to one if the adviser is at the states without FD before 2016 and vice versa. In Columns 1, 2 ,and 3, the dependent variable $\overline{D}(Misconduct)$ is the percentage of a county's advisers that commit any misconduct in a given year. In Columns 4, 5, and 6, the dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for *border* $\times$ *year* and *county* fixed effects in all models. Columns (1)- (3) and Columns (3)- (6) incrementally include controls. Observations are at the county-year level from 2012 to 2021 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) D(misconduct)	(2) D(misconduct)	(3) D(misconduct)	(4) N(misconduct)	(5) N(misconduct)	(6) N(misconduct)
Treated $\times Post$	-0.234***	-0.228***	-0.243***	-0.451***	-0.410**	-0.406**
	(-3.15)	(-2.95)	(-3.06)	(-2.74)	(-2.46)	(-2.21)
Broker Density			-0.863*			-1.787*
			(-1.73)			(-1.84)
Broker Experience			-0.110**			-0.543
			(-2.33)			(-1.39)
Observations	3877	3837	3837	3877	3837	3837
R^2	0.355	0.361	0.363	0.334	0.335	0.337
DemographicControls	No	Yes	Yes	No	Yes	Yes
Border-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

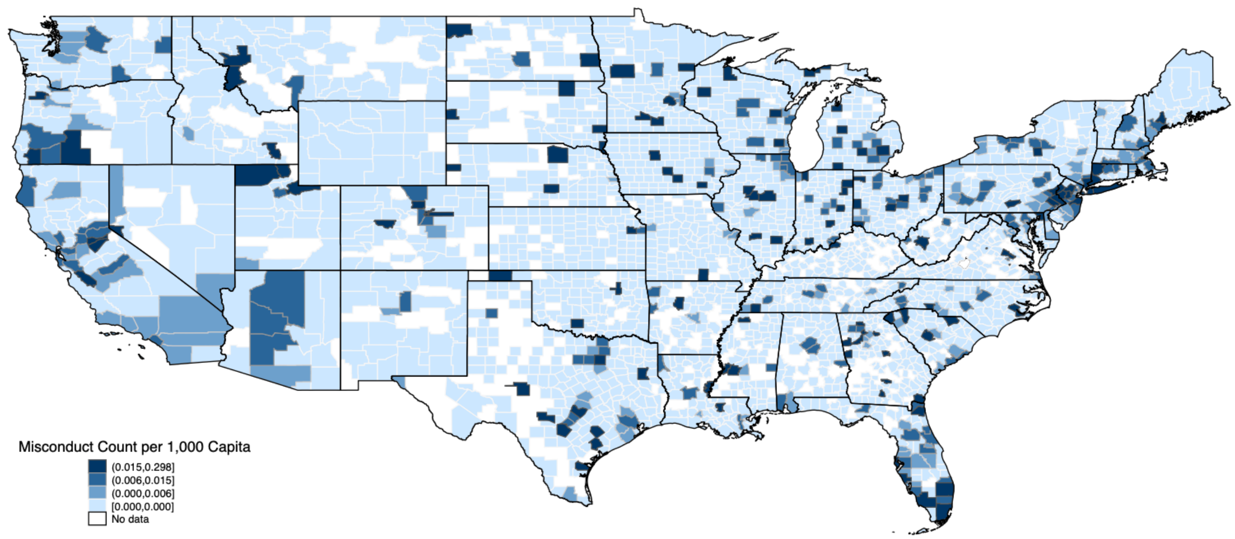
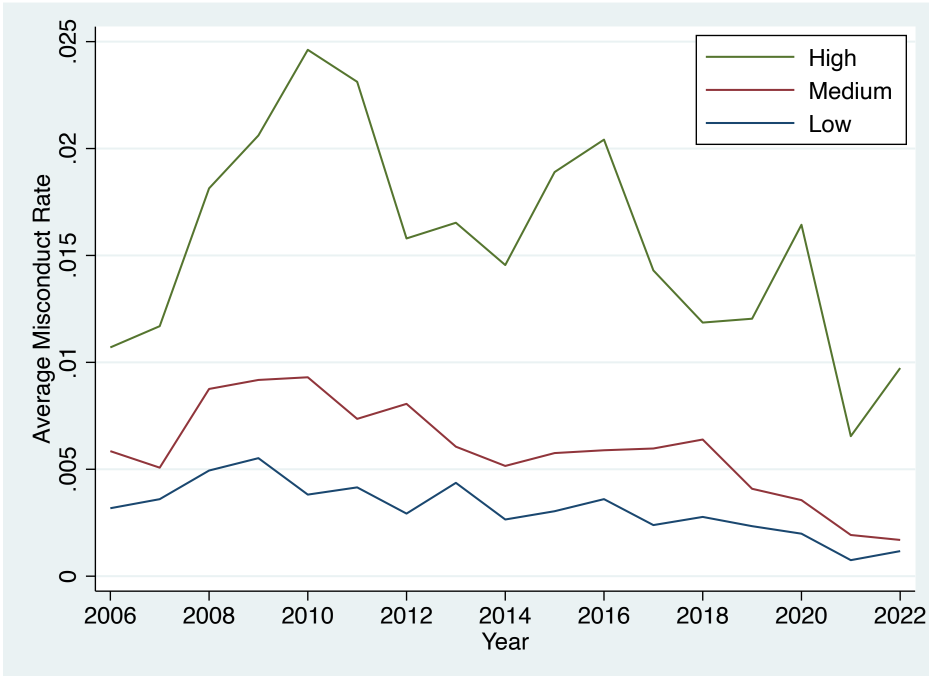
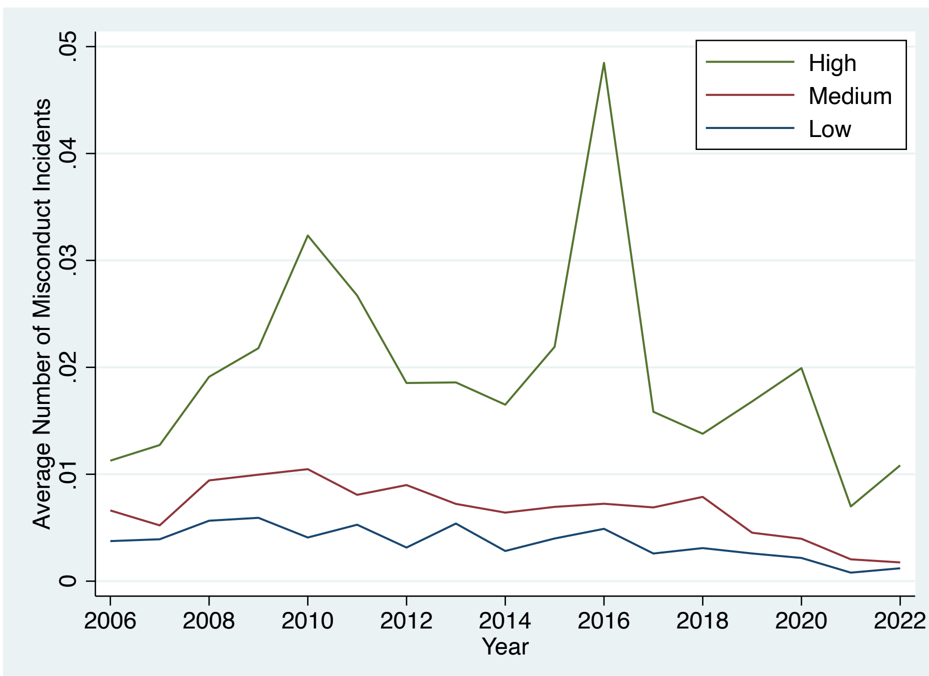


