HARVARD | BUSINESS | SCHOOL

When Harry Fired Sally: The Double Standard in Punishing Misconduct

Mark Egan
Gregor Matvos
Amit Seru

Working Paper 19-047

When Harry Fired Sally: The Double Standard in Punishing Misconduct

Mark Egan
Harvard Business School

Gregor Matvos
University of Texas at Austin

Amit Seru
Stanford University

Working Paper 19-047

When Harry Fired Sally: The Double Standard in Punishing Misconduct

Mark Egan, Gregor Matvos, and Amit Seru*

August 2018

First Version: September 2016

Abstract

We examine gender differences in misconduct punishment in the financial advisory industry. We find evidence of a "gender punishment gap": following an incident of misconduct, female advisers are 20% more likely to lose their jobs and 30% less likely to find new jobs relative to male advisers. Females face harsher outcomes despite engaging in misconduct that is 20% less costly and having a substantially lower propensity towards repeat offenses. The gender punishment gap in hiring and firing dissipates at firms with a greater percentage of female managers at the firm or local branch level. The gender punishment gap is not driven by gender differences in occupation (type of job, firm, market, or financial products handled), productivity, misconduct, or recidivism. We extend our analysis to explore the differential treatment of ethnic minorities and find similar patterns of "in-group" tolerance. Our evidence is inconsistent with a simple Bayesian model and suggests instead that managers are more forgiving of missteps among members of their own gender/ethnic group.

JEL: J71, G24, G28, D18

Keywords: Financial Advisers, Brokers, Gender Discrimination, Consumer Finance, Financial Misconduct and Fraud, FINRA executives

*We thank Jonathan Berk, Marianne Bertrand, Jules van Binsbergen, Kerwin Charles, Darrell Duffie, Elena Espinoza, Matt Gentzkow, Christopher Hennesey, Laurie Hodrick, Emir Kamenica, Lawrence Katz, Crystal Lam, Edward Lazear, Sendhil Mullainathan, Paul Oyer, Chris Palmer, Chris Parsons, Joshua Rauh, Paola Sapienza, Anna Scherbina, Andrei Shleifer, Ken Singleton, Vikrant Vig, Luigi Zingales, and the seminar participants at the Eller College of Management, London Business School, NYU Stern, Princeton University, Stanford University, Tepper School of Business, Tuck School of Business, University of Chicago (economics), University of Chicago Booth School of Business and participants at the American Association Meetings, Bank of England conference, Berkeley-Stanford joint seminar, HBS-MIT Financial Economics conference, NBER Summer Institute and RCFS conference.

I Introduction

Labor markets compensate productive activities with higher wages and non-wage compensation such as promotions and perks. Conversely, employees who engage in unproductive or even destructive activities are punished, for example, through job loss and lack of employment opportunities in the market. The existing research on the differential treatment of men and women has generally focused on gender differences in the compensation of productive activities. Firms pay female employees less than comparable male employees (Altonji and Blank, 1999). Firms are also less likely to hire and promote female employees relative to male counterparts with similar credentials or output (Goldin and Rouse, 2000). In this paper we explore whether the differential treatment of men and women carries over to the punishment of undesirable activities as well. In other words, are labor markets more forgiving of missteps by men than women? Gender differences in punishment may be equally as important as gender differences in hiring and compensation; roughly 60% of lawsuits alleging discrimination in the workplace concern discriminatory firings (Siegelman 2016). This paper documents the "gender punishment gap": gender differences in the punishment of similar undesirable activities. We study the punishment gap in the context of financial adviser misconduct and document that this punishment gap is not driven by gender differences in occupation (type of job, firm, market, or financial products), productivity, misconduct, or recidivism. We then explore the mechanisms driving the gap.

Gender differences in punishment speak to the broader idea that female employees are given less leniency for missteps than their male counterparts. This aspect of gender differences has received little attention in academia or in policy relative to differences in hiring and compensation. One possible reason is that a punishment gap is less likely to draw attention than a wage gap. For instance, when we observe a financial adviser losing her job following misconduct, the appeal that the termination was unfair or discriminatory may sound hollow. In fact, the firing may be justified. It is only after observing that, on average, male advisers were not fired for similar transgressions that one can detect a gender punishment gap. In such cases, gender differences may be a priori more difficult to detect, both by the legal system and regulators, and possibly by the employers who themselves may be unaware of their own biases (Bertrand et al., 2005).

A gender punishment gap also differs from gaps in hiring and wages in the information that the employer has about the employee. One view is that the differential treatment between men and women in the workplace mostly takes place before the employer has screened potential employees, at the CV evaluation stage. An extensive literature using correspondence and audit studies has evaluated such differences (see Bertrand and Duflo, 2016), examining differences in treatment across groups while reducing the potential employee to a bundle of characteristics, which can be captured in a CV. During the hiring process and employment, the employer learns substantially more about the employee, reducing the potential for "attention discrimination" (Bartos et al., 2016). One might therefore imagine that discrimination disappears conditional on employment. In contrast, we observe the gender punishment gap among employees with several years of tenure, suggesting a potentially different mechanism is at play. Moreover, methodologically, studying these types of gender differences does not lend itself toward audit and correspondence studies, which, by design, reduce an employee to characteristics captured in a CV.

Ours is the first study to investigate the gender punishment gap in an important setting, the financial adviser industry. Undesirable outcomes are generally difficult to measure, especially across firms. We overcome this obstacle by exploiting a novel panel data on all financial advisers (about 1.2 million) registered in the United States from 2005 to 2015, representing approximately 10% of total employment in the finance and insurance sector. Regulators require that financial advisers disclose career events such as misconduct, including customer disputes, regulatory, and criminal offenses. We also observe detailed information on the nature of misconduct;[1] the monetary cost of misconduct with settlements averaging several hundred thousand dollars; actions taken by the firm and the regulator consequent to the misconduct; and employee movement across firms in the industry.[2] This is a highly regulated industry with comprehensive licensing requirements, which determine adviser's job tasks. These features of the data allow us to account for differences across advisers in terms of job role, productivity, and misconduct, and study gender differences in punishment at both the firm and industry level.

Researching gender differences in financial sector is also interesting per se. Finance is a large and highly compensated industry, which consistently ranks among the bottom industries in terms of gender equality. Personal financial advisers, for example, have among the largest gender earning gaps across occupations (Census, 2008). Recent survey evidence found that nearly 88% of female financial service professionals believe that gender discrimination exists within the financial services industry (Tuttle, 2013). Consequently, concerns about the lack of diversity and discrimination in the financial industry have become an important policy issue. Our work speaks to this issue since it suggests that harsher punishment of women, such as termination, for similar missteps, might inherently contribute to the glass ceiling they face.[3]

This paper has two goals. First, we document key differences in the punishment of similar misconduct across male and female financial advisers at both the firm and industry level: the gender punishment gap. We show that the gap is not driven by gender differences in occupation (type of job, firm, market, or financial products), productivity, misconduct, or recidivism. This punishment gap is strongly correlated with the gender composition of the managerial team. Female managers and executives help alleviate the gender punishment gap. Moreover, we find evidence of a similar punishment gap and mitigating factors for ethnic minority men. Second, we examine the rationale behind the gender punishment gap. We begin with a benchmark that the gap is simply a product of firms' Bayesian profit maximizing behavior, i.e. statistical discrimination (Phelps, 1972; Arrow, 1973). This model has a difficult time reconciling the evidence we document. We then explore the alternative that the punishment gap is driven by managers' biased (incorrect) beliefs about the probability of repeat offenses about the members of their own group. Such bias can be either taste-based (Becker, 1957) or because market participants hold miscalibrated/incorrect beliefs about misconduct across the two groups (Bordalo et al., 2016; Arnold et al, 2017; Sarsons 2017). This simple model is consistent with the facts we document.

We first document gender differences in the financial advisory industry. Male financial advisers make up 75% of the financial advisory industry and are responsible for a disproportionately large amount of the misconduct in the industry. Moreover, male advisers engage in more severe misconduct both in terms of allegations, and

[1] Common misconduct allegations include activities such as unauthorized trading, churning accounts to generate excess commissions, misrepresenting the risks associated with a financial product, and committing outright fraud

[2] Roughly 7% of financial advisers have a past record of misconduct and the average settlement is in excess of several hundred thousand dollars.

[3] Consulting firm Oliver Wyman (2016) lists the glass ceiling it as the number one cause for concern for women in the industry. Former FDIC chairwomen Sheila Bair (2016) writes that the glass ceiling in finance is "barely cracked" for women.

eventual monetary damages to the firm. These differences are partially a result of somewhat different allocations to jobs and tasks–males are more likely to be managers with longer industry tenures, and hold more qualifications. Nevertheless, they persist after comparing male and female advisers working at the same firm, in the same location, at same point of time, and in the same job role, and even after accounting for a rich set of adviser characteristics and productivity measures.[4] The higher propensity of men to commit more nefarious activities has been found in other contexts and is "universal" across violent and nonviolent criminal activity (Steffensmeier and Allen, 1996).[5]

Next, we turn to our first main result. We find that, despite having a lower incidence of misconduct and engaging in less severe misconduct, female advisers face more severe punishment in the labor market. Female advisers are 20% more likely to experience a job separation following misconduct relative to male advisers with similar offenses. Conditional on separation, female advisers face longer unemployment spells, and are 30% less likely to find a new position in the industry within one year, with very similar effects for longer horizons. The difference is particularly striking because we find no gender differences in job turnover rates for advisers *without* misconduct. Our results suggest that firms, and the industry as a whole, discipline female advisers more severely relative to male advisers following misconduct. We term these differences in labor market outcomes the "gender punishment gap."

The central concern is that the gender punishment gap is driven by is gender occupational segregation across firms, markets, or job roles. Several pieces of evidence in the data suggest that this is not the case. First, we compare the career outcomes of male and female advisers who are working at the same firm, in the same location, and at the same point in time (firm $\times$ year $\times$ county fixed effect). These fixed effects allow us to control for differences across firms and branches such as whether they deal with institutional investors, retail investors, and/or investment banking activities. Second, because the market for financial advice is highly regulated, advisers are legally required to hold a particular set of licenses to sell certain classes of products, and perform certain job tasks. For example, a Series 6 License authorizes financial advisers to sell mutual funds and variable annuities. Registered Sales Assistant License (Series 11) allows an individual to work as a sales *assistant* in the industry, and Series 24 as a *manager* who oversees other associates. We account for 61 different professional licenses, and include firm $\times$ year $\times$ county x license fixed effects. We effectively compare the career outcomes of male and female advisers who are working for the same firm, in the same branch, at the same time, and in the same role. Finally, we also measure an individual advisers' assets under management (AUM), adviser's productivity, and nature of the misconduct allegations (e.g., related to mutual funds, variable annuities, bonds, options etc.). Accounting for these dimensions also helps condition on other aspects of the job function of the adviser. After controlling for these differences, the gender punishment gap remains virtually unchanged.

Our second main set of results finds dramatic differences in the gender punishment gap across firms. At firms with no female representation at the executive/ownership level, the gender punishment gap is 32pp. There is no gap in firms with an equal representation of male and female executives/owners. We find similar results when exploiting within-firm variation in the share of female branch-level managers. Overall, our results suggest that the gender punishment gap is related to the gender composition of executives and managers at financial advisory firms.

[4] In the specifications we include, Firm $\times$ year $\times$ county $\times$ license fixed effect.

[5] With the exception of prostitution, men are more likely to be arrested for all FBI offense categories, including violent, non-violent, and small crimes (Steffensmeier and Allen, 1996). Steffensmeier and Allen (1996) write "Criminologists agree that the gender gap in crime is universal: Women are always and everywhere less likely than men to commit criminal acts."

Male executives and managers seem to be more forgiving of misconduct by men relative to women.

We extend our analysis to minority men and show that the punishment gap, and patterns of "in-group" tolerance are not limited to gender. Males with names from traditionally discriminated minorities face a punishment gap relative to non-minority men. The punishment gap is lower in firms with a larger share of managers from their ethnic group. These results also suggest that the "in-group" tolerance we observe is not driven solely by gender specific factors. In addition, we find no evidence that male minority managers decrease the gender punishment gap. In other words, managers only alleviate the punishment gap within their gender and ethnic group. This evidence is important because it rules out several potential alternatives, under which firms with female or minority male executives attract a pool of individuals with selected misconduct propensities.

In the second half we examine the potential mechanisms generating the gender punishment gap. We explore two potential mechanisms which we nest within the scope of a simple model. Under the first mechanism, firms maximize profits and punish female advisers more severely because misconduct by female advisers is predictive of more frequent misconduct or adviser skill. Moreover, firms have the correct beliefs about the propensity to engage in misconduct across genders, and use Bayesian updating when forecasting misconduct. The second mechanism we nest generates the punishment gap as a result of firm biases. The bias could be the result of either an inherent firm prejudice against women or favoritism towards men (i.e. taste-based discrimination; Becker 1957) and/or could be due to miscalibrated beliefs held by firms (i.e. stereotyping; Bordalo et al. 2016). We then contrast the model predictions with the data.

We present several results, which are difficult to reconcile with a Bayesian updating by profit maximizing firms. Under this benchmark, firms may find it optimal to discipline women more severely if women engage in more costly misconduct or have higher rates of recidivism. The evidence we find suggests the exact opposite. Male advisers engage in misconduct that is 20% more costly to settle for firms. We also experiment with a variety of misconduct measures, and find robust results across those alternative measures. These results suggest that the gender punishment gap does not arise because female advisers engage in different types, or more egregious misconduct. Another alternative would be that female advisers are more likely to be repeat offenders conditional on misconduct. Again, the opposite is true. Male advisers are more than twice as likely to be repeat offenders in the future. These results suggest that, under this benchmark model, all else equal, firms should punish male advisers *more severely* than female advisers. In other words, even if job separation rates following misconduct were identical, these results would still suggest that punishment of misconduct is biased against women.

A more subtle prediction of this model concerns the joint distribution of ability and misconduct across genders and firms' Bayesian updating from observed misconduct across genders. The argument is as follows: female advisers are on average less likely to engage in misconduct. Firms are therefore willing to hire less productive female than comparable male advisers. Moreover, because female advisers have on average lower rates of misconduct, after observing misconduct a Bayesian firm updates its beliefs about future misconduct more dramatically for female advisers than for male advisers – and consequently punishes women more harshly. In other words, the gender punishment gap could result from Bayesian updating of the firm. Two observations suggest this is not the case.

First, one advantage of the financial adviser setting is that the productivity of financial advisers can be broadly encapsulated as the amount of assets they attract (i.e., assets under management, AUM). We observe AUM in conjunction with other productivity measures for a subset of advisers. Controlling for AUM differences, as well as other measures of productivity, has no effect on the gender punishment gap. We also control for other measures, which may reveal expected productivity. For example, we find that the gender punishment gap persists across different levels of experience. The gender punishment gap exists even for advisers whose abilities are well known to the market (15+ years experience). Career interruptions, which explain a large part of the earnings gap in finance (Bertrand et al, 2010) correlate with turnover, but not with the punishment gap. Lastly, if female advisers who engage in misconduct have less desirable characteristics, we would expect these characteristics to also lead to higher turnover prior to misconduct. We find no signs of elevated turnover for female advisers who engage in misconduct, *prior* to their initial misconduct offense.

Second, Bayesian updating has important implications for the ethnic minority punishment gap we document. The existence of the minority punishment gap and the fact that it diminishes in the presence of minority male managers, suggests that it is driven by the same mechanism as the gender punishment gap. A key distinction in the minority setting is that male minority advisers are *more* likely to engage in misconduct relative to male non-minority advisers. Thus, following the Bayesian logic, the benchmark mechanism would suggest that firms should hire more productive male minority advisers, and update less upon observing misconduct. In other words, we should find the reverse punishment gap. The existence of male minority punishment gap suggests that updating from low average misconduct rates is not driving the gender punishment gap.

Lastly, the model in which Bayesian firms maximize profits has a difficult time explaining why the gender punishment gap is larger in branches with more male managers. If male and female managers update from observed behavior following Bayes rule, then the statistical discrimination model would require a very specific type of sorting across genders into firms. Moreover, a similar sorting would have to take place among male advisers along dimensions of ethnic minorities. Finally, since we find that male minority managers do not alleviate the gender punishment gap, the sorting would have to be multi-dimensional. In sum, our benchmark model in which Bayesian firms maximize profits has a difficult time explaining a wide range of facts about the gender punishment gap.

A simple model in which managers have biased (incorrect) beliefs about the probability of repeat offenses about the members of their own group is consistent with the facts we document. It generates a gender punishment gap, even if misconduct is not indicative of a gender gap in ability or recidivism. It also explains why female managers decrease the gender punishment gap; why minority male managers decrease the minority male punishment gap; and why male minority managers do not decrease the gender punishment gap. More broadly, we find in-group favoritism in punishment of misconduct, both at the firm at which the misconduct took place, as well as at other firms in the labor market. These findings contribute to the extensive literature on gender differences in the labor market. One prominent difference with the literature is that we focus on gender differences in punishments, rather than rewards. Since the literature is extensive, we discuss the specific connection and contribution to this literature, as well as to literature on financial advisers, misconduct and fraud in greater detail in Section IV.E.

The rest of the paper is structured as follows. Section II describes the data, describes how we measure misconduct, and presents the basic facts about gender differences among financial advisers. Section III documents the gender punishment gap in the labor market for financial advisers. Section IV explores the economic mechanisms underlying the gap and discusses our results in context of the prior literature. Section V concludes.

II Gender and Financial Advisers

II.A Data Set

Our data set contains the universe of financial services employees registered with the Financial Industry Regulatory Authority (FINRA) from 2005 to 2015. The data comes from FINRA's BrokerCheck database. Additional details describing the data set are in Egan, Matvos, and Seru (2017) (also available at http://eganmatvosseru.com/). Throughout the paper, we refer to a financial adviser as any individual who is registered with FINRA, but are careful to make distinctions about additional registrations or qualifications a financial adviser may hold, such as being a registered investment adviser or a general securities principal. A broker (or stockbroker) is registered with FINRA and the SEC and is defined in the Securities and Exchange Act 1934 as "any person engaged in the business of effecting transactions in securities for the account of others." An investment adviser provides financial advice rather than transaction services. Although both are often considered "financial advisers," brokers and investment advisers differ in terms of their registration, duties, and legal requirements. Throughout the paper, we will use terminology consistent with FINRA and refer to both investment advisers and brokers as "financial advisers." This includes all brokers and the vast majority of investment advisers. The data set also contains additional information on the universe of currently active financial firms.

Our sample contains a monthly panel of all registered advisers from 2005 to 2015. For each of the roughly 1.2 million advisers in the data set, we observe the adviser's registrations, licenses, employment history, and whether or not she has any disclosures on her record. We observe each adviser's complete employment history in the industry which often dates back substantially further than 2005.

We observe detailed data on the adviser's complete employment history in the financial advisory industry including the employer, location and tenure. We also observe information on each adviser's role and job function within their firm. Relative to many other industries, the financial advisory industry is highly regulated. Financial advisers are legally required to hold regulatory licenses (i.e., pass specific exams called series exams) in order to engage in particular activities and to hold certain positions within a firm. For example, the Investment Company Products/Variable Life Contracts Representative License (Series 6 exam), authorizes an individual to sell mutual funds and variable annuities. The National Commodities Futures Exam (Series 3) is required to sell managed futures funds. The licenses also provide detail on the adviser's specific job role. An Assistant Representative (Series 11) License allows an individual to work as an assistant, while a General Securities Representative (Series 24) License is required to work as a manger. In Appendix A2 we list the 61 different types of licenses we observe in the data. These detailed, specific, and granular occupational licensing requirements allow us to compare female and male advisers with the same qualifications and engaged in the same job roles within a firm.

Measuring Misconduct The regulatory data also provides details on whether an adviser has ever engaged in misconduct and the specific details of each offense. The regulator FINRA requires that financial advisers "disclose customer complaints and arbitrations, regulatory actions, employment terminations, bankruptcy filings, and criminal or judicial proceedings." We observe the full set of such disclosures for each financial adviser in our data. A disclosure indicates any sort of dispute, disciplinary action, or other financial matters concerning the adviser.

Because not all disclosures are indicative of misconduct (i.e. personal bankruptcy), we classify only the disclosures that are indicative of fraud or wrongdoing as misconduct. Specifically, following Egan, Matvos, and Seru (2017), we restrict our classification of disclosures indicating misconduct to include only six of the twenty-three disclosure categories reported by FINRA: Customer Dispute-Settled, Regulatory-Final, Employment Separation After Allegations, Customer Dispute - Award/Judgment, Criminal - Final Disposition, Civil-Final. To summarize, misconduct includes customer disputes, internal investigations, and regulatory/criminal events where that were resolved against the adviser. Roughly 7% of the financial advisers in our dataset have a past record of misconduct.

An advantage of our data set is that we observe granular data of each misconduct disclosure, including the specific allegations, products involved, and costs. Table 1b displays the most commonly reported allegations reported against financial advisers broken down by gender. The allegations vary in terms of their severity and potential opacity/ambiguity. Several of the common allegations are relatively clear-cut in terms determining guilt such as unauthorized trading, churning, misrepresentation, and outright fraud. Unauthorized trading, for instance, involves trading in a client's account without their consent. This type of activity is easily verifiable because account activity, client activity, and legal consent are tracked and well documented. Other allegations are more vague. For example, a common allegation is that the adviser made unsuitable investments. This is not surprising. By law, brokers are required to only sell "suitable" investments to their clients. However, the exact dimension on which a given product might be unsuitable for a given client is less clear. In our analysis we explicitly account for these differences in the type and extent of misconduct.