Figure 1: **Geographical Variation in Misconduct**. This figure shows the misconduct count per 1,000 capita in 2019 across all the counties in the U.S. with white as missing data and darker blue corresponding to higher misconduct count.



(A) Panel A: $\overline{D}(misconduct)$



(B) Panel B: $\overline{N}(misconduct)$

Figure 2: **Time Series of Misconduct**. This figure plots the time-series pattern of the county-level financial misconduct level for three groups of counties sorted by their time-series average misconduct rate over the full sample, high, medium, and low. Panel A depicts $\overline{D}(Misconduct)$, which is the percentage of a county's advisers that commit any misconduct in a given year, and panel B plots $\overline{N}(Misconduct)$, which is the average number of misconduct incidents across a county's advisers in a given year.

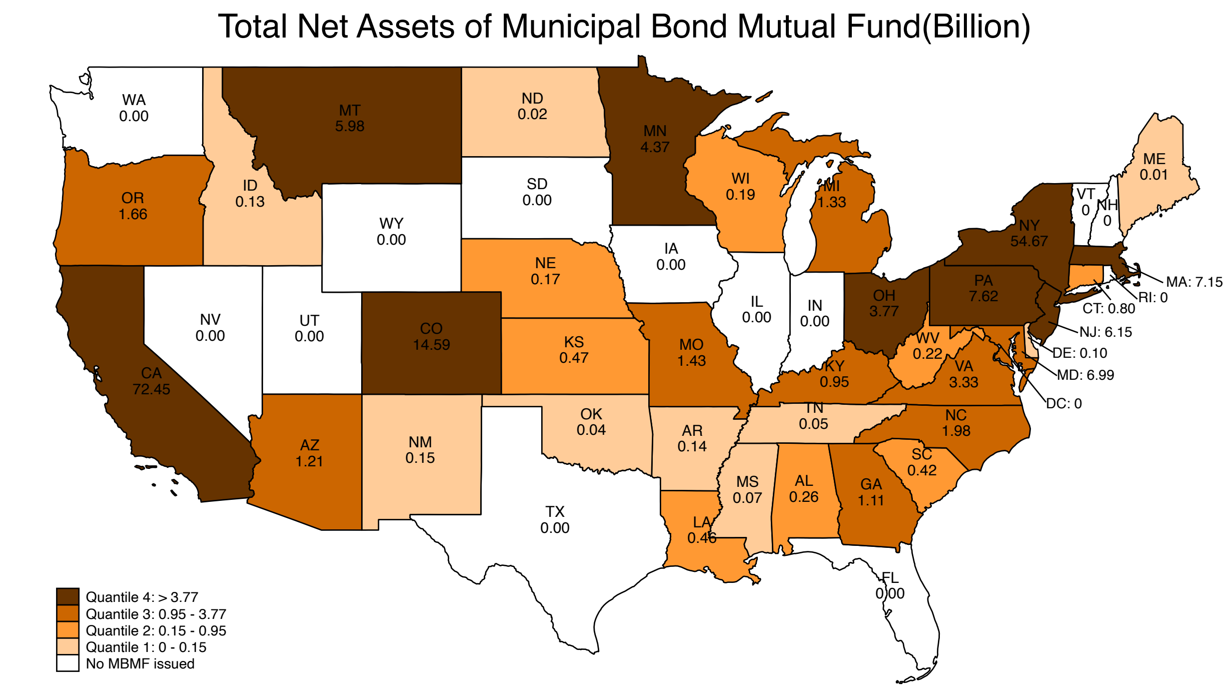


Figure 3: **Total Net Assets of MBMFs Across States**. This figure shows the total net assets of MBMFs offered in each state at year 2025.The darker orange represents a higher total net assets of MBMFs.

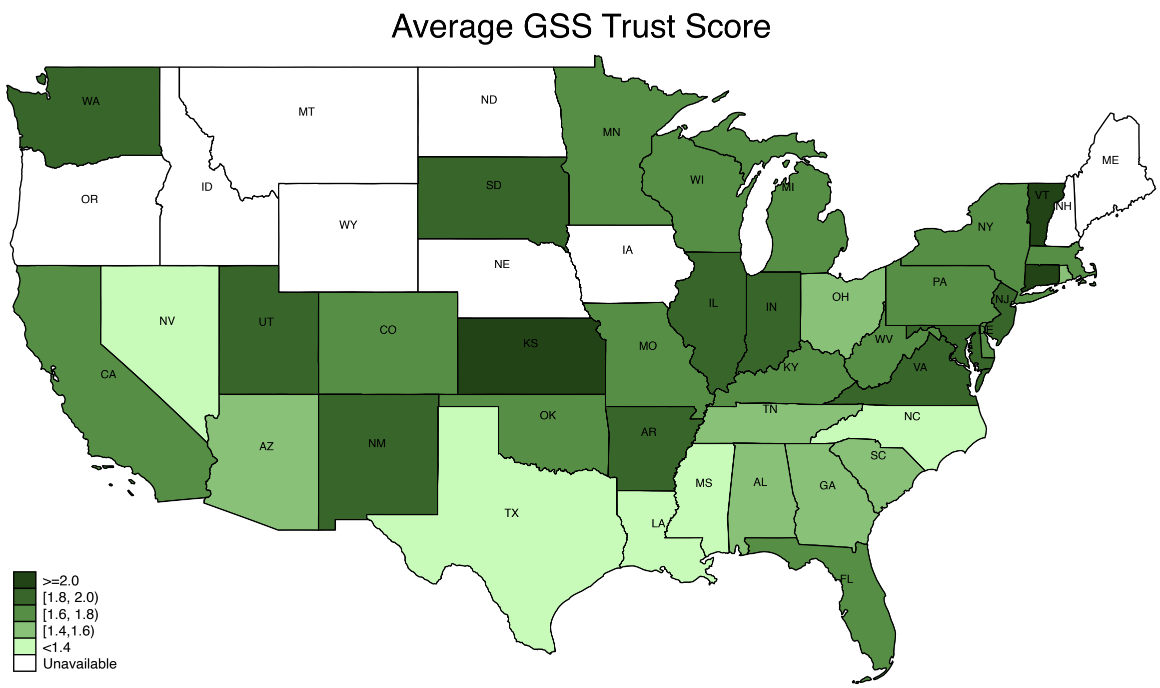


Figure 4: **GSS Trust Score Across States**. This figure shows the average GSS trust score in each state at year 2016.The darker