Misconduct is costly for the advisory firm. Our dataset provides details on the dollar awards/settlements advisers are forced to pay out to clients as a result of misconduct. The median settlement is $40,000, and the mean settlement is approximately $550,000, suggesting substantial damages to the household. We use data on the associated awards/settlements to examine the severity of misconduct by male and female advisers.

Gender Data The BrokerCheck data set does not provide information on the gender of the financial adviser. We use data from GenderChecker to match the gender of each adviser based on the first name of the adviser. GenderChecker uses data from the UK Census in conjunction with other proprietary data sources to match the first names of individuals to gender. GenderChecker takes a conservative approach to assigning genders from names. If a name appears in the census (or one of GenderChecker's other data sources) as both male and female even once, the name is classified as being unisex. We assign a specific gender to 82% of the advisers in our database: 62% of the advisers in our data set are classified as male, 20% are classified as female. The remaining 15% are classified as unisex leaving remaining 3% as unmatched in the GenderChecker database. In our main analysis, we restrict our data set to those advisers we classify as either male or female, dropping all unisex and unmatched observations. Females therefore comprise approximately 25% in the matched data. As an additional robustness check, we use name/gender data from Meridian IQ's database on financial advisers and find similar results as with the former classification. We report these robustness tests in the Appendix (Table A2). Summary statistics for the complete data set are reported in Table 1. Central to our purposes, 15% of male advisers and 8% of female advisers in our data set have disclosures on their records. These statistics are in line with previous work (Egan, Matvos, Seru 2017 and cites therein).

II.B Gender Composition of Advisers and Misconduct Across Genders

II.B.1 Gender Composition

The advisers in our data account for roughly 10% of employment in the Finance and Insurance sector (NAICS 52). 25% of financial advisers are female. Simple cuts of the data suggest that male financial advisers have more experience, more extensive qualifications, and are more likely to be in managerial and supervisory positions than their female counterparts. Figure 1 and Table 1 display some important differences between male and female advisers. Male advisers are, on average, more experienced, with three additional years of experience relative to female advisers. Similarly, male advisers have passed a somewhat larger number of qualification exams. Male and female advisers also differ in the types of qualification exams they have passed. Figure 1 reports the share of advisers who have passed any of the six most popular qualification exams taken by investment professionals.[6] Female advisers are more likely to have completed the Series 6 qualification exam, which allows an adviser to sell open-end mutual funds and variable annuities, while male advisers are more likely to hold a Series 65 qualification, which allows them to act in an investment adviser capacity. 54% of currently registered male advisers and 45% of currently registered female advisers are also registered as investment advisers.

In addition to having more seniority, male advisers are more likely to be in managerial and supervisory positions than their female counterparts. The Series 24 exam qualifies an individual to operate in a supervisory capacity. Male advisers are 7pp more likely to have completed the Series 24 exam. Similarly, female advisers are under-represented among executives/owners of the financial advisory firms. Figure 2 displays the distribution of female owner/executives across active financial advisory firms. Female advisers represent 16% of the owners and executives and 17% of managers, even though they account for 25% of all financial advisers. To summarize: male and female financial advisers differ on observables, which might be related to job tasks or financial products and firms, which employ them. It is therefore important to account for these differences when comparing advisers across genders.

II.B.2 Gender Differences in Misconduct Propensity

Approximately 7% of financial advisers have records of past misconduct (Egan, Matvos, and Seru, 2017). Here, we examine how misconduct varies across male and female advisers. Similar to the literature on white collar crime, and crime in general, we find that men are significantly more likely to engage in misconduct relative to women (Daly 1989; Steffensmeier and Allen 1996; Holtfreter 2005; Steffensmeier et al. 2013). Table 1b, columns (3) and (4) display the share of advisers with at least one record of past misconduct at a given point in time. The results indicate that 9% of male and 3% of female financial advisers have at least one misconduct on their record.[7] Columns (1) and (2) of Table 1b show that the probability that an adviser engages in new misconduct during a year is 0.72% for males and 0.29% for females. The incidence of misconduct among male advisers is more than twice the rate among female advisers. Conditional on receiving a misconduct disclosure, the distribution of the types of misconduct are comparable across male and female advisers, but there are some subtle differences. Customer

[6] Details of each qualification exam are available in the Appendix A2 and from FINRA online: http://www.finra.org/industry/qualification-exams?bc=1

[7] Because many financial advisers have multiple disclosures pertaining to misconduct, the subcategories of disclosure that we classify as misconduct in Table 1a add up to more than 9% and 3%.

initiated misconduct, i.e., customer disputes, accounts for roughly half of all misconduct (57% for men and 48% for women). Regulatory and criminal offenses account for 20% and 17% of misconduct disclosures received by men and women. Lastly, firm initiated misconduct, accounts for 28% of misconduct disclosures received by men and 41% received by women.[8]

Beyond the type of disclosure, we also observe details on the nature of the misconduct. Tables 1c and 1d display the most commonly reported types of allegations and financial products in the misconduct disclosures. In general, the distribution of the type of complaints received by male and female advisers is comparable, although there is more variation in the complaints received by female advisers. These simple summary statistics suggest that male and female advisers engage in similar types of misconduct even though the incidence of misconduct is higher among male advisers.

One potential explanation for the differences in misconduct among the two genders is that the job functions of male advisers are, on average, different from those of female advisers. For example, men may be more likely to work in a client-facing role, where they give explicit investment and financial planning advice to consumers. Conversely, women may be more likely to work in non-client facing positions, such as compliance or risk management. Customer disputes account for about one-half of all misconduct (Table 1b), so occupational segregation along these lines could well explain differences in misconduct across genders. To account for these concerns, we examine gender differences in misconduct more systematically using the following linear probability model:

$$Misconduct_{iqjlt} = \alpha Female_i + \beta X_{it} + \mu_{qjlt} + \varepsilon_{iqjlt}. \tag{1}$$

Observations are at the adviser-by-year level; i indexes an adviser with qualifications/occupational licenses q who worked for firm j, at time t, and in county l. The dependent variable $Misconduct_{iqjlt}$ is a dummy variable indicating that adviser i received a misconduct disclosure at time t. The independent variable of interest is the dummy variable $Female_i$, which indicates the gender of the adviser. Our full specification includes firm $\times$ year $\times$ county $\times$ license fixed effects μ_{qjlt}. In other words, we include a fixed effect for each set of possible licenses an adviser potentially holds within a firm, location, and time. These sets of controls allow us to compare male and female advisers who work for the same firm, in the same branch, at the same time, and in the same job role. The fixed effects also account for aggregate shocks such as the financial crisis, variation in regulatory conditions (subsuming any state- or county-level regulatory variation), and any differences in firm business models or types of clients serviced across locations. We also account for other adviser level observables such as their experience in the industry in the vector X_{it}.

Table 2a displays the results. In each specification, we estimate a negative and statistically significant relationship between the adviser's gender and the probability that the adviser engages in misconduct at time t. The estimates in column (3) indicate that the probability a female adviser engages in misconduct in a given year is 0.32pp lower than that of a male adviser. Therefore, relative to male advisers (0.72pp from Table 1b), female

[8] Firms must report whether or not adviser experienced an "Employment Separation after Allegations." For these cases where the firms report an "Employment Separation after Allegations," firms report whether or not the adviser was fired/discharged, permitted to resign, or if it was a voluntary separation. Among male advisers with this type of disclosure, 75% were discharged, 13% were permitted to resign, and 11% left voluntarily. Among female advisers with this type of disclosure, 83% were discharged, 7% were permitted to resign, and 9% left voluntarily.

advisers within the same firm at the same time in the same county (column 3) are roughly half as likely to engage in misconduct. Most importantly, in the most stringent specification with the full set of fixed effects (column 4), we find that women are 27bps less likely to engage in misconduct. Overall, these results suggest that gender differences in misconduct can be partially, but not fully explained by occupational segregation across genders in terms an adviser's job role and financial products, firm and market differences.

II.B.3 Gender Differences in Misconduct Severity

Female advisers engage in less misconduct than male advisers. However, it is possible that conditional on misconduct, female advisers engage in more costly misconduct. We examine the settlements and awards firms paid to investors as a result of misconduct. Figure 3 displays the distribution of settlements paid out as a result of misconduct among male and female advisers. The distribution of settlements from male adviser misconduct stochastically dominates the distribution of settlements resulting from female adviser misconduct. The median settlement is \$40k for male advisers and \$31k for female advisers. Furthermore, the average settlement of male advisers is more than double that of female advisers (\$832k versus \$320k).

We examine the differences in the settlements paid out on behalf of male and female advisers using the following regression specification:

$$\ln(Settlement)_{ijlt} = \alpha Female_i + \beta X_{it} + \mu_j + \phi_l + \psi_t + \varepsilon_{ijlt}. \tag{2}$$

The sample is restricted to instances of misconduct in which settlements were paid to the customer. The dependent variable is $\ln(Settlement)_{ijlt}$, which measures the settlements paid out on behalf of advisers following an incident of misconduct. The key independent variable of interest is the dummy variable $Female_i$. We control for adviser characteristics in X_{it} and firm (original firm at time t), year, and county fixed effects μ_j, ϕ_l, ψ_t. The results in Table 2c confirm that misconduct committed by male advisers is more costly than misconduct committed by female advisers. On average, settlements associated with female adviser misconduct are $11-20\%$ lower than settlements associated with male adviser misconduct. Thus, male advisers engage in more misconduct, and, conditional on engaging in misconduct, misconduct by male advisers is costlier for the firm.

III Labor Market Consequences of Misconduct: "The Gender Punishment Gap"

Egan, Matvos, and Seru (2017) show that the financial industry punishes misconduct, both through employment separations at the firm level and through worse employment opportunities at the industry level. Here we document gender differences in the labor market consequences of misconduct – the gender punishment gap – at the firm and industry level. We also establish that this gender punishment gap is not driven by gender differences in job role or in types of firms, markets, or financial products handled by the adviser.

III.A Gender Differences in Job Separation Following Misconduct

We first document that, relative to male advisers, female advisers face worse job separation prospects following misconduct. We start with a simple cut of the data in Table 3a. Both male and female advisers are likely to experience job separations following misconduct, but female advisers face harsher consequences. While 46% of male advisers experience job separations following misconduct, 55% of female advisers do so. In other words, female advisers are 20% more likely to lose their jobs following misconduct than male advisers. For ease of terminology, we call gender differences in job separation rates the "gender punishment gap." The gap does not arise because female advisers, on average, face larger job turnover. Turnover rates among male and female advisers are remarkably similar. On average, 19% of male and 19% of female advisers leave their firm in a given year. Figure 4 plots the average job turnover rates for male and female financial advisers over the past ten years. The turnover rates among male and female advisers are nearly identical over the period 2005-2015, with a correlation of 0.98. However, following misconduct, female advisers are substantially more likely to lose their jobs.

The nearly identical turnover rates among male and female advisers without misconduct suggests that the gender punishment gap is not driven by the sorting of male and female advisers across different firms or locations. Nevertheless, it may be possible that female advisers are matched with firms that punish misconduct more severely or provide services in markets in which consumers or regulators are particularly sensitive to misconduct. To evaluate this alternative, we compare female and male advisers working at the same firm, at the same location, and at the same point in time, with the same qualifications, experience, and other observable characteristics, by estimating the following linear probability model:

$$Separation_{iqjlt+1} = \beta_1 Female_i + \beta_2 Misc._{iqjlt} + \beta_3 Misc._{iqjlt} \times Female_i + \beta_4 X_{it} + \mu_{qjlt} + \varepsilon_{iqjlt}. \qquad (3)$$

Observations are at the adviser-by-year level; i indexes an adviser with qualifications/occupational licenses q who worked for firm j at time t in county l. The dependent variable $Separation_{iqjlt+1}$ is a dummy variable indicating that the adviser is *not* employed at firm j in year $t+1$. The independent variable $Misconduct_{iqjlt}$, is a dummy variable indicating that the adviser received a misconduct disclosure in year t. The independent variable of interest is $Misconduct_{iqjlt} \times Female_i$, which measures the gender punishment gap. We control for other advisers' characteristics such as experience in X_{it}. These capture the type of advising the adviser engages in. As before, our full specification includes firm $\times$ year $\times$ county $\times$ license fixed effects μ_{qjlt}, i.e. a fixed effect for each set of possible qualifications an adviser potentially holds within a firm, location, and time. These sets of controls allow us to compare male and female advisers who work for the same firm, in the same branch, at the same time, and in the same job role. Thus the effects we identify are not driven by firms' product characteristics or its attitudes towards misconduct or different turnover rates, demographics differences, local labor market conditions, types of clients serviced across locations, or differences in job roles.

We present the estimates in Table 3b. In each specification we estimate a positive and statistically significant relationship between misconduct in year t and job separation in year $t+1$. The coefficient on misconduct measures the probability that a male adviser experiences a job separation following misconduct. In the most stringent specification with full set of fixed effects, male advisers are 26pp more likely to experience an employment separation following misconduct relative to male advisers without recent misconduct (column 4). More importantly, we find evidence of a gender punishment gap. In each specification, we estimate a positive and statistically significant coefficient on $Misconduct_{iqjlt} \times Female_i$ between 8pp and 10pp. The estimated gender punishment gap changes little as we include the firm × year × county fixed effects μ_{jlt} or firm × year × county × license fixed effects μ_{qjlt}. In other words, the estimates in column (1) indicate that, following misconduct, male advisers have a 28pp higher chance of a job separation, while female advisers have a 28pp+8pp=36pp higher chance of a job separation. Relative to male advisers, female advisers are 20% more likely to lose their jobs following a misconduct disclosure. These results suggest that firms are more tolerant of misconduct among male advisers.[9] In addition to the alternatives ruled out in this section, we additionally show that this result is robust to different measures of misconduct as well as possible omitted adviser characteristics, including productivity that we measure quite precisely, in Section IV.B.

III.B Gender Differences in Reemployment Following Misconduct

In this section we document that the punishment gap extends to firms' hiring decisions. In addition to being more tolerant towards misconduct by their own male employees, firms are more tolerant of misconduct by males committed at *other* firms. The is a distinction between the hiring and separation punishment gap. One reason why the punishment gap may arise is because of differences in favoritism towards current employees, because they know them from daily interactions. This is not the case with advisers from other firms. Therefore, the existence of the punishment gap at reemployment suggests that favoritism towards existing employees is unlikely the sole driver of the phenomenon.

Simple cuts of the data displayed in Table 3a indicate that women face worse reemployment prospects following misconduct. Almost one half (47%) of male advisers who lose their jobs following misconduct find new jobs in the industry within a year. Only one third (33%) of female advisers are reemployed in the same period. This difference in reemployment partially arises because female advisers are less likely to be reemployed, even if job separations are not preceded by misconduct. To account for this difference, we compute the decrease in reemployment probabilities due to misconduct across genders. For female advisers, the reemployment rate declines from 48% to 33% following misconduct, or 15*pp*. For male advisers, the decline is substantially smaller, from 54% to 47%, or 7*pp*. Taking a difference in differences approach, the turnover rates in Table 3a indicate female advisers are 8*pp* less likely to find new employment following misconduct relative to male advisers ($-8\% = (33 - 48\%) - (47\% - 54\%)$).

To ensure that the gender differences in reemployment following misconduct are not confounded by differences in regulation and demographics across markets, in previous employment, or in activities advisers engaged in, we estimate the following linear probability model:

$$New\_Employment_{iqjlt+1} = \beta_1 Female_i + \beta_2 Misc._{iqjlt} + \beta_3 Misc._{iqjlt} \times Female_i + \beta_4 X_{it} + \mu_{qjlt} + \varepsilon_{iqjlt}. \quad (4)$$

We restrict the sample to financial advisers who were separated from their jobs in the previous year. $New\_Employment_{iqjlt+1}$ is equal to one if the adviser i with qualifications/occupational licenses q who had been employed at firm j in lo-

[9] As an extension, in Table A3 in the Appendix, we show that female advisers are also less likely to be promoted following misconduct. The economic magnitudes in the table suggest that a female adviser with a past record of misconduct is 25bps (40%) less likely to be promoted in a given year relative to a male adviser with a past record of misconduct (column 1).

cation l has found new employment in the industry between time t and $t+1$. The independent variable of interest is $Misconduct_{iqjlt} \times Female_i$, which measures the differential reemployment prospects of male and female advisers following misconduct. As before, our full specification includes firm (original firm at time t) $\times$ year $\times$ county $\times$ license fixed effects μ_{qjlt}, i.e. a fixed effect for each set of possible qualifications an adviser potentially holds within a firm (original firm at time t) , location, and time. In effect, we compare the outcomes of male and female financial advisers who had been previously employed at the same firm, at the same time, in the same county, who are licensed to engage in same activities, and examine how their reemployment depends on whether they engaged in misconduct.

The corresponding results are reported in Table 3c. We estimate a negative and significant relationship between misconduct and new employment. The negative coefficient on the interaction term $Misconduct_{iqjlt} \times Female_i$ indicates that female advisers face more severe punishment at the industry level; they are $3.5-7pp$ less likely to find a new job than a male financial adviser who engaged in misconduct. Given that male advisers who are disciplined at time t are $7.5-12pp$ less likely to find a new job in the next year, this magnitude is substantial. Relative to male advisers', the decline in reemployment opportunities following misconduct is 30% larger for female advisers.

Another way to measure differences in reemployment prospects across genders is through the time duration they spend out of the industry. In the Appendix, we estimate a Cox proportional hazards model. As results in Table A4 reveal, a female adviser's chances of finding reemployment are 8pp smaller than that of comparable male advisers following misconduct (26pp-16pp). The results from this section suggest that firms are more tolerant of misconduct by male financial advisers in their hiring decisions.

III.C Gender Punishment Gap Across and Within Firms

We now delve deeper into the source of the gender punishment gap by examining its relationship with the gender composition of decision makers in firms. Recent survey evidence suggests that a large majority of women in the financial sector believe that gender discrimination persists within their firms.[10] If the source of the gender punishment gap is indeed the firm, then it is plausible that there is heterogeneity in how firms treat male and female advisers following misconduct. We first document that such firm differences exist. Then we illustrate that the differences between firms, such as the gender composition of management, can explain differences in the gender punishment gap across firms, and across branches within firms.

We first compute differences in the gender punishment gap across firms using the following specification:

$$Separation_{it+1} = \beta_{j0} + \beta_{j1} Female_i + \beta_{j2} Misc._{it} + \beta_{j3} Misc._{it} \times Female_i + \beta_4 X_{it} + \varepsilon_{it}. \tag{5}$$

The firm-specific coefficients of interest β_{j3} measure the difference between the probability a female adviser experiences an employment separation following misconduct relative to male advisers in a given firm. Note that we also allow the turnover rates for male advisers, female advisers, and advisers with misconduct to vary across firms by

[10]Nearly 88% of female financial service professionals in a recent survey said that they believe that gender discrimination exists within the financial services industry, 46% believe gender discrimination exists in their firm, and 31% said they have personally been discriminated against based on gender (Tuttle, 2013).

including firm specific coefficients β_{j1}, β_{j2}, and β_{j3}. Figure 5a displays the dispersion in the gender punishment gap (β_{j3}) across firms, and Figure 5b the firms with the highest gap. [11] To improve statistical power, we restrict our analysis to firms in which at least twenty female advisers receive misconduct disclosures. The estimated distribution of firm coefficients (β_3) are jointly significantly different from each other, confirming differences in the gender punishment gap across firms. In terms of magnitudes, for example, the gender gap at Wells Fargo Advisers[12] is $18pp$ higher than the average gap.[13] Overall, the results suggest that the gender punishment gap varies substantially across firms.

III.C.1 Female Managers Alleviate the Gender Punishment Gap at Job Separation

If the gender punishment gap arises because of employer bias, it is probably driven by the bias of the decision makers in the firm. One proposal to limit discrimination in firms is to increase the share of women in positions of power. The idea is that decision makers in organizations can directly affect policies leading to discrimination. The members from the discriminated group, i.e., women, are more likely to recognize discrimination and less likely to support discriminatory practices. Figure 2a illustrates the substantial differences in gender composition of firm executives in our sample as of 2015. We first show that the differences in the gender composition of executive teams across firms can explain across-firm differences in the gender punishment gap. We then look within firms and illustrate that the gender composition of branch managers can also explain differences in the punishment gap across branches, within the same firm.