gree represents a higher social trust level.

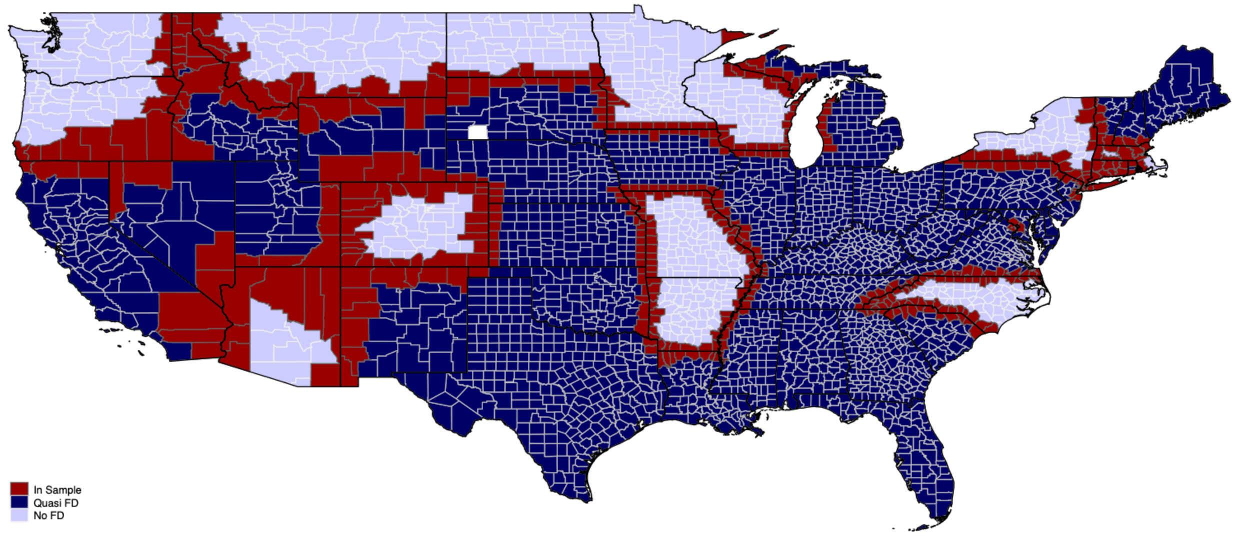
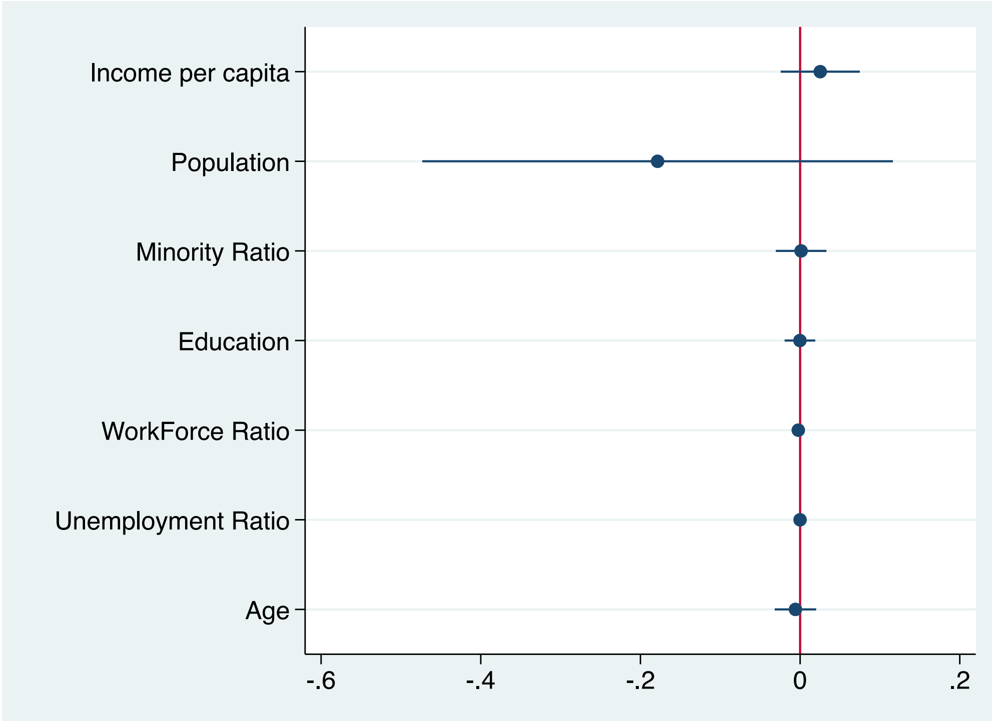
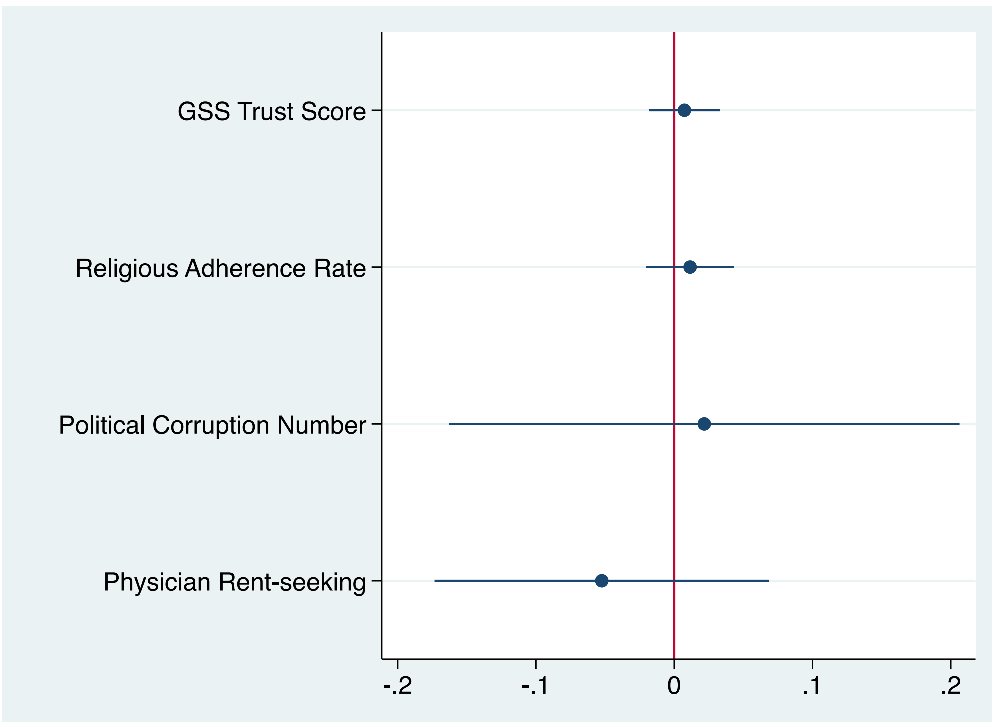