We start by examining whether the gender punishment gap is smaller in firms with more female executives using the following linear probability model:

$$\begin{aligned} Separation_{iqjlt+1} \quad = \quad & \beta_1 Misc._{iqjlt} + \beta_2 Female_i + \beta_3 Pct\,Female\,Exec_j + \beta_4 Misc._{iqjlt} \times Female_i \\ & + \beta_5 Misc._{iqjlt} \times Pct\,Female\,Exec_j + \beta_6 Female_i \times Pct\,Female\,Exec_j \\ & + \beta_7 Misc._{iqjlt} \times Female_i \times Pct\,Female\,Exec_j \\ & + \beta_8 X_{it} + \mu_{qjlt} + \varepsilon_{iqjlt}. \end{aligned} \tag{6}$$

Observations are at the adviser-by-year level; i indexes an adviser with qualifications/occupational licenses q who worked for firm j at time t in county l. The dependent variable $Separation_{iqjlt+1}$ is a dummy variable indicating that the adviser is *not* employed at firm j in year $t+1$. The variable $Pct\,Female\,Exec_j$ measures the percentage of females in executive management as of 2015; the level effect (β_3) is absorbed by the fixed effect μ_{qjlt}. The independent variable of interest is $Misconduct_{iqjlt} \times Female_i \times Pct\,Female\,Exec_j$, which measures how the differences in punishment across genders depends on the share of female executives. As before, our most stringent specification

[11] The distribution of gender differences (β_{j3}) reported in Figure 5a includes measurement error. To account for measurement error, we construct an empirical Bayes estimate of firm gender differences by shrinking $\widehat{\beta_{j3}}$. Under the assumption that the variance of the estimation error is homoskedastic (Cassella, 1992) the estimated scaling factor suggests that underlying differences across firms accounts for 78% of the variation in the distribution of the OLS estimated coefficients $\widehat{\beta_{j3}}$.

[12] Firms are defined by the corresponding CRD identification number. Firms with distinct CRD numbers can share a same parent company. For instance, Wells Fargo, operates several financial services businesses under separate numbers. In particular, Wells Fargo has several operations such as Wells Fargo Advisors Financial Network (CRD# 11025), Wells Fargo Advisors (CRD# 19616), and Wells Fargo Securities (CRD# 126292).

[13] The results Table 3a find a gender gap of $9pp$, which is $27pp$ at Wells Fargo Advisers.

accounts for differences in firms' attitudes towards misconduct or turnover rates, demographics differences, local labor market conditions as well as activities advisers engage in by including firm × year × county × license fixed effects μ_{qjlt}. We also control for advisers' characteristics such as experience in X_{it}.

Table 4a displays the corresponding estimates. Firms with a greater share of female executives exhibit a smaller gender punishment gap. In firms in which females comprise one-third of the executive team, there is almost no differential punishment for misconduct between genders.[14] In firms without any female executives, on the other hand, female advisers are 17pp more likely to experience employment separations relative to their male counterparts following misconduct (Table 4a, column 3).

We next exploit within-firm variation, by focusing on female representation in branch-level management. Female executives at the branch level may also be able to attenuate the gender punishment gap. We examine the effects of female representation in management at the branch level by constructing the variable $Pct\,Female\,Mgmt_{jlt}$, which measures the percentage of managers that are female at the firm × county × year level.[15] We also examine the effects of female representation at the branch level more generally by constructing the variable $Pct\,Female_{jlt}$, which reflects the percentage of advisers (weighted by experience) that are female at the firm × county × year level. Figures 2b and 2c display the variation in the variables $Pct\,Female\,Mgmt_{jlt}$ and $Pct\,Female_{jlt}$. We re-estimate specification eq. (6), and separately include and interact the branch-level characteristics $Pct\,Female\,Mgmt_{jlt}$ and $Pct\,Female_{jlt.}$

Tables 4b and 4c display the estimation results corresponding to eq. (6). The results indicate that female advisers are more likely to experience employment separations after receiving misconduct disclosures relative to male advisers at branches with more male management. At branches with no female representation at the management level, female advisers are 10-13pp more likely to experience an employment separation following misconduct relative to their male counterparts. In addition, female advisers also experience less differential treatment following misconduct at branches with more female advisers. The results displayed in column (2) of Table 4c indicate that female and male advisers experience similar outcomes following misconduct when male and female advisers are roughly equally represented at the firm branch.[16]

III.C.2 Female Advisers Alleviate the Punishment Gap at Reemployment

Female managers reduce the gender punishment gap for misconduct committed at their own firm. A part of the reason could be personal attachment or favoritism to those specific financial advisers. We now illustrate that female managers are also more tolerant of misconduct by female advisers from other firms. Recall that, on average, misconduct differentially decreases female advisers' chances of reemployment relative to male counterparts'. To assess how the reemployment prospects change based on share of women in positions of power in hiring firms, we

[14] The results in column (2) of Table 4a indicate that estimated coefficient on the interaction term $Misconduct \times Female \times Pct\_Female\_Exec$ is -41.4 and estimated coefficient on the term $Misconduct \times Female$ is 14.0. There is no differential in job separation probabilities for male and female advisers following misconduct if $Pct\_Female\_Exec = \frac{14.0}{41.4} = 0.34$.

[15] We classify those advisers holding a Series 24 License as managers. A Series 24 License is required to act in a supervisory role in financial advisory firm.

[16] The coefficient on the interaction term $Misconduct \times Female \times Pct\,Female$ is -16.3 and estimated coefficient on the term $Misconduct \times Pct\,Female$ is 10.3 (column (2), Table 4c). Thus, there is no differential in job separation probabilities for male and female advisers following misconduct if $Pct\,Female = \frac{10.3}{16.3} = 0.63$.

estimate the following specification:

$$Female\,Hires\,Disciplined_{jt+1} \quad = \quad \beta_1 Female\,Mgmt_{jt} + \beta_2 X_{jt} + \beta_3 Female\,Hires_{jt+1} + \mu_s + \mu_t + \varepsilon_{jt}. \quad (7)$$

Observations are at the firm × year level. The dependent variable reflects the share of new employees that were hired by firm j at time t+1 that are female and have a past record of misconduct. The independent variable of interest is again the percentage of executives/owners in the firm that are female. We also control for firm characteristics such as the formation type, size, business, etc., and include state and year fixed effects, as well as the share of female advisers hired by the firm

The estimation results are reported in Table 4d. Firms with a greater percentage of female executives hire a larger share of female advisers at time t+1 who were disciplined for misconduct at time t. The estimate in column (3) indicates that a 10pp increase in the percentage of female executives is associated with a 9.3bp increase in the share of new employees that are both female and have a record of misconduct. To put these numbers in perspective, moving from the 50th to the 75th percentile in terms of female executives (28%) is correlated with an 50% higher share of new employees that are female and have a record of misconduct. These results suggest that firms with a greater percentage of male executives are less willing to hire female advisers with past offenses. Moreover, it illustrates that the tolerance of female managers extends to female advisers who engaged in misconduct at other firms, and is not limited to their existing employees.

III.D Is Punishment Gap Gender Specific? Punishment Gap for Minority Men

In this section we show that the punishment gap extends to minority men, who have also have traditionally faced discrimination in the labor market. Several theories explaining gender differences in labor outcomes are gender specific. For example, genders exhibit differences in the value of home production, and risk aversion, which can explain several important phenomena that might look like discrimination across gender (Bertrand et al. 2010).[17] Gender identity norms (Bertrand and Kamenica, 2015) could also drive this behavior. The results of this section reveal that the punishment gap extends beyond gender. Consequently, it is unlikely that the mechanism behind it is gender specific. Instead, the results in the section are more consistent with a pattern of "in-group" tolerance or favoritism towards the members of one's own group.

We examine the labor market consequences following misconduct for male advisers of African or Hispanic ethic origin. To ensure that our results are not driven by gender differences, we limit our sample to men. We determine the ethnicity of each adviser using the name-ethnicity classifier developed in Ambekar et al. (2009) and used in the literature (Dimmock et al. 2015; Pool et al 2014).[18] We are able to classify the ethnicity of 99% of the male advisers in our sample. Roughly 4% of male advisers are classified as having Hispanic ethnic origins and 2% are classified as having African ethnic origins.

We measure the punishment gap of minority men by reestimating eq. (3) but replacing female advisers with minority men. We include additional controls for the adviser's ethnicity (African or Hispanic) and the interaction

[17]See Croson and Gneezy (2009) for a review on the literature documenting differences in risk tolerance among males and females. Croson and Gneezy find robust differences in risk preference among men and women, with women being more risk averse than men.

[18]The name-ethnicity classifier developed by Ambekar et al. (2009) is available online at http://www.textmap.org/ethnicity.

of misconduct and the adviser's ethnicity. We report the corresponding estimates in the columns (1)-(4) of Table 5b. In each specification, the estimated coefficients on the interaction terms $Misconduct \times African\,Origins$ and $Misconduct \times Hispanic\,Origins$ are positive and significant, suggesting African origin and Hispanic advisers are more likely to experience job separations following misconduct. In other words, minority men experience a punishment gap similar to female advisers. We find similar results for reemployment following misconduct (Table 5b, columns 5-8). These results suggest that Hispanic advisers face relatively worse employment prospects following misconduct relative to non-African and non-Hispanic advisers. We do not find any evidence suggesting that African advisers face worse reemployment prospects following misconduct relative to non-African origin and -Hispanic advisers. Overall, the results suggest that following misconduct, African advisers face more severe punishment at the firm level but not at the industry level while Hispanic advisers face more severe punishment at both the firm and industry level.

The existence of a punishment gap for minority men suggests a similar mechanism generates the gender and minority (male) punishment gap. There is one difference between the groups, which speaks to the potential mechanism. Female and minority male advisers differ in the average rate of misconduct. Female advisers engage in substantially *less* misconduct than their male counterparts. African and Hispanic advisers, on the other hand, are 9bp *more* likely to receive misconduct disclosures in a given year relative to other male advisers (Table 5a). One potential reason why female advisers could be treated more harshly following misconduct is precisely because of their low average rates of misconduct: firms would either trade-off lower average misconduct for lower productivity, or update more severely about specific female misconduct propensities after observing misconduct. If such a mechanism were at play for minority men, it would suggest *milder punishment*, because their average rates of misconduct are higher than non-minority men. In other words, the existence of male minority punishment gap suggests that updating from low average misconduct rates is not driving the gender punishment gap. We discuss this mechanism in more detail in Section IV,

III.D.1 Minority Male Managers Alleviate the Minority Punishment Gap

We find that firms with a larger share of female managers have a smaller gender punishment gap. Here, we document that minority male managers mitigate the minority punishment gap among male advisers.

Specifically, we re-estimate the analog of eq. (6) where we separately control for the branch level composition of manager ethnicity ($Pct\,African\,Mgmt$ and $Pct\,Hispanic\,Mgmt$). The variable $Pct\,African\,Mgmt$ ($Pct\,Hispanic\_\,Mgmt$) measures the percentage of managers that are African (Hispanic) origin at the firm in a county in a given year. In each specification, we estimate a negative and significant coefficient on the minority triple interaction terms. The results in column (1) of Table 6a suggest that minority advisers working at a branch with no African origin branch managers are 10pp more likely to experience employment separations following misconduct. However, the estimates also imply that there would be no punishment gap in branches where 50% (=10.2/20.3) of the branch managers are of the same minority as the adviser (Table 6a, column 1). Overall, our results are most consistent with in-group tolerance of executives of financial advisory firms. Male executives seem to be more forgiving of misconduct by men rather than by women, and minority (male) managers are more forgiving of misconduct from (male) members in their own minority group.

III.D.2 Minority Male Managers do not Alleviate the Gender Punishment Gap

Given that female managers alleviate the gender punishment gap and ethnic minority male managers alleviate the minority punishment gap, we now ask whether managers from disadvantaged groups lower the punishment gap in general. This test allows us to distinguish between two alternative reasons for why minority managers – gender or ethnic – matter. One alternative is that minority managers better understand that there is a punishment gap and seek to avoid it. If so, we would expect minority male managers to reduce the gender punishment gap. Alternatively, the mechanism may be related to more specific group membership. For example, managers of a group only understand that the stereotypes about their own group are incorrect but share stereotypes about other groups, or because of simple in-group favoritism. Under this alternative, we would find that minority male managers do not alleviate gender gap. More formally, we examine how the gender punishment gap varies with the ethnic composition of branch management using the following specification:

$$\begin{aligned} Separation_{ijlt+1} \quad = \quad & \beta_1 Misc._{ijlt} + \beta_2 Female_i + \beta_3 Pct\,African\,Mgmt_{jlt} + \beta_4 Misc._{it} \times Female_i \\ & + \beta_5 Misc._{ijlt} \times Pct\,African\,Mgmt_{jlt} + \beta_6 Female_i \times Pct\,African\,Mgmt_{jlt} \\ & + \beta_7 Misc._{ijlt} \times Female_i \times Pct\,African\,Mgmt_{jlt} \\ & + \beta_8 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \end{aligned} \tag{8}$$

The estimates in Table 6c indicate that female advisers with recent misconduct are 8-10pp more likely to experience employment separations relative to male advisers with recent misconduct. The estimates suggest that the gender punishment gap does not vary with the ethnic composition of the firm's branch management. The estimated coefficient on the triple interaction term $Misc._{ijlt} \times Female_i \times Pct\,African\,Mgmt_{jlt}$ is insignificant in each specification, and is positive and small when we include the fixed effects. We find similar inferences when we use $Pct\,Hispanic\,Mgmt$ instead of $Pct\,African\,Mgmt$ (Table 6d). Thus, minority male managers do not alleviate the gender punishment gap. These results suggest that while managers in power can potentially alleviate punishment gap among any group, they do so only within their gender or ethnic group. Group membership seems to play an important role in understanding the punishment gap of advisers across different genders and ethnicities.

IV What explains the Punishment Gap?

We find a punishment gap for female and minority male advisers. This gap is smaller in firms with a larger share of managers from the specific minority group. We now model two alternative explanations of why this gap exists to more formally map their predictions into our empirical results. Broadly, the benchmark is that the punishment gap is an outcome of firms' using Bayesian updating following misconduct and making profit maximizing decisions: firms punish female advisers more severely because misconduct by female advisers is predictive of worse outcomes or more frequent misconduct. In other words, the punishment gap is a function of statistical discrimination (Phelps, 1972; Arrow, 1973). The other alternative we explore is that the punishment gap is due to biases of market participants. Managers either systematically over-estimate the rate of recidivism among female advisers due to miscalibrated beliefs (i.e. stereotyping; Bordalo et al. 2016) or due to inherent prejudice against female managers (Becker 1957).

IV.A Framework

We consider a simple model of a financial advisory firm's hiring and firing decisions to help understand the features of the data. Advisers, indexed by i, differ along three dimensions: gender, productivity η, and propensity to engage in misconduct ν. Managers, who differ in gender, wish to employ advisers who are productive but have low propensities to engage in misconduct. Whether or not a manager hires an adviser i depends on expectations about the net productivity of the adviser $h_i = \eta_i - \nu_i$. For convenience, we also assume that adviser productivity η_i is perfectly observable by managers but misconduct propensity ν_i is not. Managers only observe the gender of an individual and know the distributions $\nu_F \sim F_F(\cdot)$ and $\nu_M \sim F_M(\cdot)$. Each period, $t = 1, 2, ...,$ the firm observes whether or not the adviser received a misconduct disclosure d_{it} in period t, and then elects to fire or retain the adviser.

We next consider a manager's decision to fire an adviser following his/her first misconduct disclosure. We model a misconduct disclosure as a noisy signal about an adviser's true propensity to engage in misconduct. At the end of the each period, a firm observes a noisy signal d_{it}:

$$d_{it} = \nu_i + \epsilon_{it},$$

where ν_i reflects an adviser's misconduct propensity and ϵ_{it} is some idiosyncratic misconduct shock. Managers only observe disclosure signals d_{it} if misconduct was sufficiently large and is detected, such that $d_{it} > D^*$. Managers use this information to update their beliefs regarding an adviser's propensity to engage in misconduct, which we denote $\tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i)$, where $\vec{d}_{it}$ is a vector of the adviser's disclosure history and g_m indicates gender of the manager (M or F), and g_a the gender of the adviser (M or F). A manager's beliefs over an adviser's propensity to engage in misconduct could be unbiased (derived using Bayesian updating and consistent with the actual distribution of misconduct and ability) such that $\tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i) = E[\nu|\vec{d}_{it}, g_{a,i}, \eta_i]$, or systematically biased such that the bias could vary across genders of managers or advisers.

Consider an adviser who received a misconduct disclosure at time t. A manager elects to fire the employee if the firm believes his/her net productivity is below some threshold $S_{g_m g_a}$ where g_a and g_m indicates the manager's and adviser's gender. An adviser with disclosure history $\vec{d}_{it}$ and productivity η is fired if:

$$S_{g_m g_a} > \eta_i - \tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i) \tag{9}$$

where $S_{g_m g_a}$ is the threshold which potentially varies across gender of the adviser and manager, η_i is the adviser's productivity and $\tilde{\nu}_{g_m g_a}$ is the updated belief of manager of gender g_m about the propensity of adviser of gender g_a to engage in misconduct.

IV.B Alternative 1: Bayesian Updating and Profit Maximization

We first consider the case in managers hold male and female advisers are held to the same standard ($S_{g_m M} = S_{g_m F} = S^*$), and managers' have unbiased beliefs about future misconduct across genders $\tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i) = E[\nu|\vec{d}_{it}, g_{a,i}, \eta_i]$). This implies that male and female *managers* hold the same beliefs about misconduct for a given *adviser* with observable characteristics $\vec{d}_{it}, g_{a,i}$ and η_i. In other words, since managers are fully Bayesian and have the same information set, male and female managers update about misconduct in the same way. The firm firing condition can be rewritten more simply as

$$S^* > \eta_i - E[\nu|\vec{d}_{it}, g_{a,i}, \eta_i]$$

We next discuss the implications of this alternative for misconduct propensity, productivity and manager's gender composition. We then discuss how these implications square with our empirical findings.

Misconduct Propensity/Recidivism/Type of Misconduct We document a gender gap: conditional on all observable adviser characteristics, female advisers are more likely to experience an employment separation following misconduct. If firms are profit maximizing, and have unbiased beliefs generated through Bayesian updating, there are two potential reasons for this finding. First, it could be the case that past misconduct is more predictive of future misconduct for female advisers with a recent disclosure, $d_{it} = 1$, than it is for male advisers.

$$E[\nu|\vec{d}_{it}, Female, \eta_i, d_{it} = 1] > E[\nu|\vec{d}_{it}, Male, \eta_i, d_{it} = 1]$$

This implies that women would have higher rates of recidivism and/or engage in more costly misconduct. Relatedly, it could be the case that the disclosure events observed for male and female advisers differ in a way such that the types of misconduct female advisers engage in are relatively more predictive of future misconduct or just fundamentally different from the misconduct that the average male adviser engages in.

Productivity A second potential reason for the gender punishment gap under this alternative is that males have higher unobserved (to the econometrician) productivity relative to female advisers. Suppose an adviser's true productivity η_i is a function of observable characteristics $X_i\beta$ plus some unobservable (to the econometrician) term ε_i. Then, conditional on other observable characteristics, female advisers would have lower unobserved productivity,

$$E[\varepsilon_i|X_i, \vec{d}_{it}, Female] < E[\varepsilon_i|X_i, \vec{d}_{it}, Male].$$

Under the benchmark, there may be several potential reasons why female advisers could have lower unobserved productivity than comparable male advisers. Firms wish to employ advisers who are productive but also less likely to engage in misconduct. Thus, even though productivity η and propensity to engage in misconduct ν are potentially uncorrelated in the population, we would expect them to be potentially negatively correlated among the population of advisers employed in the industry. Given that female advisers are less likely to engage in misconduct on average, a profit maximizing firm would potentially find it optimal to hire women that are less productive on average relative to male advisers. In this simple framework, it is then possible that the unobserved productivity of female advisers is lower than that of comparable male advisers.

Managers' Gender Composition This simple statistical discrimination alternative also predicts how the gender punishment gap changes with the gender of the manager:

$$
\begin{aligned}
&= \left(\tilde{\nu}_{MF}(\vec{d}_{it}, \eta_i) - \tilde{\nu}_{MM}(\vec{d}_{it}, \eta_i)\right) - \left(\tilde{\nu}_{FF}(\vec{d}_{it}, \eta_i) - \tilde{\nu}_{FM}(\vec{d}_{it}, \eta_i)\right) \\
&= \left(E[\nu|\vec{d}_{it}, Female, \eta_i] - E[\nu|\vec{d}_{it}, Male, \eta_i]\right) - \left(E[\nu|\vec{d}_{it}, Female, \eta_i] - E[\nu|\vec{d}_{it}, Male, \eta_i,]\right) \\
&= 0
\end{aligned}
$$

Since a *manager's* gender does not play a role in how they update on *advisers'* misconduct, the gender punishment gap generated by the model does not differ across the managers' gender. In other words, the benchmark model has a difficult time explaining why the gender punishment gap changes with the gender of the manager. We next turn to the data to explore the predictions of the benchmark model.

IV.B.1 Gender Does Not Proxy for Misconduct

The first implication of the benchmark model is that gender de-facto proxies for the severity of current or future misconduct of female advisers conditional on observing misconduct in our data. In this subsection we present several tests that are inconsistent with this alternative.

Recidivism We find that men unconditionally have higher rates of misconduct. However, it is possible that female advisers with misconduct records are more likely to re-engage in misconduct than their male counterparts. If so, it would be optimal for firms to fire female advisers with a higher probability. In this section, we show that instead, male advisers are more likely to re-offend.