Figure 5: **State Regulatory Regimes of Fiduciary Duty on Brokers**. This map shows the states with at least some degree of FD (Darker Blue) and those with no FD (light Blue) on brokers, per the classification in Finke and Langdon (2012)). Counties in red are located at borders between states with different fiduciary standards and comprise my main sample.



(A) Panel A: Demographic and Economic Variables



(B) Panel B: Political and Culture Variables

Figure 6: **Balance of Covariates**. This figure illustrates the balance of covariates including demographic and economic (panel A), and culture-related (panel B) for the counties with or without FD using the sample from 2005 to 2015. The reported coefficients are derived from regressing these variables on dummy w/FD and control for year fixed effects. The bands correspond to the 95% confidence interval.

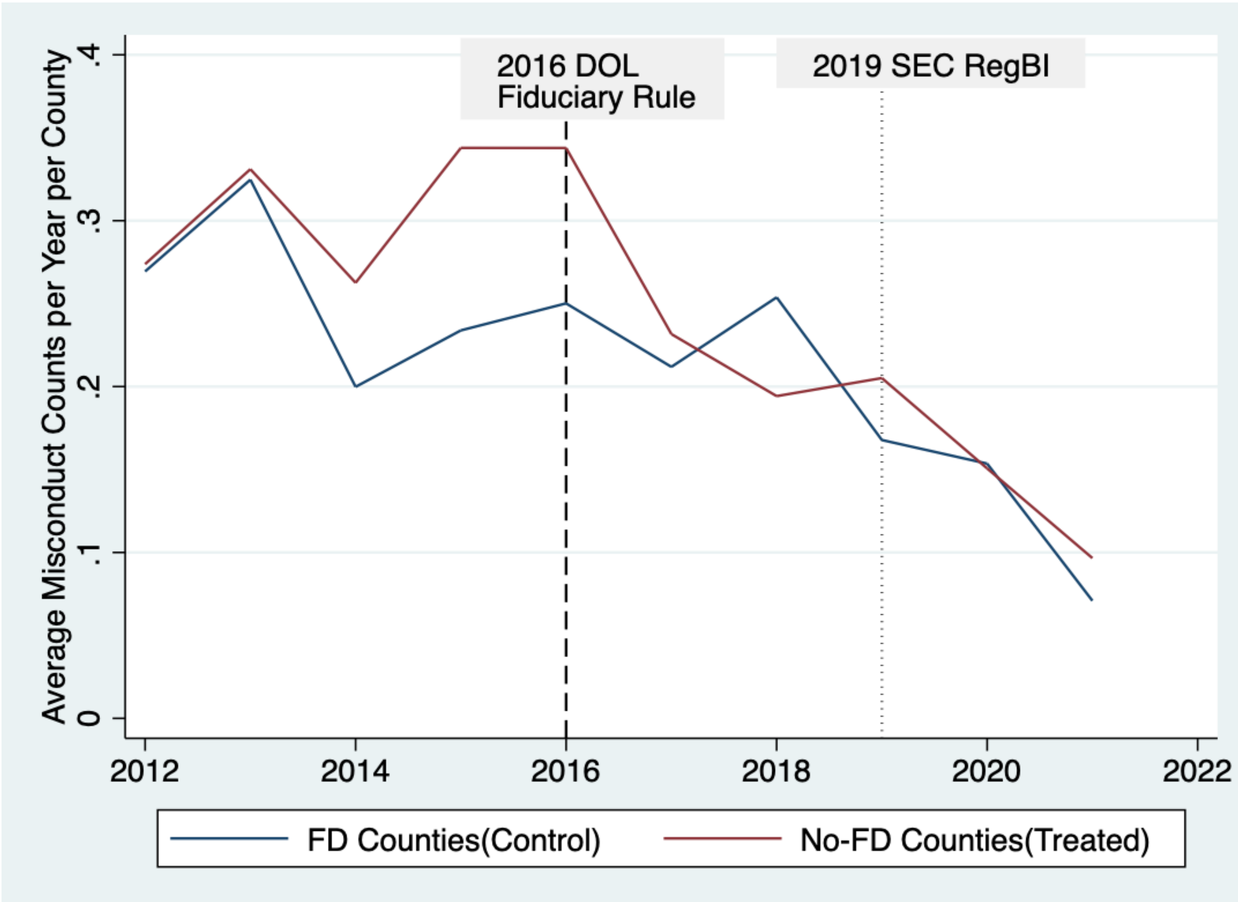
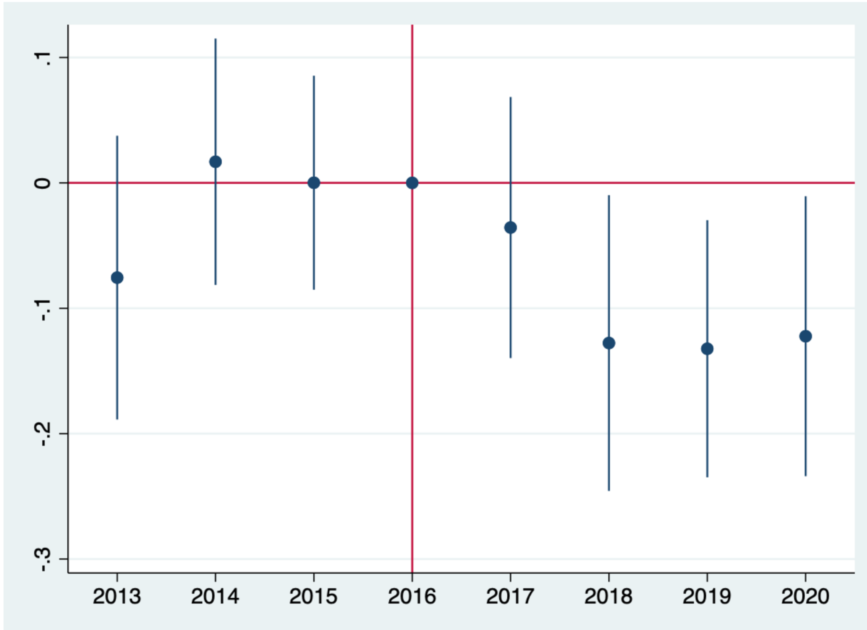
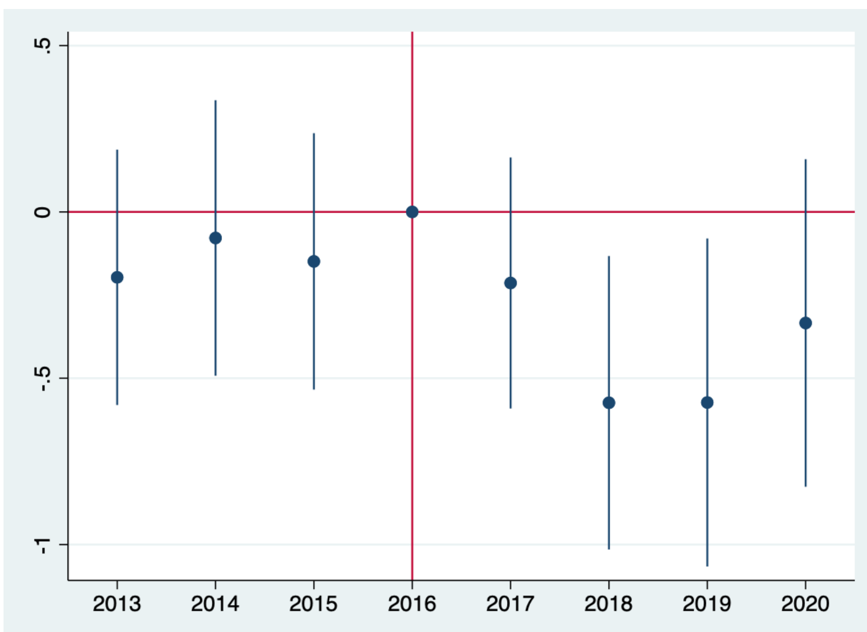


Figure 7: **Average Misconduct Counts Around 2016 DOL Fiduciary Rule**. The figure plots the average misconduct count per year per county of the cross-border counties who are divided into FD counties where the brokers were already subject to FD before 2016 and No-FD counties where the states the county located do not have FD on brokers.



(A) Panel A: Fiduciary Rule Effect on $\overline{D}(Misconduct)$



(B) Panel B: Fiduciary Rule Effect on $\overline{N}(Misconduct)$

Figure 8: **DiD Analysis: Coefficient Plot**.This figure plots the coefficient estimates for β_t in Eq. 6.2, using either $\overline{D}(Misconduct)_{i,b,t}$ (Panel A) or $\overline{N}(Misconduct)_{i,b,t}$ (Panel B) as the dependent variable. Observations are at the county-year level and are weighted by the number of advisers in the county.