Figure 6a displays the share of male and female repeat offenders. 41% of men with misconduct records are repeat offenders. Conversely, only 22% of female advisers are repeat offenders. Male advisers are therefore roughly twice as likely to be repeat offenders than female advisers. To ensure that these gender differences in recidivism are not driven by different possibilities to re-offend, differences in firms, regulators, or job role, we more formally examine recidivism using a linear probability model:

$$Misc._{iqjlt} = \beta_1 Female_i + \beta_2 PriorMisc._{iqjlt} + \beta_3 PriorMisc._{iqjlt} \times Female_i + \beta X_{it} + \mu_{qjlt} + \eta_{iqjlt}. \qquad (10)$$

The dependent variable $Misconduct_{iqjlt}$ is a dummy variable indicating that the adviser was disciplined for misconduct at time t. The variable $PriorMisconduct_{iqjlt}$ is a dummy variable indicating whether the adviser was ever reprimanded for misconduct prior to time t. The main independent variable of interest is $PriorMisconduct_{iqjlt} \times Female_i$. The interaction measures the difference in propensity of male and female advisers to engage in repeat offenses. We also control for the adviser's gender to account for any differences in the baseline misconduct rate across the two genders. Our most stringent specification controls for firm $\times$ year $\times$ county $\times$license fixed effects

μ_{qjlt}. We also control for the adviser's characteristics, such as experience in the industry in X_{it}.

Similar to Egan et al. (2017), the $PriorMisconduct_{iqjlt}$ coefficient of 2.4pp suggests that a male adviser who has a past record of misconduct is 2.4pp more likely to receive a new misconduct disclosure in the upcoming year (Table 7, column 1). More importantly, the negative coefficient of $-0.7pp$ on $PriorMisconduct_{iqjlt} \times Female_i$, suggests that women are significantly less likely to be repeat offenders. The financial advisory industry may find it optimal to punish female advisers more severely if they engage in more repeated misconduct. However, the evidence presented in Figure 6a and Table 7 indicates the exact opposite; male advisers are substantially more likely to be repeat offenders than female advisers.

We next show that men have higher recidivism rates relative to females, both in the sample of advisers whose previous misconduct was punished with a job separation, and in the sample of advisers who were allowed to keep their job following misconduct. In other words, differential separation rates across genders following misconduct are not driving the different recidivism rates. We extend our previous regression specification (10) by including the dummy variable $PriorDiscipline_{iqjlt}$, which indicates that an adviser previously lost his/her job following misconduct, and the interaction term $Female_i \times PriorDiscipline_{iqjlt}$. Columns (5)-(8) in Table 7 display the corresponding estimates. The results suggest that firms are shedding advisers that are more likely to engage in misconduct in the future (coefficient on $PriorDiscipine$ is positive). Among those who suffered a job separation following misconduct, male advisers are 2.5pp ($\approx 0.56 + 1.70 + 0.27$) more likely to engage in misconduct in a given year than female advisers (column 5). Similarly, among advisers who kept their job following misconduct, male advisers are roughly 1pp ($\approx 0.5 + 0.27$) more likely to engage in misconduct than female advisers (column 5). Overall, these results suggest that past misconduct is actually more predictive of future misconduct for male advisers than for female advisers. Thus, observed differences in recidivism run contrary to the predictions of our simple model in which firms use Bayesian updating from misconduct, and take profits maximizing actions.[19]

Type of Misconduct Another reason why firms would want to punish female advisers harsher is if they engaged in costlier misconduct. In Section II.B.3 we show the opposite is the case: male advisers' misconduct is 11-20% more costly to the firm. While monetary costs should be a sufficient statistic for firms' cost, we additionally show here that our results are robust to different measures of misconduct, and that the punishment gap persist even within specific types of misconduct.

The summary statistics displayed in Table 1c suggest that the types of misconduct men and women engage in are roughly comparable in terms of the associated allegations, with men's misconduct allegations more likely related to unsuitable investments, misrepresentation, and/or omission of key facts. We show that the gender punishment gap is robust to different types of misconduct by reexamining the probability an adviser experiences an employment separation in (3) while controlling for the allegations. Columns (1)-(4) in Table 8a displays the corresponding estimates. We estimate a positive and significant coefficient on the interaction term $Misconduct \times Female$ in each specification. The results in column (4) indicate that female advisers are 8pp more likely to experience an

[19] Note that in these tests we separately compare recidivism of advisers who did and did not face job separation after misconduct. We observe recidivism among advisers who remained in the industry following their first misconduct offense. In the Appendix we address this selection issue using a semi-parametric control function approach similar to the original parametric approach in Heckman (1979). Accounting for selection, we continue to find that male advisers are roughly 0.5-1pp more likely to be repeat offenders in a given year relative to female advisers.

employment separation following misconduct. We also reexamine an adviser's reemployment prospects in eq. (4) and present results in columns (5)-(8) of Table 8a. Again, we find that female advisers are less likely to be find reemployment in the industry following misconduct.

In addition to controlling for additional characteristics of misconduct, we also separately focus on one specific type of misconduct, unauthorized activity, and show our results within that narrowly defined setting. We examine unauthorized activity because it is a relatively common offense, accounting for roughly 15% of misconduct disclosures. Moreover, unauthorized activity generally represents unauthorized trading and/or forgery, making its definition and measurement relatively precise. We re-estimate gender differences in job separation and reemployment following unauthorized activity similar in eq. (3) and report the corresponding estimates in Table 8b. Columns (1)-(4) indicate a positive and significant coefficient on the interaction term $Unauthorized\,Activity \times Female$ in each specification suggesting that, relative to their male counterparts, female advisers experience significantly higher job separation rates following misconduct.[20] In columns (5)-(8) we also examine advisers' reemployment prospects conditional on receiving unauthorized activity related misconduct disclosures. We find that female advisers are less likely to find new employment relative to their male counterparts following such a disclosure. These results suggest that the gender punishment gap is not driven by differences in the type of misconduct across genders.

IV.B.2 Gender Does Not Proxy for Productivity

Under our benchmark model, the gender punishment gap can arise because firms trade off lower average female rates of misconduct with lower productivity, all else equal. Once misconduct is detected, this lower productivity results in more termination among female advisers. We now present several tests, which suggest that the gender punishment gap does not proxy for productivity differences.

Selection on Unobservables In our earlier analysis we account for much of the differences among financial advisers by controlling for each adviser's qualifications, experience, the firm and location at which they work, and other characteristics. We start by bounding our main estimates by accounting for the impact of unobservables (such as unobserved productivity) following Oster (2016) and Altonji, Elder, and Taber (2005a, 2005b, 2008). Following Oster (2016) we bound the gender punishment gap between 10pp and 11.2pp.[21] Intuitively, as we increase the number of additional controls, the amount of explained variation in turnover (R^2) increases substantially in Table 3b; the gender gap does not change much, increasing slightly.

In addition, there are two other reasons why it is unlikely that productivity differences are driving the punishment gap. First, the benchmark model would predict this result only if the unobserved productivity of female advisers is substantially lower than that of men – i.e. productivity is poorly measured by the researcher. Below we show that including high quality measures of productivity does not explain the punishment gap. Moreover, the punishment gap exists even for experienced advisers for whom productivity is well known.

Second, under the benchmark model, suppose the lower average misconduct rate of female advisers implies their

[20] The results in column (3) indicate that, conditional on receiving unauthorized activity related misconduct disclosures, female advisers are 14pp more likely to experience job separation relative to their male counterparts, a 52% increase.

[21] In particular, following Oster (2016), we calculate the lower bound using $R^2_{max} = 1.3 \times \tilde{R}^2$ and $\delta = 1$, where $\tilde{R}^2 = 0.46$ (Table 3b column 4).

lower productivity and generates a gender punishment gap. Then a higher average misconduct rate of minority men would lead to minority men facing less turnover than non-minority men following misconduct. Despite that, we find that minority males, just like females, face a punishment gap, suggesting that updating from average misconduct rates does nor drive the punishment gap in the data.

Observable Productivity Differences For a large subset of active advisers, we observe detailed productivity data: productivity (revenues brought to a firm), assets under management (AUM), and "quality" rating from the Meridian IQ database as of 2016. One advantage of our setting is that the productivity of financial advisers can be broadly encapsulated as the amount of assets they manage (AUM). We report the productivity summary statistics for male and female advisers in the bottom panel of Table 1a. The summary statistics suggest that male advisers are marginally more productive, and manage more assets. However, the economic magnitudes of the differences in AUM and productivity are quite small. On average, male advisers are 6% more productive than female advisers.

We now show that observable productivity differences across genders cannot explain the gender punishment gap. Because we observe productivity data for a subset of advisers, we first reestimate the punishment gap using this data (eq. 3), and then compare the estimates once we control for adviser productivity. We report the corresponding estimates in column (3)-(5) of Table 9.[22] Controlling for productivity differences, the punishment gap remains statistically significant, and even slightly increases. This does not imply that productivity has no effect on job separation rates. Advisers that are more productive, manage more assets, and have high quality ratings are less likely to experience employment separations. This validates the view that productivity does offset turnover. Similarly, the results in column (5) suggests that firms are more tolerant of misconduct advisers that manage more assets and have high quality ratings. However, as is clear, the observed differences in productivity do not explain, and slightly increase, the gender punishment gap.

Career Interruptions Bertrand et al. (2010) find that career interruptions, which can impact productivity, explain about one-third of the gender wage gap in young professionals in the financial and corporate sectors. We show that the gender punishment gap is not explained by career interruptions. Following Bertrand et al. (2010), we define a career interruption as an out of the industry spell lasting six months or longer. Roughly 19% of the advisers in our data set have experienced career interruptions. After controlling for observable characteristics, female advisers are 1.26pp more likely to experience a career interruption. In columns (1)-(4) of Table 10 , we re-estimate the gender punishment gap in separation and reemployment using eq. (3) and (4). Career interruptions do little to explain gender punishment gap. This does not imply that career interruptions have no effect on labor market outcomes. An interruption is correlated with a 4*pp* increase in job separation rate and a 2*pp* decrease in reemployment rates, which is consistent with observations in Bertrand et al. (2010).

[22] We also reexamine the probability that male and female advisers engage in misconduct. We re-estimate the linear probability model discussed in Section II.B (eq. 1), controlling for adviser productivity. The results in column (2) of Table 9 suggest that female advisers are 46% less likely to receive misconduct disclosures in a given year. The results in column (2) also suggest that more productive advisers are more likely to receive misconduct disclosures, but the economic magnitude of this effect is very small. A 100% increase in assets under management is associated with a very small, 3bp increase in the probability of receiving a misconduct disclosure in a given year. Thus, controlling for productivity leaves the estimates comparable to those corresponding to our baseline specification displayed in column (1) of Table 2a.

Pre-misconduct Turnover To further illustrate that the punishment gap is unlikely driven by gender differences in unobserved characteristics (including unobserved productivity), we focus on job separation rates of financial advisers *before* they engage in misconduct. That is, we focus on advisers who eventually engage in misconduct. If the punishment gap arises because female advisers who eventually engage in misconduct have worse unobservable characteristics than male advisers (such as productivity), one would expect these characteristics to result in higher turnover rates even before misconduct appears. We present the results in the Appendix (Table A5), and find no evidence of differential turnover rates in the periods before misconduct appears.

Human Capital Accumulation and Expected Productivity The career paths of male and female advisers may evolve differently over time. For example, male and female advisers may acquire human capital and develop career networks on the job at different rates, or female advisers may be more likely than male advisers to experience career interruptions. Here, we show that the punishment gap exists across adviser experience levels. Previous research suggests that gender differences in pre-market human capital among men and women are negligible (Blau and Kahn 1997; Altonji and Blank 1999). If we find that the gender punishment gap exists for advisers with little experience, this suggests that our results are not due to differences in human capital acquisition over time. Similarly, after 15 years in the industry, the difference between realized and future productivity should be small. If we find that the same gender punishment gap for more experienced advisers, this suggests that differences in *future* productivity growth are not likely to be a source.

The corresponding estimates are displayed in Tables 11a and 11b. The results in Table 11a indicate that the gender punishment gap exists for less experienced advisers: relative to male advisers, female advisers are 9*pp* more likely to experience employment separations following misconduct, and 2*pp* less likely to find new jobs following misconduct relative to male advisers (On average, 24% of male advisers with five or fewer years of experience experience an employment separation in a year) . We find similar patterns for more experienced advisers: female advisers are 4*pp* more likely to experience employment separations following misconduct. In both sub-samples we find weaker evidence suggesting that female advisers face worse reemployment prospects following misconduct relative to male advisers. However, this is likely due to a statistical power given the smaller sample sizes. Our conclusion from this analysis is that gender punishment gap documented in Section III is persistent regardless of the female adviser's level of experience.

IV.C Alternative 2: Firm Bias –Taste-Based and Miscalibrated Beliefs

As noted earlier, firm biases could also drive the observed differences in the treatment of male and female advisers. We extend our simple framework to allow for managerial bias, and show that this model is consistent with the facts we document. The bias may be the result of favoritism towards male advisers or an inherent prejudice against female advisers (taste-based discrimination) and/or may be the result of miscalibrated firm beliefs.

Recall that a manager of gender g_m decides to fire an adviser of gender g_a following misconduct if the manager's estimate of the advisers expected net productivity, $\eta_i - \tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i)$ is below some threshold $S_{g_m g_a}$

$$S_{g_m g_a} > \eta_i - \tilde{\nu}_{g_m g_a}(\vec{d}_{it}, \eta_i))$$

There are two potential mechanisms for why a biased manager would be more likely to fire female adviser over a comparable male adviser. First, managers engaging in taste-based discrimination could be holding male advisers to a lower standard than female advisers such that $S_{g_m M} > S_{g_m F}$. Second, advisers could have miscalibrated beliefs about future misconduct among women relative to men. In other words, even though we find in the data that women are less likely to be repeat offenders, $E[\nu|\vec{d}_{it}, Female, \eta_i] < E[\nu|\vec{d}_{it}, Male, \eta_i]$, it is possible that firms have incorrect beliefs such that $\tilde{\nu}_{g_m F}(\vec{d}_{it} = 1, \eta_i) > \tilde{\nu}_{g_m M}(\vec{d}_{it} = 1, \eta_i)$. For example, managers engaging in stereotyping may overreact to observing misconduct by female advisers, given that female advisers are generally perceived to be clean.

A key prediction of the model with managerial bias, either taste-based or miscalibrated beliefs, is that the rate of recidivism should be higher for comparable male advisers at the margin of being fired. To see this first consider the extended model with taste-based discrimination. For male and female advisers at the margin of being fired:

$$S_{g_m F} = \eta_i - E[\nu|\vec{d}_{it}, Female, \eta_i] > S_{g_m M} = \eta_i - E[\nu|\vec{d}_{it}, Male, \eta_i] \implies E[\nu|\vec{d}_{it}, Female, \eta_i] < E[\nu|\vec{d}_{it}, Male, \eta_i]$$

Intuitively, since firms exhibit more tolerance towards male managers – hold them to a lower standard – the resulting pool of men is worse on the margin of recidivism. The same idea applies to a model with miscalibrated beliefs. By definition, in the miscalibrated beliefs model managers systematically overestimate the rate of recidivism among female advisers relative to male advisers, leading to a gender punishment gap. It is worth noting that the prediction regarding higher recidivism of men in the model with firm bias – whether due to taste or due to miscalibrated beliefs – is in sharp contrast to the prediction of the benchmark statistical discrimination model. The findings on recidivism, discussed in Section IV.B.1, support the model with firm biases.

Moreover, managerial biases may also vary across firms depending on the gender composition of management. For example, male managers may hold men to a lower standard such that $S_{MF} > S_{MM}$. Similarly, male managers may systematically overestimate the probability that women are repeat offenders such that $\tilde{\nu}_{MF}(\vec{d}_{it}, \eta_i) > \tilde{\nu}_{FF}(\vec{d}_{it}, \eta_i) = [\nu|\vec{d}_{it}, Female, \eta_i]$ or underestimate the probability that men are repeat offenders $\tilde{\nu}_{MM}(\vec{d}_{it}, \eta_i) < \tilde{\nu}_{FM}(\vec{d}_{it}, \eta_i) = [\nu|\vec{d}_{it}, Male, \eta_i]$. In other words, the biased manager model naturally generates a larger punishment gap when managers are from the same group as the adviser, consistent with our findings in Section).

IV.D Summary and Discussion

Our empirical evidence suggests that the gender punishment gap is inconsistent with our simple benchmark model, in which managers update after observing misconduct using Bayes rule, and impose differential punishment as a consequence of profit maximization. The model is inconsistent with the data on the following broad dimensions:

1. The model suggests that female misconduct is either costlier for the firm or, conditional on misconduct, female advisers are more likely to re-offend. The data suggest the opposite.

2. The model suggests that female advisers may be less productive. While productivity measures – that we can reasonably capture – are related to turnover, they do not affect the punishment gap. Moreover, the punishment gap exists even for experienced advisers for whom productivity is well known. Finally, pre-

misconduct turnover does not differ across genders.

3. The model suggests that the gender of the manager is not related to the punishment gap. In the data, the punishment gap, both at job separation and reemployment is lower when managers are members of the minority group (but not members of other minority groups).

4. The model suggests that female advisers could be treated more harshly following misconduct because upon observing misconduct, the market updates its beliefs more dramatically about female advisers given that female advisers have lower baseline rates of misconduct. Such a mechanism would suggest *milder punishment for minority men*, whose baseline rates of misconduct are higher; we observe the opposite.

To summarize, we would need a substantially more complex model with Bayesian managers and profit maximizing behavior to rationalize the patterns in the data. This model would need to account for the joint distribution of adviser minority status, manager minority status, adviser productivity, and adviser misconduct propensity. Our simple benchmark statistical model does not have such features and is rejected by the data.

A relatively simple model in which managers from the same group as the adviser have more favorable beliefs about the probability of re-offending – either due to taste or miscalibration – can explain the patterns in the data in an intuitive and straightforward way. Such a model would generate a punishment gap with managers being more forgiving of missteps among members of their own gender/ethnic group.

IV.E Connection to the Literature

Our findings contribute to the large literature on gender discrimination. We document a new type of gender gap in a large industry: gender differences in job separation and reemployment for similar missteps. More broadly, our analysis indicates that the absence of a gender gap in compensation or hiring rate at the entry level does not imply the absence of differential treatment across gender – such differences can emerge long after employees are working inside a firm. In establishing this novel mechanism, we connect to the vast literature on discrimination dating back to the theoretical work of Becker (1957; rev. 1971), Phelps (1972), Arrow (1973), and Aigner and Cain (1977).

Our paper also contributes to empirical literature documenting gender differences in the workplace. A large literature finds gender differences in hiring decisions, such as such as Neumark (1996), Goldin and Rouse (2000), Booth and Leigh (2010), Carlsson (2011), and Moss-Racusin et al. (2012), and gender discrimination more in promotions and compensation (Altonji and Blank, 1999, Blackaby et al. (2005), Blau and Kahn (1997), Ginther and Kahn (2004). For extensive surveys, see Altonji (1999), Bertrand (2011), Bertrand and Duflo (2016), Blau and Kahn (2017). While the existing research on gender has generally focused on gender differences in the compensation of productive activities, we explore whether such gender differences carry over to punishment of undesirable activities as well. In the criminal system, females are frequently punished less severely for similar crimes (Goulette et al. 2015). This contrasts with our finding of a gender punishment gap in the labor market. In the gender punishment gap that we establish, the employer knows the employee, thus reducing the potential for "attention discrimination" (Bartos et al., 2016). Sarsons (2017) documents similar patterns in the medical industry. She finds that female surgeons experience a larger drop in patient referrals relative to male surgeons following a patient death. The main difference in our analysis (and discussion) is that we focus on differences in punishment (job separations and re-hiring) rather than rewards— referrals by other physicians. We also document differences at the firm at which the issue occurred (current employer) and other firms in the labor market (re-hiring).

We also contribute to the growing literature documenting that significant male/female participation and wage gaps exist in competitive, high paying jobs (Bertrand and Hallock, 2001; Bell, 2005; Wolfers, 2006; Niederle and Vesterlund, 2007; Bertrand, Goldin, and Katz, 2010). We complement this literature by focusing on a large market of financial advisers, who are perhaps more representative of the part of the labor population with high compensation, rather than the tail of the population represented by CEOs or directors of corporate boards.

Our work also relates to the literature on the effect of females in management and evaluation positions. The evidence in the literature is mixed, finding no effect (Hamermesh and Abrevaya, 2013; Bertrand et al., 2014; Jayasinghe et al., 2003); finding that female evaluators are harsher towards females (Broder, 1993); and that the consequences are not always straightforward (Zinovyeva and Bagues, 2011). For example, Bagues et al (2017) find that female evaluators are not significantly more favorable towards female candidates but male evaluators are discriminant against female candidates upon female evaluators joining. Our findings suggest that that female evaluators and leaders undo gender punishment gap, consistent with the findings of Beaman et al. (2012), De Paola and Scoppa (2015), and Cardoso and Winter-Ebmer (2007).

After documenting gender punishment gap in the financial advisory industry, we empirically examine whether the observed pattern is consistent with a simple statistical discrimination model or with a model with firm biases driven due to taste or miscalibrated beliefs (Bordalo et al., 2016). In doing so we closely relate to work of Altonji and Pierret (2001), Barres (2006), Knowles et al. (2001), Charles and Guryan (2008), Arnold et al. (2017), and Sarsons (2017). Our paper is also related to Lavy (2008) and Beaman et al. (2009) who provide evidence of the importance of stereotypes in driving discrimination but focus on compensation as the labor outcome rather than job separations and hiring.

Finally, our work also relates to a literature on financial misconduct and punishment. The framework of our analysis relates closely to the work of Becker on crime and punishment (1968). Our paper relates to the recent literature on fraud and misconduct among financial advisers (Egan, Matvos, and Seru, 2017; Dimmock et al., 2015; Qureshi and Sokobin, 2015) and in the mortgage industry (Piskorski, Seru, and Witkin, 2013; Griffin and Maturana, 2014). The paper also relates to the literature on corporate fraud, including: Povel et al. (2007), Dyck et al. (2010; 2014), Wang et al. (2010), Khanna et al. (2015), and Parsons et al. (2015).

V Conclusion

We find evidence of a "gender punishment gap" following an incident of misconduct. Female advisers are 20% more likely to lose their jobs relative to comparable male advisers. Females are also punished more severely for misconduct committed at other firms, and are 30% less likely to find new jobs following misconduct. Females face harsher outcomes despite engaging in misconduct that is 20% less costly and having a substantially lower propensity towards repeat offenses. A plethora of tests suggest that the gender punishment gap is not likely to be driven by gender differences in occupation (type of job, firm, market, or financial products handled), productivity, misconduct, or recidivism. The punishment gap is not limited to gender, but also extends to minority men, suggesting a non-gender specific mechanism is driving the gap.

We find evidence that the punishment gap is driven by in-group favoritism. The gap decreases when a larger share of managers are from the specific disadvantaged group: the gender punishment gap decreases with a larger share of female managers, and the punishment gap for minority men decreases with a larger share of minority male managers. Minority male managers, on the other hand, do not alleviate the gender punishment gap. In other words, specific group membership seems to play an important role in understanding the punishment gap of advisers across different genders and ethnicities. We provide a simple model, in which such in-group favoritism arises because managers have miscalibrated beliefs about future misconduct among members of their own group.

Our findings provide new insight into the gender gap in the workplace. We examine an inconspicuous and potentially costly channel: punishment following cause. This aspect has received little attention in academia, despite generating approximately 60% of lawsuits alleging discrimination in the workplace (Siegelman 2016). We do not explore the long term consequences of the gender punishment gap. Since females face a narrower margin for error, the gender punishment gap may be partially responsible for the glass ceiling observed in the industry, which remains an area of future research.

References

Aigner, Dennis J. and Glenn G. Cain. 1977. “Statistical Theories of Discrimination in Labor Markets.” *Industrial and Labor Relations Review,* 30(1): 175-187.

Altonji, Joseph. 1999. “Race and Gender in the Labor Market,” In Orley and Ashenfelter and Daid Card, eds. *Handbook of labor economics,* Vol. 30. Amsterdam: North-Holland.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005a. "An evaluation of instrumental variable strategies for estimating the effects of catholic schooling." *Journal of Human Resources*, 40(4): 791-821.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005b. "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools." *Journal of Political Economy*, 113(1): 151-184.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2008. "Using selection on observed variables to assess bias from unobservables when evaluating swan-ganz catheterization." *The American Economic Review*, 98(2): 345-350.

Altonji, Joseph G., and Charles R. Pierret. 2001. "Employer learning and statistical discrimination." *The Quarterly Journal of Economics,* 116(1): 313-350.

Anrold, David, Will Dobbie and Crystal S. Yang. 2017. “Racial Bias in Bail Decisions.” Working Paper.

Arrow, Kenneth, J. 1973. “The Theory of Discrimination,” in Orley Ashenfelter and Albert Rees eds., *Discrimination in labor markets.* Princeton, NJ: Princeton University Press.

Ayres, Ian, and Peter Siegelman. 1995. “Race and gender discrimination in bargaining for a new car.” *The American Economic Review* 304–321.

Bair, Sheila. 2016. “BankThink The Glass Ceiling in Finance: Barely Cracked.” *American Banker*, https://www.americanbanker.com/opinion/the-glass-ceiling-in-finance-barely-cracked. Accessed 6 March 2017.

Bagues, Manuel F, and Berta Esteve-Volart. 2010. “Can gender parity break the glass ceiling? Evidence from a repeated randomized experiment.” *The Review of Economic Studies*, 77(4): 1301–1328.

Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva. 2017. “Does the gender composition of scientific committees matter?” *The American Economic Review*, 107(4): 1207– 1238.

Barres, Ben A. 2006. “Does gender matter?” *Nature*, 442(7099): 133–136.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka. 2016. "Attention Discrimination: Theory and Field Experiments with Monitoring Information Acquisition." *The American Economic Review,* 106(6): 1437-1475.

Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, and Petia Topalova. 2009. “Powerful women: does exposure reduce bias?” *The Quarterly Journal of Economics,* 124(4): 1497–1540.

Beaman, Lori, Esther Duflo, Rohini Pande, and Petia Topalova. 2012. “Female leadership raises aspirations and educational attainment for girls: A policy experiment in India.” *Science,* 335(6068): 582–586.

Becker, Gary S. 1968. “Crime and Punishment: An Economic Approach.” *Journal of Political Economy,* 76: 169-217

Becker, Gary S. 2010. *The Economics of Discrimination.* University of Chicago Press.

Bell, Linda A. 2005. “Women-led firms and the gender gap in top executive jobs.”

Bertrand, Marianne. 2011. “New Perspectives on Gender,” in O. Ashenfelter and D. Card eds, *Handbook of Labor Economics*, Volume 4B, 1543-1590.

Bertrand, Marianne, and Esther Duflo. Forthcoming. “Field Experiments on Discrimination,” in Abhijit Banerjee and Esther Duflo eds., *Handbook of Field Experiments.*

Bertrand, Marianne, Claudia Goldin and Lawrence F. Katz. 2010. “Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors.” *American Economic Journal: Applied Economics*, 2(3): 228-255.

Bertrand, Marianne, and Kevin F. Hallock. 2001. "The Gender Gap in Top Corporate Jobs." *Industrial and Labor Relations Review,* 55(1): 3–21.

Bertrand, Marianne, Sandra E Black, Sissel Jensen, and Adriana Lleras-Muney. 2014. "Breaking the glass ceiling? The effect of board quotas on female labor market outcomes in Norway."Technical report, National Bureau of Economic Research.

Blackaby, David, Alison L Booth, and Jeff Frank. 2005. "Outside offers and the gender pay gap: Empirical evidence from the UK academic labour market." *The Economic Journal*, 115(501): F81-F107.

Blau, Francine D. and Lawrence M. Kahn. 1997. "Swimming upstream: trens in the gender wage differential in the 1980s." *Journal of Labor Economics* 15(1):1-42.

Blau, Francine D. and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations," Journal of Economic Literature, vol 55(3), pages 789-865

Bohnet, Iris, Alexandra Van Geen, and Max Bazerman. 2015. "When performance trumps gender bias: Joint vs. separate evaluation." *Management Science*, 62(5): 1225–1234.

Booth, Alison, and Andrew Leigh. 2010. "Do employers discriminate by gender? A field experiment in female-dominated occupations." *Economics Letters*, 107(2): 236–238.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2016. "Stereotypes." *Quarterly Journal of Economics*, 131(4): 1753-1794.

Boschini, Anne, and Anna Sjögren. 2007. "Is team formation gender neutral? Evidence from coauthorship patterns." *Journal of Labor Economics*, 25(2): 325–365.

Broder, Ivy E. 1993. "Review of NSF economics proposals: Gender and institutional patterns." *The American Economic Review*, 83(4): 964–970.

Cardoso, Ana Rute, and Rudolf Winter-Ebmer. 2007. "Mentoring and segregation: femaleled firms and gender wage policies."

Carlsson, Magnus. 2011. "Does Hiring Discrimination Casue Gender Segregation in the Swedish Labor Market?" *Feminist Economics*, 17(3): 71-102.

Charles, Kerwin Kofi and Jonathan Guryan. 2008. "Prejudice and Wages: An Empirical Assessment of Becker's the Economics of Discrimination." *Journal of Political Economy,* 116(5): 773-809.

Croson, Rachel, and Uri Gneezy. "Gender Differences in Preferences." *Journal of Economic Literature,* 47(2): 448-474.

Daly, Kathleen. 1989. "Gender and Varieties of White-Colar Crime." *Criminology,* 27: 769-794.

De Paola, Maria, and Vincenzo Scoppa. 2015. "Gender discrimination and evaluators' gender: evidence from Italian academia." *Economica*, 82(325): 162–188.

Dimmock, Stephen G., William C. Gerken and Nathaniel P. Grahm. 2015. "Is Fraud Contagious? Career Networks and Fraud by Financial advisers." Working Paper

Dyck, Alexander, Adair Morse and Luigi Zingales. 2010. "Who Blows the Whistle on Corporate Fraud." *Journal of Finance,* 65(6): 2213-2253

Dyck, Alexander, Adair Morse and Luigi Zingales. 2014. "How Pervasive is Corporate Fraud?" Rotman School of Managment Working Paper No. 2222608

Egan, Mark, Gregor Matvos, and Amit Seru. 2017. "The Market for Financial Adviser Misconduct." *Journal of Political Economy,* Forthcoming.

Esteve-Volart, Berta, and Manuel Bagues. 2012. "Are women pawns in the political game? Evidence from elections to the Spanish Senate." *Journal of Public Economics*, 96(3): 387–399.

Gennaioli, Nicola, and Andrei Shleifer. 2010. "What Comes to Mind." *Quarterly Journal of Economics*, 125(4): 1399-1433.

Ginther, Donna K, and Shulamit Kahn. 2004. "Women in economics: moving up or falling off the academic career ladder?" The Journal of Economic Perspectives, 18(3): 193–214.

Goldin, Claudia and Cecilia Rouse. 2000. "Orchestrating Impartiality: The Impact of Blind Auditions on Female Musicians." *American Economic Review*, 90(4): 715-741.

Gompers, Paul A., Vladimir Mukharlyamov, Emily Weisburst, and Yuhai Xuan. 2014. "Gender effects in venture capital." Working Paper.

Goulette, Natalie, John Wooldredge, James Frank, and Lawrence Travis III. 2015. "From Initial Appearance to Sentencing: Do Female Defendants Experience Disparate Treatment?" Journal of Criminal Justice, 43 (5): 406-417.

Griffin, John M. and Gonzalo Maturana. 2014. "Who Facilitated Misreporting in Securitized Loans?" Forthcoming in *Review of Financial Studies*.

Hamermesh, Daniel S, and Jason Abrevaya. 2013. "Beauty is the promise of happiness?" *European Economic Review*, 64 351–368.

Heckman, James. 1979. "Sample selection bias as a specification error." *Econometrica* 47(1): 153-161.

Heckman, James, Sergio Urzua, and Edward Vytlacil. 2006. "Understanding Instrumental Variables in Models with Essential Heterogeneity." *Review of Economics and Statistics*, 88(3):389-432.

Holtfreter, Kristy. 2005. "Is Occupational Fraud 'Typical' White-Collar Crime? A Comparison of Individual and Organizational Characteristics." *Journal of Criminal Justice*, 33: 353-365.

Jayasinghe, Upali W, Herbert W Marsh, and Nigel Bond. 2003. "A multilevel crossclassified modeling approach to peer review of grant proposals: the effects of assessor and researcher attributes on assessor ratings." *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 166(3): 279–300.

Khanna, Vikramaditya S., E. Han Kim and Yao Lu. 2015. "CEO Connectedness and Corporate Fraud." *Journal of Finance*, 70(3): 1203-1252.

Knowles, John, Nicola Persico, and Petra Todd. 2001. "Racial Bias in Motor Vehicle Searches: Theory and Evidence." *Journal of Political Economy*, 109(1): 203-232.

Lavy, Victor. 2008. "Do gender stereotypes reduce girls' or boys' human capital outcomes? Evidence from a natural experiment." *Journal of public Economics*, 92(10): 2083–2105.

Moss-Racusin, Corinne A, John F Dovidio, Victoria L Brescoll, Mark J Graham, and Jo Handelsman. 2012. "Science faculty's subtle gender biases favor male students." Proceedings of the National Academy of Sciences, 109(41): 16474–16479.

Neumark, David. 1996. "Sex Discrimniation in Restaurant Hiring: An Audit Study." *Quarterly Journal of Economics,* 111(3): 915-942.

Niederle, Muriel, and Lise Vesterlund. 2007. "Do Women Shy Away from Competition? Do Men Compete too Much?" *Quarterly Journal of Economics*, 122(3): 1067–1101.

Oliver Wyman. 2016. "Women in Financial Services." http://www.oliverwyman.com/content/dam/oliver-wyman/global/en/2016/june/WiFS/WomenInFinancialServices_2016.pdf. Accessed 6 March 2017.

Oster, Emily. 2016. "Unobservable Selection and Coefficient Stability." *Journal of Business Economics and Statistics,* Forthcoming.

Parsons, Christopher A., Johan Sulaeman and Sheridan Titman. 2014. "The Geography of Financial Misconduct." NBER Working Paper No. w20347.

Phelps, Edmund S. 1972. "The statistical theory of racism and sexism." *American Economic Review*, 62(4): 659-661.

Piskorski, Tomasz, Amit Seru and James Witkin. 2015. "Asset Quality Misrepresentation by Financial Intermediaries: Evidence from the RMBS Market." Forthcoming in the *Journal of Finance*

Povel, Paul, Rajdeep Sign and Andrew Winton. 2007. "Booms, Busts, and Fraud." *Review of Financial Studies*, 20(4): 1219-1254.

Price, Joseph, and Justin Wolfers. 2010. "Racial Discrimination Among NBA Referees." *Quarterly Journal of Economics*, 125(4): 1859–1887.

Qureshi, Hammad and Jonathan Sokobin. 2015. "Do Investors Have Valuable Information About Brokers?" FINRA Office of the Chief Economist Working Paper.

Sarsons, Heather. 2017. "Interpreting Signals in the Labor Market: Evidence from Medical Referrals." Working paper.

Steffensmeier, Darrell, and Emilie Allan. 1996. "Gender and crime: Toward a gendered theory of female offending." A*nnual Review of Sociology,* 22(1): 459-487.

Steffensmeier, Darrel J., Jennifer Schwartz, and Michael Roche. 2013. “Gender and Twenty-First-Century Corporate Crime: Female Involvement and the Gender Gap in Enron-Era Corporate Frauds.” *American Sociological Review,* 78(3):448-476.

Tuttle, Beecher. 2014. “How female bankers react to gender bias today.” *eFinancialCareers*, http://news.efinancialcareers.com/us-en/184541/female-bankers-recommend-gender-biased-firm-women-colleagues/. Accessed 6 March 2017.

Tversky, Amos and Daniel Kahneman. 1983. “Extensional versus Intuitive Reasoning: the Conjunction Fallacy in Probability Judgment." *Psychological Review*, 90(4): 293-315.

Wang, Tracy Yu, Andrew Winton and Xiaoyun Yu. 2010. “Coporate Fraud and Business Conditions: Evidence from IPOs.” *Journal of Finance*, 65(6): 2255-2291.

Wolfers, Justin. 2006. “Diagnosing Discrimination: Stock Returns and CEO Gender.” *Journal of the European Economic Association*, 4(2–3): 531–41.

Zinovyeva, Natalia, and Manuel Bagues. 2011. “Does Gender Matter for Academic Promotion? Evidence from a Randomized Natural Experiment.”

Figure 1: Qualifications Held by of Male and Female Financial Advisers

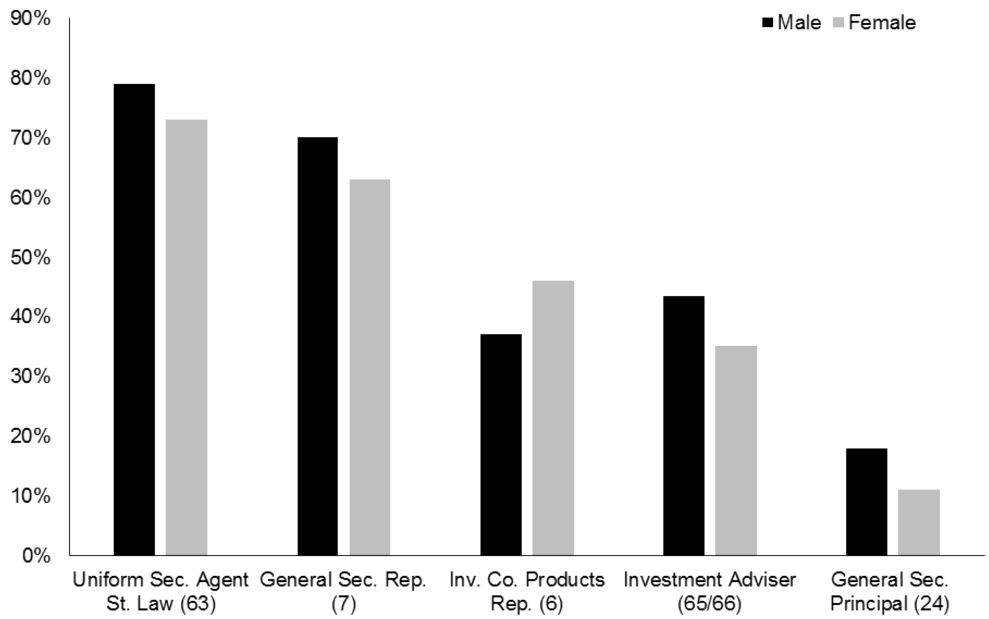
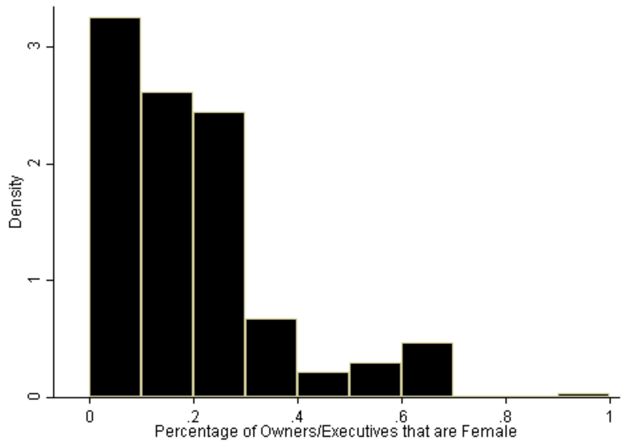


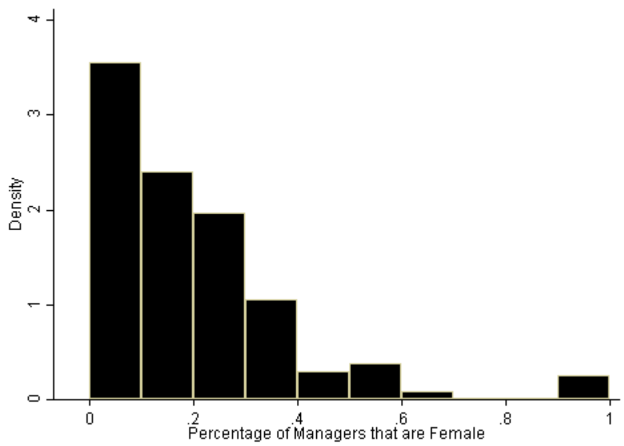
Figure 1 displays the percentage of female and male advisers that hold a particular license. We examine the six most popular licenses. Observations are at the adviser-by-year level over the period 2005-2015.