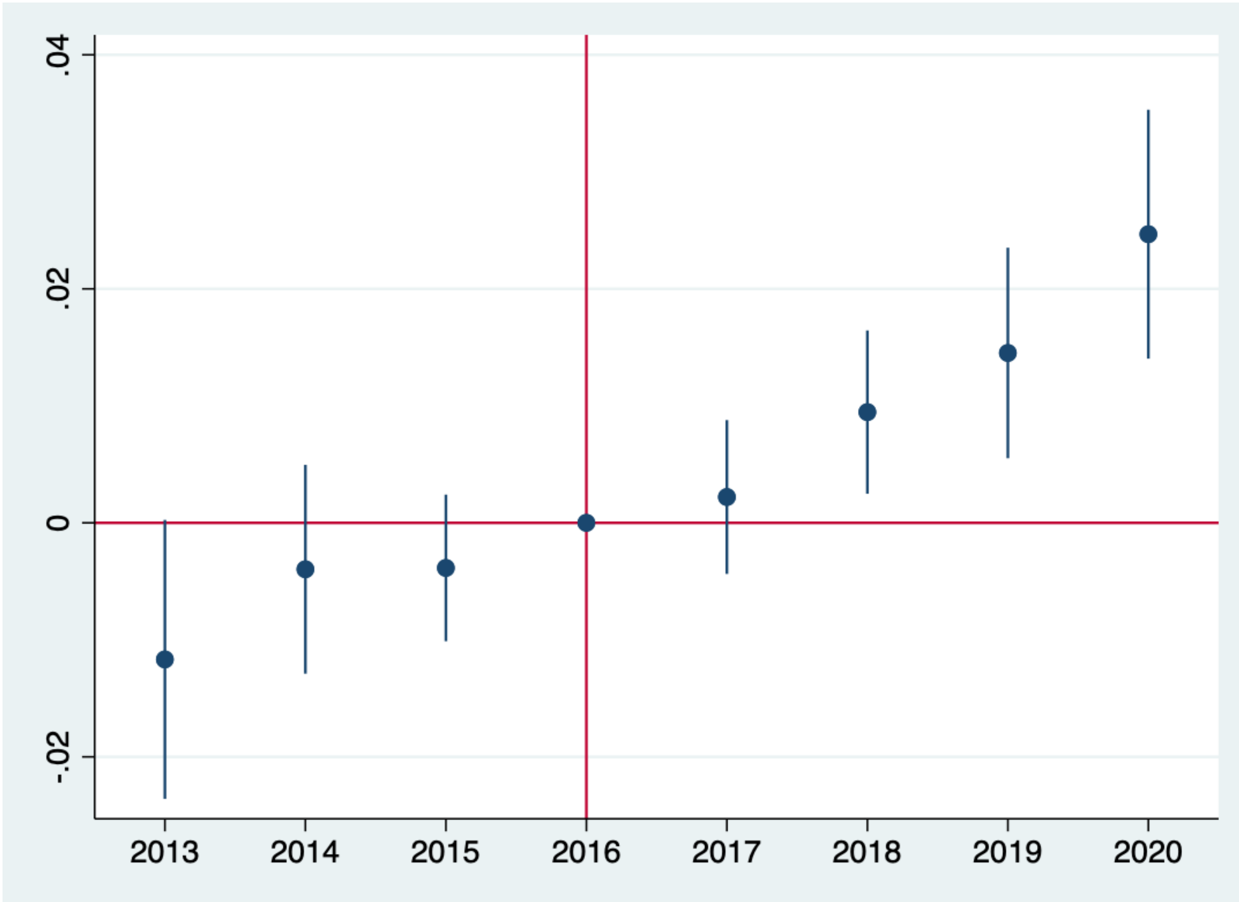


Figure 9: **Fiduciary Rule Effect on Dual-Registered Ratio**. This figure plots the dynamic treatment effect on $DualRegis$. Observations are at the county-year level and are weighted by the number of advisers in the county.

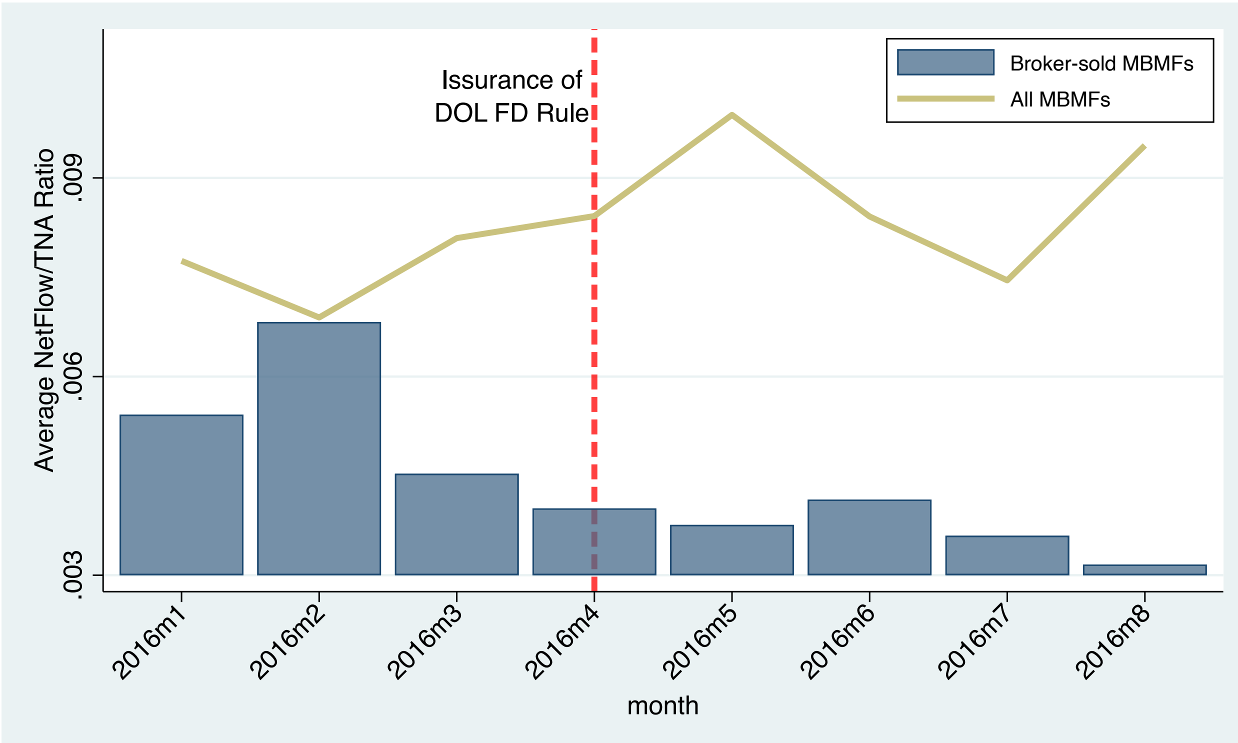


Figure 10: **Monthly Flow Rate of MBMFs Around the 2016 DOL Fiduciary Rule**. This figure shows the average net flow rate of MBMFs around the issuance of the 2016 DOL fiduciary rule in April 2016. The blue bar represents the net flow rate for commission-based MBMFs, and the yellow line represents the net flow rate for the overall MBMFs market.