Figure 2: Female Representation at Financial Advisory Firms

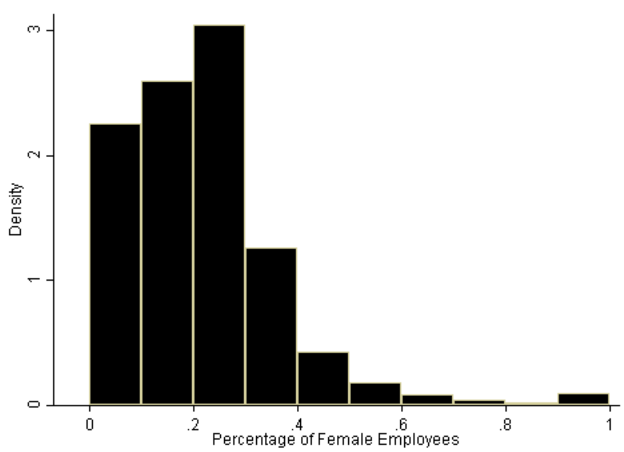
(a) Firm Executives/Ownership



(b) Branch Management

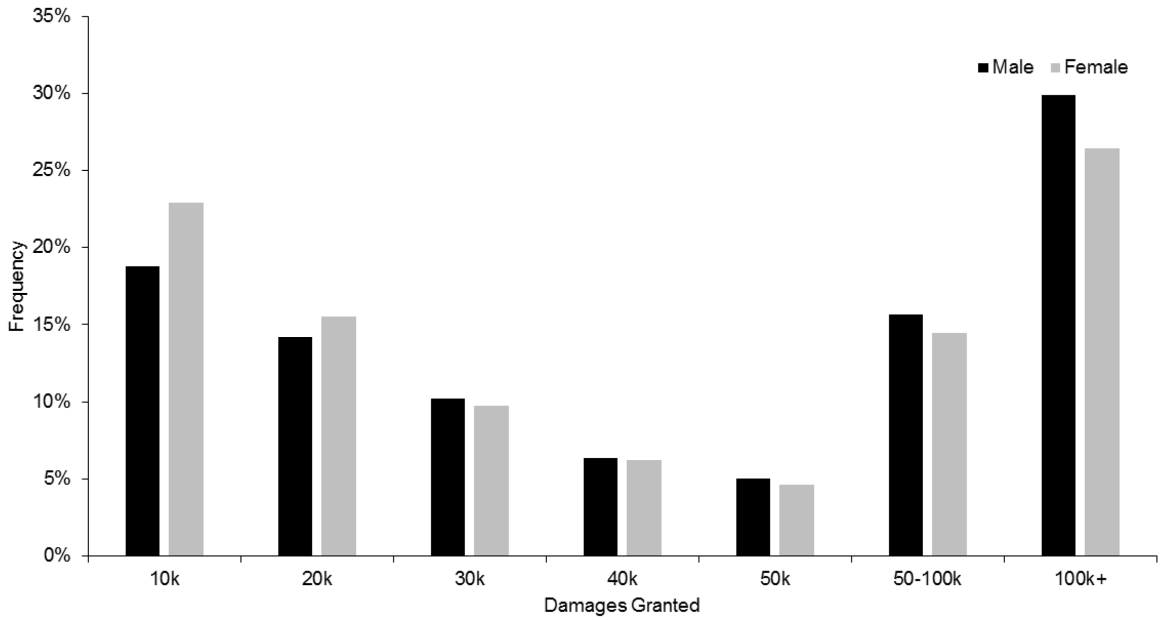


(c) Branch Adviser



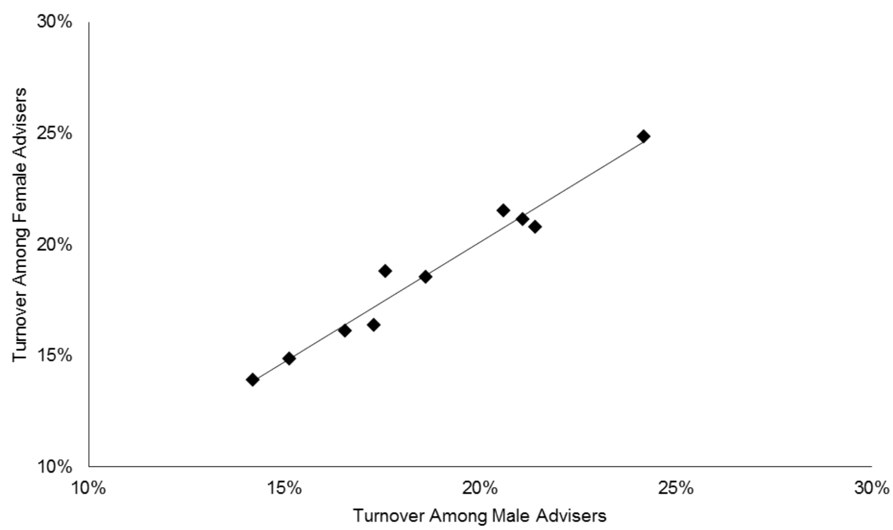
Note: Figure 2a displays the percentage of owners/executives that are female. Figure 2b displays the percentage of managers that are female at the branch level, i.e., at the firm by county by year level. Figure 2c displays the percentage of advisers (weighted by experience) that are female at the branch level, i.e., at the firm by county by year level. Observations in 2a are at the adviser-by-year level as of 2015. Observations in Figures 2b and 2c are at the adviser-by-year level over the period 2005-2015.

Figure 3: Miscondut Severity: Distribution of Settlements/Damages



Note: Figure 3 displays the distribution of settlements/damages for male and female advisers that were granted over the period 2005-2015. In the BrokerCheck database, we observe the settlements/damages details for 45.80% of misconduct-related disclosures and 0.55% of the other types of disclosures. Observations are at the financial adviser by year level.

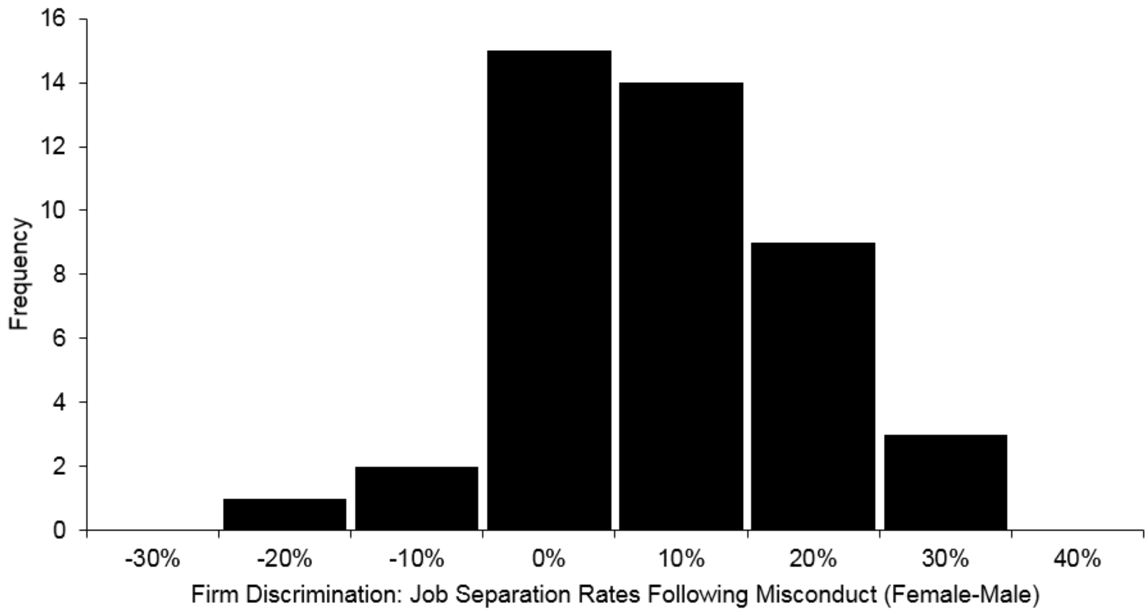
Figure 4: Job Turnover - Male vs. Female Advisers



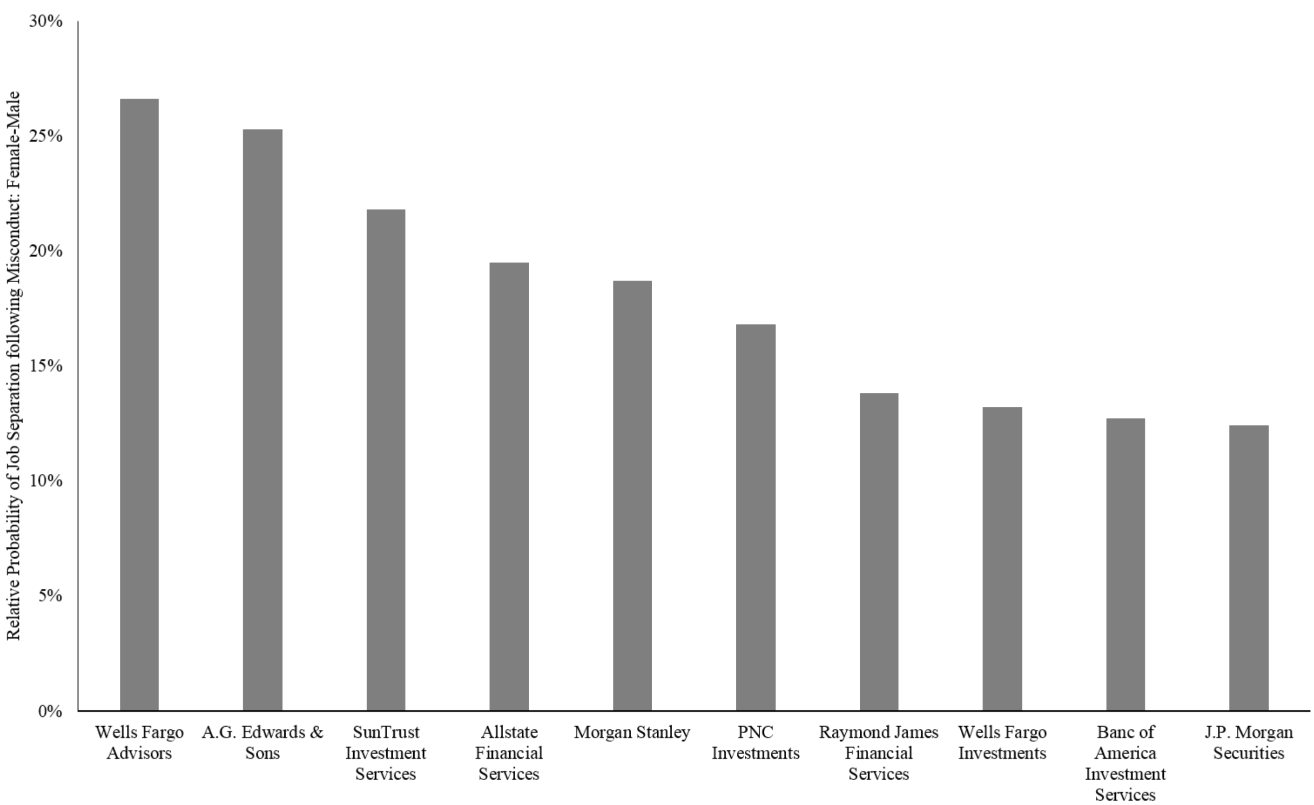
Note: Figure 4 plots the annual job turnover among male and female advisers over the period 2005-2014.

Figure 5: Firm Differences in the Gender Punishment Gap

(a) Distribution of Gender Punishment Gap



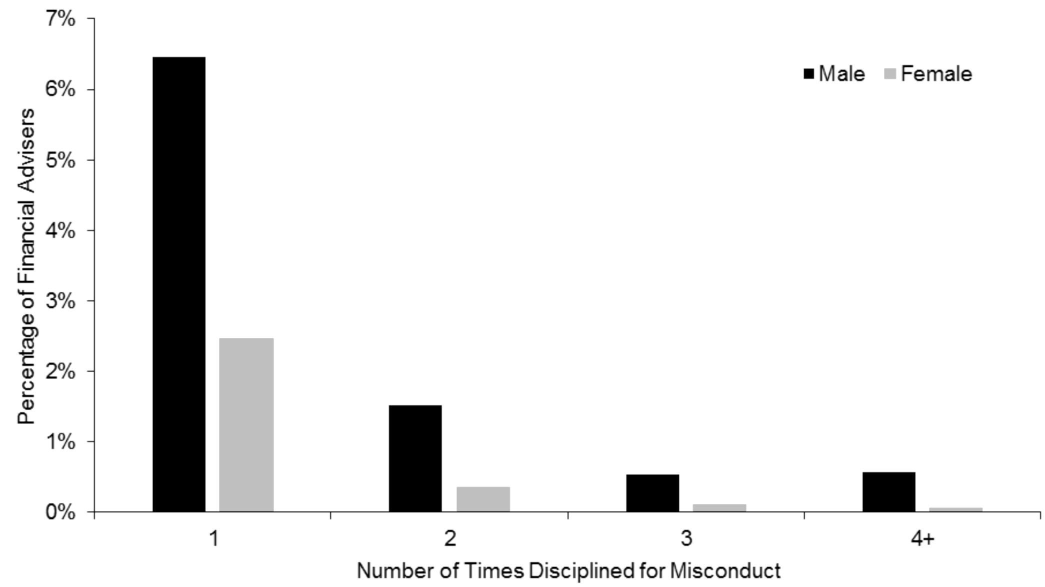
(b) Firms with the Largest Gender Punishment Gap



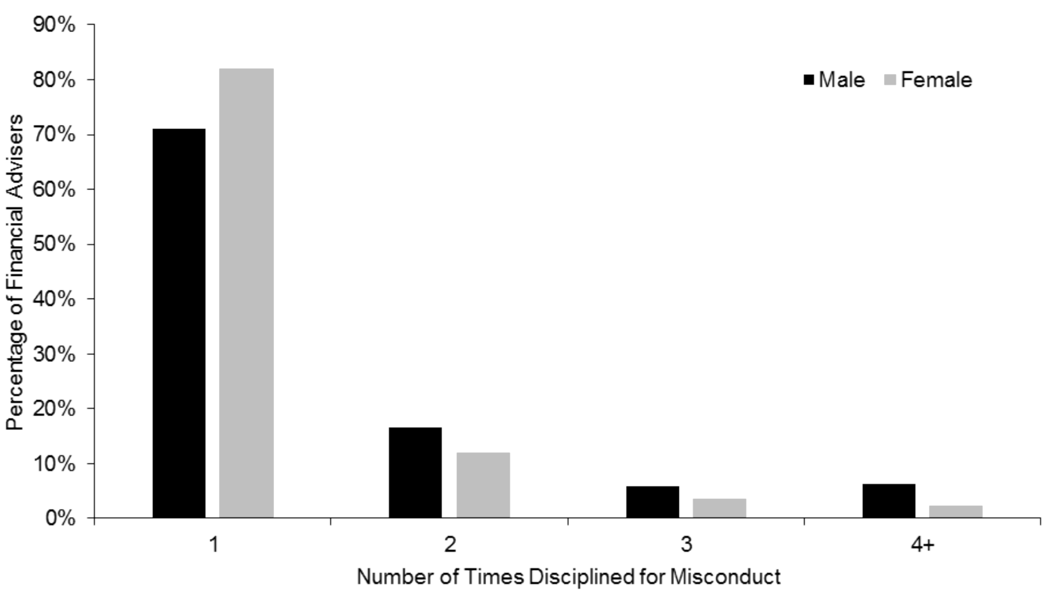
Note: Figures 5a and 5b display the distribution of the gender punishment gap across firms. The figures plot the distribution of the coefficient β_{j3} from eq. (5), which captures the differential probability that female advisers experience employment separations following misconduct relative to male advisers' (i.e., the difference in differences for female and male advisers with and without misconduct). Figure 5b displays the firms with the ten highest coeffcient estimates. For power considerations, we restrict our analysis to 44 firms with at least twenty observations of female advisers receiving misconduct disclosures.

Figure 6: Recidivism

(a) Distribution of Misconduct



(b) Distribution of Misconduct - Repeat Offenders



Note: Figures 6a and 6b display the percentage of male and female advisers who have misconduct disclosures and the number of misconduct disclosures. Figure 6a displays the unconditional distribution of misconduct disclosures and 6b displays the distribution of misconduct among those advisers with at least one misconduct disclosure. Observations are at the adviser-by-year level over the period 2005-2015.

Table 1: Summary Statistics

(a) Adviser Summary Statistics

Variable	Male		Female	
	Obs	Mean	Obs	Mean
Experience (years)	4,932,478	12.31	1,615,496	9.37
Registration:				
Currently Registered	4,932,478	0.72	1,615,496	0.66***
Registered as an IA	3,529,429	0.54	1,067,656	0.45***
Disclosures:				
Disclosure (in a year)	4,932,478	1.83%	1,615,496	1.08%***
Misconduct (in a year)	4,932,478	0.72%	1,615,496	0.29%***
Disclosure (ever)	4,932,478	14.89%	1,615,496	7.61%***
Misconduct (ever)	4,932,478	9.08%	1,615,496	3.00%***
Exams and Qualifications (Series):				
No. Qualifications	4,932,478	2.88	1,615,496	2.51***
Uniform Sec. Agent St. Law (63)	4,932,478	77%	1,615,496	71%***
General Sec. Rep. (7)	4,932,478	0.68%	1,615,496	61%***
Inv. Co. Products Rep. (6)	4,932,478	37%	1,615,496	46%***
Uniform Combined St. Law (66)	4,932,478	19%	1,615,496	19%
Uniform Inv. Adviser Law (65)	4,932,478	21%	1,615,496	13%***
General Sec. Principal (24)	4,932,478	16%	1,615,496	10%***
Productivity:				
Assets Under Management ($mm)	988,217	54.7	169,641	53.2***
Productivity ($100k)	560,519	532	90,572	503***
High Quality Indicator	2,272,975	0.45	559,589	0.32***

Note: Table 1a displays the summary statistics corresponding to our panel of male and female financial advisers. Observations are at the adviser by year level over the period 2005-2015. We denote statistically significant differences across male and female characteristics, *** p<0.01, ** p<0.05, * p<0.10.

Table 1: Summary Statistics (contd.)

(b) Financial Adviser Disclosures and Misconduct

Disclosure	Disclosure/Misconduct			
	Current		Current and Past	
	Male	Female	Male	Female
Misconduct Related Disclosures				
Customer Dispute - Settled	0.39%	0.13%	4.74%	1.35%
Employment Separation After Allegations	0.20%	0.12%	1.21%	0.43%
Regulatory - Final	0.12%	0.04%	1.62%	0.35%
Criminal - Final Disposition	0.03%	0.01%	2.46%	0.98%
Customer Dispute - Award/Judgment	0.02%	0.01%	0.75%	0.15%
Civil - Final	0.00%	0.00%	0.04%	0.01%
Any Misconduct Related Disclosure	**0.72%**	**0.29%**	**9.08%**	**3.01%**
Other Disclosures:				
Financial - Final	0.33%	0.39%	1.95%	2.47%
Customer Dispute - Denied	0.38%	0.15%	3.92%	1.49%
Judgment/Lien	0.24%	0.15%	1.10%	0.76%
Customer Dispute - Closed-No Action	0.09%	0.03%	1.20%	0.38%
Financial - Pending	0.05%	0.07%	0.18%	0.24%
Customer Dispute - Pending	0.07%	0.02%	0.36%	0.10%
Customer Dispute - Withdrawn	0.02%	0.01%	0.20%	0.06%
Criminal - Pending Charge	0.01%	0.00%	0.02%	0.01%
Investigation	0.01%	0.00%	0.03%	0.01%
Regulatory - Pending	0.01%	0.00%	0.02%	0.00%
Civil - Pending	0.00%	0.00%	0.02%	0.01%
Customer Dispute - Final	0.00%	0.00%	0.02%	0.01%
Customer Dispute - Dismissed	0.00%	0.00%	0.02%	0.00%
Civil Bond	0.00%	0.00%	0.03%	0.01%
Regulatory - On Appeal	0.00%	0.00%	0.00%	0.00%
Criminal - On Appeal	0.00%	0.00%	0.00%	0.00%
Civil - On Appeal	0.00%	0.00%	0.00%	0.00%
Total	1.83%	1.08%	14.89%	7.61%

(c) Reasons for Misconduct Disclosure

	Gender	
	Male	Female
Unsuitable	22.8%	18.3%
Misrepresentation	18.3%	14.6%
Unauthorized Activity	14.9%	14.1%
Omission of Key Facts	11.6%	8.1%
Fee/Commission Related	8.1%	6.0%
Fraud	7.8%	5.2%
Fiduciary Duty	7.1%	4.9%
Negligence	6.4%	4.6%
Risky Investments	3.9%	3.0%
Churning/ Excessive Trading	2.9%	1.0%
Other	41.7%	50.9%

(d) Products Involved in Misconduct Disclosure

	Gender	
	Male	Female
Products		
Insurance	13.2%	14.4%
Annuity	8.7%	9.7%
Stocks	6.1%	3.98%
Mutual Funds	4.7%	5.0%
Bonds	2.1%	1.6%
Options	1.3%	0.8%
Other/Not Listed	69.9%	70.3%

Note: Table 1b displays the incidence of disclosures/misconduct among male and female financial advisers. Observations are at the year by financial adviser level over the period 2005-2015. We classify the six categories listed at the top of the table as indicative of adviser misconduct. The column "Current" displays the share of observations (year by adviser) in which the adviser received one or more of a given type of disclosure that particular year. The column "Current and Past" displays the share of observations (year by adviser) in which the adviser received a given type of disclosure in that particular year and/or previously. Tables 1b and 1c display the most frequently reported allegations and products corresponding to misconduct disclosures that occurred over the period 2005-2015. We observe allegations for 91.89% of the misconduct-related disclosures. The allegation and product categories are not mutually exclusive. The "Other" category includes all other allegations/classifications that were reported with a frequency of less than 2%.

Table 2: Gender and Misconduct

(a) Incidence of Misconduct

	(1)	(2)	(3)	(4)
Female	-0.43***	-0.33***	-0.32***	-0.27***
	(0.025)	(0.022)	(0.027)	(0.030)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	6,547,974	6,547,974	6,221,173	4,465,068
R-squared	0.001	0.002	0.098	0.206
Mean of Dependent Variable	0.61%	0.61%	0.61%	0.51%

(b) Settlements/Damages

Variable	Obs	Mean	Std. Dev.	Median
Male Advisers:				
Settlements/Damages Granted	27,469	549,791	9,199,107	40,000
Settlements/Damages Requested	21,749	1,719,226	69,458,640	100,000
Female Advisers:				
Settlements/Damages Granted	2,749	262,530	2,281,979	32,500
Settlements/Damages Requested	2,119	449,282	3,107,101	60,000

(c) Settlements/Damages Granted by Gender

	(1)	(2)	(3)
Female	-0.20***	-0.11**	-0.14***
	(0.052)	(0.047)	(0.038)
Other Adviser Controls		X	X
Year F.E.			X
County F.E.			X
Firm F.E.			X
Observations	21,537	21,537	20,485
R-squared	0.001	0.041	0.249

Table 2a displays the regression results for a linear probability model (eq. 3). The dependent variable is a dummy variable indicating whether or not the adviser received a misconduct disclosure year t. Coefficients are in percentage points. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.
Table 2b displays the settlements/damages (in $) that were granted and requested over the period 2005-2015. We observe the settlements/damages details for 45.80% of misconduct related disclosures. Table 2c displays the results for linear regression model (eq. 2). The dependent variable is the log settlements paid out on behalf of a financial adviser as the result of a misconduct settlement/arbitration. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the financial adviser by year level over the period 2005-2015. We restrict the data set to only those observations in which the adviser received a misconduct disclosure and paid out a settlement/damages. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Gender Punishment Gap: Labor Market Outcomes Following Misconduct

(a) Industry and Firm Separation

	No Misconduct		Misconduct	
	Male	Female	Male	Female
Remain with the Firm	81%	81%	54%	45%
Leave the Firm	19%	19%	46%	55%
Leave the Industry	46%	52%	53%	67%
Join a Different Firm	54%	48%	47%	33%

(b) Firm Level Analysis: Employment Separation

	(1)	(2)	(3)	(4)
Misconduct	27.6***	29.0***	22.3***	25.7***
	(1.47)	(1.37)	(1.52)	(2.22)
Misconduct × Female	8.32***	8.07***	10.2***	9.99***
	(2.05)	(1.93)	(1.90)	(1.91)
Female	0.14	-0.54	-0.54***	-0.50***
	(0.29)	(0.34)	(0.15)	(0.16)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	6,002,088	6,002,088	5,698,577	4,093,438
R-squared	0.004	0.014	0.332	0.403
Mean of Dependent Variable	18.8%	18.8%	18.8%	19.2%

(c) Industry Level Analysis: New Employment

	(1)	(2)	(3)	(4)
Misconduct	-7.66***	-12.2***	-9.15***	-8.94***
	(2.13)	(1.41)	(1.09)	(1.46)
Misconduct × Female	-7.22***	-5.40***	-3.44***	-3.54***
	(1.80)	(1.31)	(1.22)	(1.27)
Female	-6.22***	-2.42***	-4.04***	-3.83***
	(0.65)	(0.61)	(0.26)	(0.29)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	1,125,715	1,125,715	1,006,760	660,127
R-squared	0.003	0.101	0.365	0.464
Mean of Dependent Variable	52.8%	52.8%	54.0%	51.4%

Note: Table 3a displays the average annual job turnover among financial advisers over the period 2005-2015. Leave the Industry is defined as an adviser not being employed as a financial adviser for at least one year; Join a Different Firm is a dummy variable that takes the value of one if the adviser is employed at a different financial advisory firm within a year. The job transitions are broken down by whether or not the adviser received a misconduct disclosure in the previous year. Tables 3b and 3c display the regression results corresponding to linear probability models (eq. 3 and 4). The dependent variable in Table 3b is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). The dependent variable in Table 3c is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 3c, we restrict the sample to those advisers who left their firms in a given year. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Coefficients are in percentage points. Observations are at the financial adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: Female Managers and the Gender Punishment Gap

(a) Executive Gender Composition, Firm Separation and Punishment Gap

	(1)	(2)	(3)	(4)
Misconduct	53.5***	54.1***	51.4***	57.8***
	(4.86)	(4.40)	(5.30)	(5.97)
Misconduct × Female	14.7***	14.0***	16.5***	13.0***
	(3.03)	(2.97)	(3.53)	(3.81)
Misconduct × (Pct Female Exec)	-24.5	-23.5*	-25.4	-32.1*
	(15.6)	(14.2)	(16.8)	(18.7)
Misconduct × Female × (Pct Female Exec)	-40.7***	-41.4***	-44.4***	-39.1*
	(14.3)	(14.2)	(16.2)	(20.7)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	564,905	564,905	541,137	389,112
R-squared	0.010	0.021	0.145	0.238
Mean of Dependent Variable	13.3%	13.3%	13.3%	13.4%

(b) Branch Manager Gender Composition, Firm Separation and Punishment Gap

	(1)	(2)	(3)	(4)
Misconduct	25.2***	26.8***	20.1***	22.9***
	(1.31)	(1.20)	(1.35)	(2.06)
Misconduct × Female	10.9***	10.4***	13.4***	11.6***
	(2.68)	(2.53)	(2.29)	(2.23)
Misconduct × (Pct Female Mgmt)	10.6***	10.3***	11.6***	13.6***
	(2.34)	(2.20)	(2.12)	(3.09)
Misconduct × Female × (Pct Female Mgmt)	-13.7***	-12.8***	-18.5***	-10.5**
	(4.47)	(4.28)	(3.36)	(4.18)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	4,839,243	4,839,243	4,722,832	3,480,225
R-squared	0.003	0.014	0.315	0.393
Mean of Dependent Variable	19.6%	19.6%	19.6%	20.1%

(c) Branch Gender Composition, Firm Separation and Punishment Gap

	(1)	(2)	(3)	(4)
Misconduct	24.3***	25.7***	16.7***	17.0***
	(1.11)	(1.06)	(1.29)	(2.00)
Misconduct × Female	10.4***	10.3***	11.8***	8.40**
	(3.23)	(3.04)	(3.10)	(3.61)
Misconduct × (Pct Female)	19.8**	19.3**	29.9***	42.5***
	(8.27)	(7.55)	(8.80)	(13.1)
Misconduct × Female × (Pct Female)	-15.9*	-16.3**	-16.2**	-6.31
	(8.16)	(7.51)	(6.76)	(9.63)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	5,990,929	5,990,929	5,695,544	4,091,147
R-squared	0.004	0.014	0.332	0.403
Mean of Dependent Variable	18.8%	18.8%	18.8%	19.2%

Table 4: Female Managers and the Gender Punishment Gap (contd.)

(d) Firm Hiring

	(1)	(2)	(3)	(4)
Pct Female Exec	0.0079***	0.0079***	0.0087***	0.0059**
	(0.0028)	(0.0028)	(0.0029)	(0.0026)
Pct Female New Hires				0.037*
				(0.0060)
Firm Controls	X	X	X	X
Year F.E.		X	X	X
State F.E.			X	X
Observations	1,982	1,982	1,982	1,982
R-squared	0.012	0.012	0.049	0.079
Mean of Dependent Variable	0.56%	0.56%	0.56%	0.56%

Note: Table 4a displays the results for a linear probability model (eq. 6). The dependent variable is a dummy variable indicating whether or not the adviser experienced a job separation between time t and $t+1$. The key independent variables of interest are Pct Female Exec, Pct Female Mgmt, and Pct Female, and their interaction with the variables Misconduct and Female. The variable Pct Female Exec measures the percentage of executives/owners that are female as of May 2015. The variable Pct Female Mgmt measures the percentage of managers working for a firm in a given county and year that are female. The variable Pct Female measures the percentage of advisers (weighted by experience) working for a firm in a given county and year that are female. Coefficients are in percentage points. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations in Table 4a are at the adviser level in 2015. Observations in Tables 4b and 4c are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. Table 4d displays the estimation results corresponding to a firm's hiring patterns. The dependent variable is the percentage of new hires made by a firm who are female and have a history of misconduct. For comparability we restrict our attention to those new hires who previously worked in the industry. If the firm did not hire any new employees with prior adviser experience in a given year, the observation is treated as missing. The key independent variable of interest is Pct Female Mgmt. In column (4) we also control for the percentage of new hires made by a firm that are female. We control for the firm's formation type (corporation, limited liability, etc.) and firm age, as well as whether or not it has a referral arrangement with other advisory firms. Observations are at the firm level as of 2014. Each observation is weighted by the square root of the number of advisers the firm hired in a given year. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 5: Punishment Gap for Minority Males

(a) Misconduct

	(1)	(2)	(3)	(4)
African	0.088**	0.16***	0.096***	0.079**
	(0.043)	(0.043)	(0.032)	(0.032)
Hispanic	0.16***	0.28***	0.096***	0.093***
	(0.048)	(0.047)	(0.026)	(0.025)
Adviser Controls		X	X	X
Year×Firm×County F.E.			X	
Year×Firm×County×License F.E.				X
Observations	4,904,653	4,904,653	4,598,081	3,114,361
R-squared	0.000	0.002	0.111	0.222
Mean of Dep. Var.	0.72%	0.72%	0.71%	0.59%

(b) Punishment Gap

Dependent Variable	Job Separation				New Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Misconduct	27.1***	28.6***	21.8***	24.8***	-7.22***	-12.1***	-9.07***	-8.58***
	(1.37)	(1.27)	(1.39)	(2.04)	(1.95)	(1.28)	(1.07)	(1.37)
Misc. × African	8.98***	8.95***	7.58***	8.96***	2.08	2.91	3.36	-2.16
	(2.00)	(1.91)	(2.17)	(2.55)	(3.51)	(3.08)	(2.96)	(3.37)
Misc. × Hispanic	6.02**	5.67**	6.53**	9.07***	-8.43***	-6.31***	-5.84***	-6.66***
	(2.50)	(2.39)	(2.74)	(3.27)	(2.79)	(2.10)	(1.49)	(1.97)
African	2.41***	1.45***	0.44***	0.38**	-2.93***	-1.14	-1.13***	-0.80
	(0.32)	(0.27)	(0.15)	(0.17)	(0.75)	(0.72)	(0.38)	(0.52)
Hispanic	2.79***	1.57***	0.40**	0.094	-0.62	2.74**	1.70***	1.99***
	(0.62)	(0.51)	(0.19)	(0.21)	(1.22)	(1.23)	(0.27)	(0.32)
Adviser Controls		X	X	X		X	X	X
Yr×Firm×Cnty F.E.			X				X	
Yr×Firm×Cnty×Lic. F.E.				X				X
Observations	4,494,607	4,494,607	4,210,431	2,853,942	842,622	842,622	735,946	454,715
R-squared	0.001	0.101	0.365	0.464				
Mean of Dep. Var	18.7%	18.7%	18.9%	19.4%	54.3%	54.3%	55.7%	53.1

Tables 5a and 5b display the regression results corresponding to linear probability models (eq. 1, 3, and 4) where we examine the relationship between misconduct and ethnicity among male advisers. The dependent variable in Table 5a is a dummy variable indicating whether or not the adviser received a misconduct disclosure in a given year. The dependent variable in columns (1)-(4) of Table 5b is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). The dependent variable in columns (5)-(8) of Table 5b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In columns (5)-(8) of Table 5b, we restrict the sample to those advisers who left their firms in a given year. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Coefficients are in percentage points. Observations are at the financial adviser by year level over the period 2005-2015 and are restricted to the set of male financial advisers. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Minority Male Managers, and Female Advisers

(a) Male Advisers and African Male Managers

	(1)	(2)	(3)
Misconduct	26.4***	28.1***	21.6***
	(1.41)	(1.29)	(1.43)
Misconduct × African	10.2***	10.0***	8.60***
	(2.37)	(2.26)	(2.43)
Misconduct × (Pct African Mgmt)	13.9**	13.1**	13.2**
	(5.55)	(5.38)	(6.08)
Misconduct × African × (Pct African Mgmt)	-20.3**	-20.5**	-38.7***
	(10.1)	(9.80)	(10.1)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	3,613,837	3,613,837	3,508,932
R-squared	0.004	0.016	0.321
Mean of Dependent Variable	19.6%	19.6%	19.7%

(b) Male Advisers and Hispanic Male Managers

	(1)	(2)	(3)
Misconduct	26.2***	27.9***	21.3***
	(1.32)	(1.20)	(1.31)
Misconduct × Hispanic	7.71***	7.13***	7.76**
	(2.95)	(2.77)	(3.12)
Misconduct × (Pct Hispanic Mgmt)	11.0*	10.5*	11.2*
	(5.75)	(5.44)	(5.95)
Misconduct × Hispanic × (Pct Hispanic Mgmt)	-24.1**	-23.3***	-20.0**
	(9.56)	(8.94)	(9.90)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	3,613,837	3,613,837	3,508,932
R-squared	0.004	0.016	0.321
Mean of Dependent Variable	19.6%	19.6%	19.7%

(c) Female Advisers and African Male Managers

	(1)	(2)	(3)
Misconduct	26.6***	28.2***	21.8***
	(1.45)	(1.33)	(1.46)
Misconduct × Female	8.32***	8.07***	9.81***
	(2.02)	(1.88)	(1.91)
Misconduct × (Pct African Mgmt)	10.7**	10.4**	8.22
	(4.86)	(4.73)	(5.54)
Misconduct × Female × (Pct African Mgmt)	15.2	14.0	9.71
	(14.3)	(13.9)	(13.6)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	4,839,243	4,839,243	4,722,832
R-squared	0.003	0.014	0.315
Mean of Dependent Variable	19.6%	19.6%	19.6%

Table 6: Minority Male Managers, and Female Advisers(contd.)

(d) Female Advisers and Hispanic Male Managers

	(1)	(2)	(3)
Misconduct	26.6***	28.2***	21.6***
	(1.40)	(1.27)	(1.40)
Misconduct × Female	8.71***	8.48***	10.4***
	(2.05)	(1.92)	(1.91)
Misconduct × (Pct Hispanic Mgmt)	5.89	5.60	7.95*
	(4.40)	(4.20)	(4.51)
Misconduct × Female × (Pct Hispanic Mgmt)	-5.23	-5.62	-11.6*
	(7.83)	(7.63)	(6.89)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	4,839,243	4,839,243	4,722,832
R-squared	0.003	0.014	0.315
Mean of Dependent Variable	19.6%	19.6%	19.6%

Note: Table 6 displays the results for a linear probability model (eq. 6). The dependent variable is a dummy variable indicating whether or not the adviser experienced a job separation between time t and $t+1$. The key independent variables of interest are Pct African Mgmt and Pct Hispanic Mgmt, and the corresponding interaction terms. The variable Pct African Mgmt (Pct Hispanic) measures the percentage of managers working for a firm in a given county and year that are African (Hispanic). Coefficients are in percentage points. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level over the period 2005-2015. In panels (a) and (b), we restrict the data set to male advisers. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Gender and Repeat Offenses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prior Misconduct	2.42***	2.29***	1.91***	1.72***	2.09***	1.96***	1.64***	1.49***
	(0.10)	(0.098)	(0.076)	(0.088)	(0.089)	(0.084)	(0.067)	(0.082)
Prior Misconduct × Female	-0.69***	-0.69***	-0.58***	-0.56***	-0.56***	-0.55***	-0.50***	-0.46***
	(0.099)	(0.098)	(0.090)	(0.11)	(0.095)	(0.095)	(0.086)	(0.10)
Prior Discipline					3.94***	3.89***	3.49***	3.34***
					(0.28)	(0.28)	(0.25)	(0.35)
Prior Discipline × Female					-1.70***	-1.70***	-1.17***	-1.32**
					(0.43)	(0.43)	(0.45)	(0.63)
Female	-0.27***	-0.22***	-0.23***	-0.20***	-0.27***	-0.22***	-0.24***	-0.20***
	(0.017)	(0.017)	(0.024)	(0.026)	(0.017)	(0.017)	(0.023)	(0.026)
Adviser Controls		X	X	X		X	X	X
Year×Firm×County F.E.			X				X	
Year×Firm×County×Lic. F.E.				X				X
Observations	6,547,974	6,547,974	6,221,173	4,465,068	6,547,974	6,547,974	6,221,173	4,465,068
R-squared	0.007	0.007	0.101	0.208	0.008	0.009	0.102	0.209
Mean of Dependent Variable	0.61%	0.61%	0.61%	0.51%	0.61%	0.61%	0.61%	0.51%

Note: Table 7 displays the regression results for a linear probability model (eq. 10). The dependent variable is whether or not a financial adviser received a misconduct disclosure at time t. The independent variable Prior Discipline is a dummy variable indicating whether an adviser previously experienced an employment separation following misconduct. Coefficient units are percentage points. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. Observations are at the adviser-by-year level. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Conditioning on Type of Misconduct

(a) Labor Market Outcomes Conditional on the Reported Misconduct Complaint

Dependent Variable	Job Separation				New Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Misconduct	34.0***	34.9***	28.7***	32.2***	-9.17***	-12.1***	-9.10***	-10.3***
	(1.99)	(1.90)	(2.11)	(2.84)	(2.45)	(1.69)	(1.45)	(1.83)
Misconduct × Female	6.64***	6.51***	8.42***	7.90***	-6.36***	-5.16***	-3.29***	-2.71**
	(1.69)	(1.61)	(1.56)	(1.58)	(1.54)	(1.17)	(1.14)	(1.23)
Female	0.14	-0.53	-0.54***	-0.50***	-6.22***	-2.43***	-4.04***	-3.83***
	(0.29)	(0.34)	(0.15)	(0.16)	(0.65)	(0.61)	(0.26)	(0.29)
Allegations								
Unauthorized Activity	9.06***	8.84***	7.09***	6.53***	-5.60***	-5.18***	-3.73***	-2.45
	(1.12)	(1.08)	(1.07)	(1.36)	(1.29)	(1.08)	(1.34)	(1.97)
Omission of Key Facts	6.89***	7.10***	5.19***	5.39***	-9.60***	-9.83***	-5.92***	-4.02*
	(1.47)	(1.39)	(1.32)	(1.92)	(2.00)	(1.61)	(1.55)	(2.30)
Fee/Commission Related	-3.80**	-3.55**	-5.67***	-7.78***	-0.78	-1.82	-2.09	4.31*
	(1.69)	(1.67)	(1.33)	(1.57)	(1.81)	(1.81)	(1.75)	(2.30)
Unsuitable	-21.5***	-20.1***	-19.1***	-22.0***	18.7***	12.3***	8.93***	12.4***
	(1.93)	(1.69)	(1.62)	(2.21)	(2.07)	(1.50)	(1.29)	(1.63)
Misrepresentation	-15.5***	-14.9***	-15.5***	-17.1***	13.9***	8.51***	5.44***	6.46***
	(2.23)	(2.12)	(1.43)	(1.99)	(3.21)	(2.48)	(1.87)	(1.95)
Fraud	0.63	0.87	-1.73	-0.36	-17.6***	-16.1***	-14.3***	-10.8***
	(1.70)	(1.63)	(1.36)	(1.88)	(2.15)	(1.92)	(2.05)	(3.04)
Adviser Controls		X	X	X		X	X	X
Yr×Firm×Cnty F.E.			X				X	
Yr×Firm×Cnty×Lic. F.E.				X				X
Observations	6,002,088	6,002,088	5,698,577	4,093,438	1,125,715	1,125,715	1,006,760	660,127
R-squared	0.004	0.014	0.333	0.403	0.004	0.101	0.365	0.465
Mean of Dependent Variable	18.8%	18.8%	18.8%	19.2%	54.0%	54.0%	54.0%	51.4%

(b) Labor Market Outcomes following Misconduct related to Unauthorized Activity

Dependent Variable	Job Separation				New Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unauthorized Activity	35.6***	36.7***	27.9***	30.5***	-11.3***	-15.5***	-11.5***	-9.99***
	(1.57)	(1.45)	(1.86)	(2.63)	(2.47)	(1.71)	(1.26)	(1.71)
Unauthorized Act.× Female	10.3***	9.99***	14.5***	14.3***	-13.4***	-11.7***	-7.20**	-5.96
	(3.21)	(3.03)	(3.21)	(3.47)	(2.48)	(2.66)	(3.66)	(4.90)
Female	0.057	-0.60*	-0.58***	-0.54***	-6.21***	-2.38***	-4.01***	-3.80***
	(0.29)	(0.34)	(0.15)	(0.16)	(0.65)	(0.61)	(0.26)	(0.29)
Adviser Controls		X	X	X		X	X	X
Yr×Firm×Cnty F.E.			X				X	
Yr×Firm×Cnty×Lic. F.E.				X				X
Observations	6,002,088	6,002,088	5,698,577	4,093,438	1,125,715	1,125,715	1,006,760	660,127
R-squared	0.001	0.011	0.330	0.401	0.003	0.100	0.364	0.464
Mean of Dependent Variable	18.8%	18.8%	18.8%	19.2%	54.0%	54.0%	54.0%	51.4%

Tables 8a and 8b display the regression results corresponding to linear probability models (eq. 3 and 4). The dependent variable in columns (1)-(4) of Tables in Tables 8a and 8b is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). The dependent variable in columns (5)-(8) of Tables 8a and 8b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In columns (5)-(8) of Tables 8a and 8b, we restrict the sample to those advisers who left their firm in a given year. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Coefficients are in percentage points. Observations are at the financial adviser by year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Conditioning on Observed Productivity

Dependent Variable	Misconduct		Job Separation		
	(1)	(2)	(3)	(4)	(5)
Female	-0.36***	-0.33***	-0.38***	-0.65***	-0.65***
	(0.057)	(0.056)	(0.10)	(0.11)	(0.11)
Misconduct			8.81***	8.93***	28.2***
			(0.89)	(0.88)	(10.5)
Misconduct × Female			4.26***	4.36***	4.44***
			(1.58)	(1.58)	(1.62)
High Rating		-0.0068		-4.05***	-3.91***
		(0.059)		(0.64)	(0.64)
ln(AUM)		0.033**		-0.43***	-0.43***
		(0.016)		(0.073)	(0.073)
ln(Production)		0.18***		-0.24***	-0.24***
		(0.022)		(0.072)	(0.072)
High Rating×Misconduct					-12.5***
					(1.89)
ln(AUM)×Misconduct					-0.77*
					(0.44)
ln(Production)×Misconduct					0.34
					(0.60)
Adviser Controls	X	X	X	X	X
Year×Firm×County F.E.	X	X	X	X	X
Observations	487,159	487,159	442,159	442,159	442,159
R-squared	0.181	0.181	0.624	0.627	0.627
Mean of Dependent Variable	1.0%	1.0%	10.1%	10.1%	10.1%

Note: Table 9 displays the regression results for two linear probability models (eq. 1 and 3). The dependent variable in columns (1) and (2) is a dummy variable indicating whether or not the adviser received a misconduct disclosure in year t. The dependent variable in column (3)-(5) is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). We observe the adviser's quality rating (as per Meridian IQ), AUM, and revenue (production) generated by the adviser as of 2016. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Conditioning on Career Interruptions