APPENDICES

Table A.1: County-Level Pre-Treatment Summary Statistics

This table shows the comparison between counties in the treatment (w/o FD before 2016) and the control groups (w/ FD before 2016). Only cross-border counties are included. Panel A, B, and C display the comparison for demographic, financial advisory market-related, and ethical culture-related variables, respectively. The observations are county-year at year 2016. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. County Demographic

	Treated(w/o FD)			Control(w/ FD)			Diff.(Control-Treated)
	mean	sd	p50	mean	sd	p50	b
Income per capita	40288	12292	37599	42049	14807	38430	1761*
Population	137340	307096	35498	133348	303993	32782	-3992
Minority Ratio	0.16	0.16	0.10	0.17	0.18	0.09	0.01
MoreThanCollage Ratio	0.22	0.10	0.19	0.22	0.10	0.19	0.00
Workforce Ratio	0.64	0.04	0.64	0.64	0.04	0.63	-0.00
Median Age	41.04	5.28	41.00	40.66	5.26	41.00	-0.38
Unemployment Rate	6.46	2.50	6.10	6.34	2.66	6.10	-0.12
Observations	634			729			1363

Panel B: County-Level Financial Advisory Market

	Treated(w/o FD)			Control(w/ FD)			Diff.(Control-Treated)
	mean	sd	p50	mean	sd	p50	b
Broker Density per 1,000 capita	0.89	1.11	0.58	1.01	1.32	0.63	0.12
Dual-Registered Ratio	0.37	0.23	0.38	0.37	0.23	0.39	-0.00
Broker Experience	15.26	4.59	15.50	15.83	4.51	15.71	0.57*
$\overline{D}(misconduct) * 100$	0.71	4.89	0.00	0.67	4.39	0.00	-0.04
$\overline{D}(cust) * 100$	0.22	4.04	0.00	0.19	3.74	0.00	-0.03
$\overline{D}(reg) * 100$	0.12	1.39	0.00	0.12	1.06	0.00	0.01
$\overline{D}(civil) * 100$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\overline{D}(criminal) * 100$	0.01	0.09	0.00	0.02	0.41	0.00	0.01
$\overline{N}(misconduct) * 100$	0.77	4.92	0.00	0.73	4.51	0.00	-0.05
$\overline{N}(cust) * 100$	0.29	2.32	0.00	0.37	3.97	0.00	0.08
$\overline{N}(reg) * 100$	0.12	1.39	0.00	0.13	1.06	0.00	0.01
$\overline{N}(civil) * 100$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\overline{N}(criminal) * 100$	0.01	0.09	0.00	0.02	0.41	0.00	0.01
$\overline{Dollar}(misconduct)$	74522	203820	28000	710257	5003388	39127	635735
Observations	634			729			1363

Panel C: County-Level Culture and Ethical Related

	Treated(w/o FD)			Control(w/ FD)			Diff.(Control-Treated)
	mean	sd	p50	mean	sd	p50	b
Republican Ratio	0.57	0.14	0.58	0.58	0.16	0.60	0.02*
Democratic Ratio	0.39	0.14	0.37	0.38	0.16	0.36	-0.02
Religion Adherence Rate	0.51	0.18	0.50	0.53	0.16	0.51	0.01
Religion Concentration	0.58	0.15	0.56	0.58	0.16	0.57	0.01
Number of Political Corruption	6.95	7.49	5.00	8.23	10.17	5.00	1.28**
Physician Rent-Seeking	2.40	0.65	2.28	2.30	0.51	2.39	-0.09
Observations	634			729			1363

Table A.2: Potential Mechanism: Other Results

This table displays the DiD regression results on sub-samples, splitting based on age (Panel A), physicians' rent-seeking behavior (Panel B), and political leaning (Panel C). The dependent variable $\overline{N}(Misconduct)$ is the average number of misconduct incidents across a county's advisers in a given year. I control for $border \times year$ and $county$ fixed effects in all models. The F-test of coefficients from subsample analysis are displayed in the last row. Observations are at the county-year level from 2013 to 2020 and are weighted by the number of advisers in the county. Standard errors are clustered at the county level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Income per capita

	(1) Low-Income $\overline{N}(misconduct)$	(2) High-Income $\overline{N}(misconduct)$
Treated $\times Post$	0.041	-0.215**
	(0.24)	(-2.29)
Broker Density	6.367*	-0.280
	(1.65)	(-0.37)
Dual-Registered Ratio	-0.242	0.621
	(-0.63)	(0.86)
Broker Experience	0.007	-0.024
	(0.49)	(-0.49)
Observations	1900	1834
R^2	0.417	0.688
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,t-value	0.268	

Panel B: Education

	(1) Low-Education $\overline{N}(misconduct)$	(2) High-Education $\overline{N}(misconduct)$
Treated $\times Post$	0.209	-0.223**
	(1.22)	(-2.45)
Broker Density	3.133	-0.150
	(1.20)	(-0.21)
Dual-Registered Ratio	0.316	0.599
	(0.91)	(0.81)
Broker Experience	-0.005	-0.030
	(-0.39)	(-0.62)
Observations	1857	1915
R^2	0.467	0.667
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.045	

Panel C: Unemployment Rate

	(1) Low-Unemployment $\overline{N}(misconduct)$	(2) High-Unemployment $\overline{N}(misconduct)$
Treated $\times Post$	-0.380**	0.045
	(-2.47)	(0.39)
Broker Density	1.315	-0.247
	(1.56)	(-0.22)
Dual-Registered Ratio	0.130	-0.419
	(0.18)	(-0.86)
Broker Experience	-0.028	-0.012
	(-0.62)	(-0.53)
Observations	1935	1810
R^2	0.663	0.475
DemographicControls	Yes	Yes
Border-Year FE	Yes	Yes
County FE	Yes	Yes
F-Test: low-high,p-value	0.011	

REFERENCES CITED

Anagol, Santosh, Shawn Cole, and Shayak Sarkar, 2017, Understanding the Advice of Commissions-Motivated Agents: Evidence from the Indian Life Insurance Market, *Review of Economics and Statistics* 99, 1–15.

Becker, Gary S., 1968, Crime and Punishment: An Economic Approach, *Journal of Political Economy* 76, 169–217, Publisher: University of Chicago Press.

Bergstresser, Daniel, John M. R. Chalmers, and Peter Tufano, 2009, Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry, *The Review of Financial Studies* 22, 4129–4156.

Bhattacharya, Utpal, Amit Kumar, Sujata Visaria, and Jing Zhao, 2023, Do Women Receive Worse Financial Advice?

Bhattacharya, Vivek, Gaston Illanes, and Manisha Padi, 2019, Fiduciary Duty and the Market for Financial Advice.

Black, Barbara, 2010, How to Improve Retail Investor Protection After the Dodd-Frank Wall Street Reform and Consumer Protection Act, *University of Pennsylvania Journal of Business Law* 13, 59.

Bollen, Nicolas P. B., and Veronika K. Pool, 2012, Suspicious Patterns in Hedge Fund Returns and the Risk of Fraud, *The Review of Financial Studies* 25, 2673–2702.

Boulton, Aaron J., and Anne Williford, 2018, Analyzing Skewed Continuous Outcomes With Many Zeros: A Tutorial for Social Work and Youth Prevention Science Researchers, *Journal of the Society for Social Work and Research* 9, 721–740, Publisher: The University of Chicago Press.

Chang, Briana, and Martin Szydlowski, 2020, The Market for Conflicted Advice, *The Journal of Finance* 75, 867–903, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12848.

Christoffersen, Susan E. K., Richard Evans, and David K. Musto, 2013, What Do Consumers' Fund Flows Maximize? Evidence from Their Brokers' Incentives, *The Journal of Finance* 68, 201–235, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2012.01798.x.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Del Guercio, Diane, and Jonathan Reuter, 2014, Mutual Fund Performance and the Incentive to Generate Alpha, *The Journal of Finance* 69, 1673–1704, Publisher: [American Finance Association, Wiley].

Dimmock, Stephen G., and William C. Gerken, 2012, Predicting fraud by investment managers, *Journal of Financial Economics* 105, 153–173.

Dimmock, Stephen G., William C. Gerken, and Tyson Van Alfen, 2021, Real Estate Shocks and Financial Advisor Misconduct, *The Journal of Finance* 76, 3309–3346, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.13067.

Dyreng, Scott D., William J. Mayew, and Christopher D. Williams, 2012, Religious Social Norms and Corporate Financial Reporting, *Journal of Business Finance & Accounting* 39, 845–875, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-5957.2012.02295.x.

Egan, Mark, 2019, Brokers versus Retail Investors: Conflicting Interests and Dominated Products, *The Journal of Finance* 74, 1217–1260, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12763.

Egan, Mark, Shan Ge, and Johnny Tang, 2022, Conflicting Interests and the Effect of Fiduciary Duty: Evidence from Variable Annuities, *The Review of Financial Studies* 35, 5334–5386.

Egan, Mark, Gregor Matvos, and Amit Seru, 2019, The Market for Financial Adviser Misconduct, *Journal of Political Economy* 127, 233–295, Publisher: The University of Chicago Press.

Engelberg, Joseph, Christopher A. Parsons, and Nathan Tefft, 2014, Financial Conflicts of Interest in Medicine.

Finke, Michael S., and Thomas Patrick Langdon, 2012, The Impact of the Broker-Dealer Fiduciary Standard on Financial Advice, *SSRN Electronic Journal* .

Finke, Michael S., Aron Szapiro, and David Blanchett, 2022, Does Advisor Channel Influence Passive Fund Choice?, *SSRN Electronic Journal* .

Glaeser, Edward L., and Raven E. Saks, 2006, Corruption in America, *Journal of Public Economics* 90, 1053–1072.

Guiso, Luigi, Andrea Pozzi, Anton Tsoy, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2022, The cost of steering in financial markets: Evidence from the mortgage market, *Journal of Financial Economics* 143, 1209–1226.

Gurun, Umit G, Noah Stoffman, and Scott E Yonker, 2018, Trust Busting: The Effect of Fraud on Investor Behavior, *The Review of Financial Studies* 31, 1341–1376.

Gurun, Umit G., Noah Stoffman, and Scott E. Yonker, 2021, Unlocking clients: The importance of relationships in the financial advisory industry, *Journal of Financial Economics* 141, 1218–1243.

Hayes, Rachel M., Feng Jiang, and Yihui Pan, 2021, Voice of the Customers: Local Trust Culture and Consumer Complaints to the CFPB, *Journal of Accounting Research* 59, 1077–1121, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-679X.12364.

Holden, Sarah, and Daniel Schrass, 2024, The Role of IRAs in US Households' Saving for Retirement, 2023.

Hutton, Irena, Danling Jiang, and Alok Kumar, 2015, Political Values, Culture, and Corporate Litigation, *Management Science* 61, 2905–2925, Publisher: INFORMS.

Inderst, Roman, and Marco Ottaviani, 2012a, Competition through Commissions and Kickbacks, *American Economic Review* 102, 780–809.

Inderst, Roman, and Marco Ottaviani, 2012b, How (not) to pay for advice: A framework for consumer financial protection, *Journal of Financial Economics* 105, 393–411.

Kasten, Connor, 2023, Broker Conflict of Interest Mitigation Efforts and Mutual Funds: Evidence from the 2016 Department of Labor Fiduciary Rule .

Kim, Hugh H., Raimond Maurer, and Olivia S. Mitchell, 2021, How financial literacy shapes the demand for financial advice at older ages, *The Journal of the Economics of Ageing* 20, 100329.

Lusardi, Annamaria, and Olivia S. Mitchell, 2014, The Economic Importance of Financial Literacy: Theory and Evidence, *Journal of Economic Literature* 52, 5–44.

McGuire, Sean T., Thomas C. Omer, and Nathan Y. Sharp, 2012, The Impact of Religion on Financial Reporting Irregularities, *The Accounting Review* 87, 645–673.

Parsons, Christopher A., Johan Sulaeman, and Sheridan Titman, 2018, The Geography of Financial Misconduct, *The Journal of Finance* 73, 2087–2137, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12704.

Patel, Tarun, 2019, Do Commissions Cause Investment Adviser Misconduct?, *SSRN Electronic Journal* .

Prendergast, Canice, 2002, Consumers and Agency Problems, *The Economic Journal* 112, C34–C51, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1468-0297.00023.

Reiter, Miranda, Martin Seay, and Ajamu Loving, 2022, Diversity in financial planning: Race, gender, and the likelihood to trust a financial planner, *FINANCIAL PLANNING REVIEW* 5, e1134, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/cfp2.1134.

Robles-Garcia, Claudia, 2019, Competition and Incentives in Mortgage Markets: The Role of Brokers .

Sheen, Albert, Youchang Wu, and Yuwen Yuan, 2021, Private Equity and Financial Adviser Misconduct.

Sirri, Erik R., and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *The Journal of Finance* 53, 1589–1622, Publisher: [American Finance Association, Wiley].

Stoughton, Neal M., Youchang Wu, and Josef Zechner, 2011, Intermediated Investment Management, *The Journal of Finance* 66, 947–980, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2011.01656.x.

Thiel, Jurre H., 2022, Adviser Compensation, Endogenous Entry, and the Advice Gap, *American Economic Journal: Microeconomics* 14, 76–130.

Vokata, Petra, 2021, Engineering lemons, *Journal of Financial Economics* 142, 737–755.