Dependent Variable	Job Separation		New Employment	
	(1)	(2)	(3)	(4)
Female	-0.50***	-0.50***	-3.84***	-3.84***
	(0.16)	(0.16)	(0.29)	(0.29)
Misconduct	25.8***	25.5***	-9.01***	-8.27***
	(2.21)	(2.38)	(1.45)	(1.51)
Misconduct × Female	9.95***	9.98***	-3.49***	-3.59***
	(1.90)	(1.89)	(1.27)	(1.28)
Career Interruption	4.05***	4.04***	-2.38***	-2.32***
	(0.21)	(0.21)	(0.30)	(0.30)
Career Interruption ×Misconduct		1.76		-4.85***
		(1.89)		(1.55)
Adviser Controls	X	X	X	X
Year×Firm×County×License F.E.	X	X	X	X
Observations	4,093,438	4,093,438	660,127	660,127
R-squared	0.404	0.404	0.465	0.465
Mean of Dependent Variable	19.2%	19.2%	51.4%	51.4%

Note: Table 10 displays the regression results for two linear probability models. The dependent variable in columns (1) and (2) is a dummy variable indicating whether or not a financial adviser left his firm (eq. 3). The dependent variable in columns (3) and (4) is a dummy variable indicating whether or not a financial adviser joined a new firm within one year (eq. 4). In columns (3) and (4), we restrict the sample to advisers who left their firms in a given year. Career interruption is a dummy variable indicating whether or not an adviser has previously left the financial services industry for more than six months. Coefficients are in percentage points. Other adviser controls include the adviser's experience. Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 11: Stratifying on Adviser Industry Experience

(a) Advisers with 5 or Fewer Years Industry Experience

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.18***	-1.14***	-2.19***
	(0.026)	(0.23)	(0.28)
Misconduct		37.2***	-12.6***
		(3.76)	(2.06)
Misconduct × Female		8.87***	-2.06
		(1.67)	(1.32)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	1,985,627	1,854,824	409,506
R-squared	0.098	0.311	0.359
Mean of Dependent Variable	0.34%	23.8%	45.7%

(b) Advisers with 15 or More Years Industry Experience

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.49***	0.23*	-6.67***
	(0.033)	(0.12)	(0.44)
Misconduct		18.0***	-6.89***
		(1.08)	(1.27)
Misconduct × Female		4.45***	1.13
		(1.51)	(2.53)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	1,887,084	1,663,752	209,358
R-squared	0.151	0.411	0.434
Mean of Dependent Variable	0.88%	14.8%	63.4%

Note: Tables 11a and b display the regression results for three linear probability models. The dependent variable in column (1) is a dummy variable indicating whether or not the adviser received a misconduct disclosure in year t (eq. 1). The dependent variable in column (2) is a dummy variable indicating whether or not a financial adviser left his firm (eq. 3). The dependent variable in column (3) is a dummy variable indicating whether or not a financial adviser joined a new firm within one year (eq. 4). In column (3), we restrict the sample to those advisers who left their firms in a given year. In panel (a), we restrict our analysis to those advisers with five or fewer years of industry experience. In panel (b), we restrict our analysis to those advisers with fifteen or more years of experience. Coefficients are in percentage points. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Appendix

A1: Disclosure Definitions[23]

Civil-Final: This type of disclosure event involves (1) an injunction issued by a court in connection with investment-related activity, (2) a finding by a court of a violation of any investment-related statute or regulation, or (3) an action brought by a state or foreign financial regulatory authority that is dismissed by a court pursuant to a settlement agreement.

Civil - Pending: This type of disclosure event involves a pending civil court action that seeks an injunction in connection with any investment-related activity or alleges a violation of any investment-related statute or regulation.

Customer Dispute - Award/Judgment: This type of disclosure event involves a final, consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the adviser that resulted in an arbitration award or civil judgment for the customer.

Customer Dispute - Settled: This type of disclosure event involves a consumer-initiated, investment-related complaint, arbitration proceeding or civil suit containing allegations of sale practice violations against the adviser that resulted in a monetary settlement to the customer.

Customer Dispute - Closed-No Action/Withdrawn/Dismissed/Denied/Final: This type of disclosure event involves (1) a consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the individual adviser that was dismissed, withdrawn, or denied; or (2) a consumer-initiated, investment-related written complaint containing allegations that the adviser engaged in sales practice violations resulting in compensatory damages of at least $5,000, forgery, theft, or misappropriation, or conversion of funds or securities, which was closed without action, withdrawn, or denied.

Customer Dispute - Pending: This type of disclosure event involves (1) a pending consumer-initiated, investment-related arbitration or civil suit that contains allegations of sales practice violations against the adviser; or (2) a pending, consumer-initiated, investment related written complaint containing allegations that the adviser engaged in, sales practice violations resulting in compensatory damages of at least $5,000, forgery, theft, or misappropriation, or conversion of funds or securities.

Employment Separation After Allegations: This type of disclosure event involves a situation where the adviser voluntarily resigned, was discharged, or was permitted to resign after being accused of (1) violating investment-related statutes, regulations, rules or industry standards of conduct; (2) fraud or the wrongful taking of property; or (3) failure to supervise in connection with investment-related statutes, regulations, rules, or industry standards of conduct.

Judgment/Lien: This type of disclosure event involves an unsatisfied and outstanding judgments or liens against the adviser.

[23] Definitions as per http://brokercheck.finra.org/

Criminal - Final Disposition: This type of disclosure event involves a criminal charge against the adviser that has resulted in a conviction, acquittal, dismissal, or plea. The criminal matter may pertain to any felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property.

Financial - Final: This type of disclosure event involves a bankruptcy, compromise with one or more creditors, or Securities Investor Protection Corporation liquidation involving the adviser or an organization the adviser controlled that occurred within the last 10 years.

Financial - Pending: This type of disclosure event involves a pending bankruptcy, compromise with one or more creditors, or Securities Investor Protection Corporation liquidation involving the adviser or an organization the adviser controlled that occurred within the last 10 years.

Investigation: This type of disclosure event involves any ongoing formal investigation by an entity such as a grand jury state or federal agency, self-regulatory organization or foreign regulatory authority. Subpoenas, preliminary or routine regulatory inquiries, and general requests by a regulatory entity for information are not considered investigations and therefore are not included in a BrokerCheck report.

Regulatory - Final: This type of disclosure event may involves (1) a final, formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulatory such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation of investment-related rules or regulations; or (2) a revocation or suspension of a adviser's authority to act as an attorney, accountant, or federal contractor.

Civil Bond: This type of disclosure event involves a civil bond for the adviser that has been denied, paid, or revoked by a bonding company.

Criminal - On Appeal: This type of disclosure event involves a conviction for any felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property that is currently on appeal.

Criminal - Pending Charge: This type of disclosure event involves a formal charge for a crime involving a felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property that is currently pending.

Regulatory - On Appeal: This type of disclosure event may involves (1) a formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulator such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation of investment-related rules or regulations that is currently on appeal; or (2) a revocation or suspension of a adviser's authority to act as an attorney, accountant, or federal contractor that is currently on appeal.

Regulatory - Pending: This type of disclosure event involves a pending formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulatory agency such as the Securities and Exchange Commission, foreign financial regulatory body) for alleged violations of investment-related rules or regulations.

Civil - On Appeal: This type of disclosure event involves an injunction issued by a court in connection with investment-related activity or a finding by a court of a violation of any investment-related statute or regulation that is currently on appeal.

A2: FINRA Qualifications and Exams[24]

Series 1, 7, 7a, and 7b Exam: The Series 7 exam – the General Securities Representative Qualification Examination (GS) – assesses the competency of an entry-level registered representative to perform his or her job as a general securities representative. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a general securities representative, including sales of corporate securities, municipal securities, investment company securities, variable annuities, direct participation programs, options and government securities. The Series 7 exam replaced the Series 1 Exam (Registered Representative Examination).

Series 2 Exam: The Series 2 exam is the Non-Member General Securities Examination and was retired in 1996.

Series 3 Exam: The Series 3 exam –the National Commodities Futures Examination–is a National Futures Association (NFA) exam administered by FINRA

Series 4 Exam: The Series 4 - Registered Options Principal Exam (OP) The Series 4 exam—the Registered Options Principal Qualification Examination (OP)—assesses the competency of an entry-level options principal candidate to perform his or her job as a registered options principal.

Series 5 Exam: The Series 5 exam is the Interest Rate Options Exam. The Series 5 exam was retired in 2010.

Series 6 Exam: The Series 6 exam—the Investment Company and Variable Contracts Products Representative Qualification Examination (IR)—assesses the competency of an entry-level representative to perform his or her job as an investment company and variable contracts products representative. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of an investment company and variable contract products representative, including sales of mutual funds and variable annuities.

Series 8, 9, 10, and 12 Exam: The General Securities Sales Supervisor Qualification Examination (Series 9 and 10) is intended to test a candidate's knowledge of securities industry rules and certain statutory provisions applicable to the supervision of sales activities at a general securities-oriented branch office. The examination question bank and question allocation is developed through a committee of securities industry professionals with experience in retail securities sales. The Series 9 and 10 exams replaced the Series 8 and Series 12 exam (NYSE Branch Manager Examination).

Series 11 Exam: The Series 11 exam—the Assistant Representative - Order Processing Examination (AR)—assesses the competency of an entry-level registered assistant representative to perform his or her job as an order-processing assistant representative.

Series 14 and 14a Exam: The Series 14 exam—the Compliance Official Qualification Examination (CO) — assesses the competency of an entry-level compliance official candidate to perform his or her job as a compliance officer. The exam measures the degree to which each candidate, who will supervise 10 or more people engaged in

[24] Definitions as per http://www.finra.org/industry/qualification-exams?bc=1 and http://www.finra.org/industry/qualification-exam-effective-dates

compliance activities or are responsible for the overall day-to-day compliance activities of the firm, possesses the knowledge needed to perform the job responsibilities.

Series 15 Exam: The Series 15 exam is the Foreign Currency Options Examination. The Series 15 exam was retired in 2008.

Series 16 Exam: The Series 16 exam—the Supervisory Analysts Qualification Examination (SA)—assesses the competency of an entry-level supervisory analyst to perform his or her job as a supervisory analyst. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a supervisory analyst, including the rules and statutory provisions applicable to the preparation and approval of research reports.

Series 17 Exam: The Series 17 exam—the United Kingdom Securities Representative Qualification Examination (IE)—an abbreviated version of the Series 7 exam, is appropriate for candidates who hold a registration in good standing with the Financial Conduct Authority (FCA) in the United Kingdom and are seeking registration in the U.S.

Series 18 Exam: The Series 18 exam is the Securities Industry Rules and Regulations Examination. The Series 18 exam was retired in 1988.

Series 21 Exam: The Series 21 exam is the NYSE Front Line Specialist Clerk Examination.

Series 22 Exam: The Series 22 exam — the Direct Participation Programs Limited Representative Examination (DR) — assesses the competency of an entry-level registered representative to perform his or her job as a direct participation programs representative.

Series 23 Exam: The Series 23—the General Securities Principal Qualification Examination-Sales Supervisor Module (GP)—assesses the competency of an entry-level general securities principal candidate to perform his or her job.

Series 24 Exam: The Series 24 exam—the General Securities Principal Qualification Examination (GP)—assesses the competency of an entry-level general securities principal candidate to perform his or her job as a general securities principal. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a general securities principal, including the rules and statutory provisions applicable to the supervisory management of a general securities broker-dealer.

Series 25 Exam: The Series 25 exam is the NYSE Trading Assistant Examination. The Series 25 exam was retired in 2016.

Series 26 Exam: The Series 26 exam—the Investment Company and Variable Contracts Products Principal Examination (IP)—assesses the competency of an entry-level investment company and variable products principal candidate to perform his or her job.

Series 27 Exam: The Series 27 exam—the Financial and Operations Principal Qualification Examination (FN)—assesses the competency of an entry-level financial and operations principal (FINOP) candidate to perform his or her job as a FINOP. The exam measures the degree to which each candidate possesses the knowledge and understanding of the financial responsibilities, rules and recordkeeping requirements of broker-dealers.

Series 28 Exam: The Series 28 exam—the Introducing Broker-Dealer Financial and Operations Principal Qualification Examination (FI)—assesses the competency of an entry-level financial and operations principal (FINOP) candidate to perform his or her job as a FINOP in an introducing broker-dealer that does not carry customer accounts or hold customer funds or securities.

Series 30 Exam: The Series 30 exam—the NFA Branch Managers Examination—is a National Futures Association (NFA) exam administered by FINRA.

Series 31 Exam: The Series 31 exam—the Futures Managed Funds Examination—is a National Futures Association (NFA) exam administered by FINRA.

Series 32 Exam: The Series 32 exam—the Limited Futures Examination-Regulations—is a National Futures Association (NFA) exam administered by FINRA.

Series 33 Exam: The Series 33 exam is the Financial Instruments Examination. The Series 33 exam was retired in 2005.

Series 34 Exam: The Series 34 exam—the Retail Off-Exchange Forex Examination—is a National Futures Association (NFA) exam administered by FINRA.

Series 37 Exam: The Series 37 exam—the Canada Securities Representative Qualification Examination (CD)—an abbreviated version of the Series 7 exam, is appropriate for candidates who hold a registration in good standing with Canadian securities regulatory authorities and are seeking registration in the U.S. The exam assesses the competency of the candidate to perform his or her job as a general securities representative in the U.S. It measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a general securities representative, including sales of corporate securities, investment company securities, variable annuities, direct participation programs, options and government securities.

Series 38 Exam: The Series 37 exam—the Canada Securities Representative Qualification Examination (CD)—an abbreviated version of the Series 7 exam, is appropriate for candidates who hold a registration in good standing with Canadian securities regulatory authorities and are seeking registration in the U.S. The exam assesses the competency of the candidate to perform his or her job as a general securities representative in the U.S. It measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a general securities representative, including sales of corporate securities, investment company securities, variable annuities, direct participation programs, options and government securities.

Series 39 Exam: The Series 39 exam—the Direct Participation Programs Principal Qualification Examination (DP)—assesses the competency of a direct participation program (DPP) principal candidate to perform his or her job as a DPP principal. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a DPP principal, including the rules and statutory provisions applicable to the supervisory management of a broker-dealer that limits its products to direct participation programs.

Series 40 Exam: The Series 40 exam is the Registered Principal Examination. The Series 40 exam was retired in 1979.

Series 41 Exam: The Series 41 exam is the NYSE Allied Member Examination.

Series 42 Exam: The Series 42 exam—the Registered Options Representative Qualification Examination (OR) — assesses the competency of an entry-level registered representative to perform his or her job as an options representative. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of an options representative, including handling option accounts and the understanding of equity, debt, foreign currency and index options.

Series 44 Exam: The Series 44 exam is the Pacific Exchange Inc. (PCX) Market Maker Exam.

Series 45 Exam: The Series 45 exam is the Pacific Exchange Inc. (PCX) Floor Broker Exam.

Series 46 Exam: The Series 46 exam is the Pacific Exchange Inc. (PCX) Market Maker acting as a Floor Broker Exam.

Series 48 Exam: The Series 48 exam is the AMEX Market Maker Exam.

Series 49 Exam: The Series 49 exam is the AMEX Floor Broker Exam.

Series 50 Exam: Series 50—Municipal Advisor Representative Examination—is a Municipal Securities Rulemaking Board (MSRB) exam.

Series 51 Exam: The Series 51 exam—the Municipal Fund Securities Limited Principal Qualification Examination (FP)—is a Municipal Securities Rulemaking Board (MSRB) exam.

Series 52 Exam: The Series 52 exam—the Municipal Securities Representative Qualification Examination (MR)—is a Municipal Securities Rulemaking Board (MSRB) exam.

Series 53 Exam: The Series 53 exam—the Municipal Securities Principal Qualification Examination (MP)—is a Municipal Securities Rulemaking Board (MSRB) exam.

Series 54 Exam: The Series 54 exam is the Municipal Securities Financial and Operations Principal Examination. The exam was retired in 1989.

Series 55, Series 56 and 57 Exam: The Series 57 exam — the Securities Trader Representative Exam — assesses the competency of an entry-level registered representative to perform their job as a securities trader representative. The Series 57 exam replaced the Series 55 exam (the Equity Trader Examination) and the Series 56 exam (the Proprietary Trader Examination).

Series 62 Exam: The Series 62—the Corporate Securities Representative Qualification Examination (CS)—assesses the competency of an entry-level representative to perform his or her job as a corporate securities representative.

Series 63 Exam: The Uniform Securities Agent State Law Examination was developed by NASAA in cooperation with representatives of the securities industry and industry associations. The examination, called the Series 63 exam, is designed to qualify candidates as securities agents. The examination covers the principles of state securities regulation reflected in the Uniform Securities Act (with the amendments adopted by NASAA and rules prohibiting dishonest and unethical business practices). The examination is intended to provide a basis for state securities administrators to determine an applicant's knowledge and understanding of state law and regulations.

Series 64 Exam: The Series 65 exam is the NASAA Real Estate Securities Exam.

Series 65 Exam: The Uniform Investment Adviser Law Examination and the available study outline were developed by NASAA. The examination, called the Series 65 exam, is designed to qualify candidates as investment adviser representatives. The exam covers topics that have been determined to be necessary to understand in order to provide investment advice to clients.

Series 66 Exam: The Uniform Combined State Law Examination was developed by NASAA based on industry requests. The examination (also called the "Series 66″) is designed to qualify candidates as both securities agents and investment adviser representatives. The exam covers topics that have been determined to be necessary to provide investment advice and effect securities transactions for clients.

Series 72 Exam: The Series 72 exam—the Government Securities Representative Qualification Examination (RG)—assesses the competency of an entry-level registered representative to perform his or her job as a government securities representative. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a government securities representative, including transacting a firm's business in Treasury, government agency and mortgage-backed securities.

Series 79 Exam: The Series 79 exam — the Investment Banking Representative Exam — assesses the competency of an entry-level registered representative to perform their job as an investment banking representative.

Series 82 Exam: The Series 82 exam — the Private Securities Offerings Representative Exam — assesses the competency of an entry-level registered representative to perform their job as a private securities offerings representative.

Series 86 and 87 Exams: The Series 86/87 exam — the Research Analyst Exam — assesses the competency of an entry-level registered representative to perform their job as a research analyst.

Series 99 Exam: The Series 99 exam — the Operations Professional Exam — assesses the competency of an entry-level registered representative to perform their job as an operations professional.

A3: Gender Punishment Gap in Reemployment: Duration Analysis

Another way to measure differences in reemployment prospects across genders is through the duration out of the industry. Figure A3 displays the duration out of the industry survival function for male and female advisers, cut by whether the adviser engaged in misconduct in the year prior to unemployment. As the figure illustrates, on average, the duration out of the industry spells for female advisers are longer than those for male advisers. This is the case both for advisers with misconduct in the past year and for advisers without misconduct. Roughly 50% of female advisers remain out of the industry after 24 months, while only 44% of male advisers remain out of the industry after 24 months. More relevant to differential punishment across genders is the increase in the duration out of the industry due to misconduct. The probability of long-term unemployment out of the industry following misconduct increases substantially more for female advisers than for their male counterparts.

The simple non-parametric survival analysis in Figure A3 does not account for other differences among financial advisers, such as their experience or qualifications. We formally analyze the impact of misconduct on an adviser's job search by estimating the following Cox proportional hazards model:

$$\lambda_{it}(\tau) = \lambda_0(\tau) exp\left(\gamma_1 Female_i + \gamma_2 Misc._{it-1} \times Male_{it} + \gamma_3 Misc._{it-1} \times Female_i + \beta X_{it} + \mu_t\right), \tag{11}$$

where $\lambda_i(\tau)$ is the hazard rate of finding new employment in the industry for individual i conditional on being unemployed for τ months. The hazard rate is a function of the baseline hazard $\lambda_0(\tau)$ and changes proportionally depending on whether the financial adviser was reprimanded for misconduct in the year preceding the unemployment spell, $Misconduct_{it-1}$, gender, and the interaction of the two. We also control for an adviser's characteristics X_{it} and include time fixed effects μ_t to account for aggregate fluctuations in the employment market.

Table A4 reports the hazard ratios corresponding to our Cox proportional hazards model. Any reported hazard ratio less than one suggests that the covariate is correlated with longer unemployment spells. The estimates reaffirm the results displayed in Figure A3. The results indicate that female advisers face longer duration out of the industry spells relative to male advisers. Female advisers have a 4% smaller chance of finding new employment in the industry at any given moment in time relative to male advisers. Misconduct results in longer duration out of the industry spells for both male and female advisers, but the effect is much larger for female advisers. A male adviser who had engaged in misconduct in the year prior to the start of his unemployment spell has a 16% smaller chance of finding new employment in the industry at any given moment in time relative to a male adviser without recent misconduct (Table A4 column 1). Conversely, a female adviser who engaged in misconduct has a 26% smaller chance of finding new employment in the industry at any given moment in time relative to a female adviser without misconduct (Table A4 column 1).

A3: Recidivism and Selection

A challenge in accessing the relative recidivism propensities across genders is that we only observe recidivism among advisers who remain employed in the industry. Here, we account for sample selection using a semi-parametric two step method. In the first step we estimate the probability an adviser experience's an employment separation following his/her initial misconduct offense

$$Separation_{it+1} = \beta_g X_{it} + \mu_{jg} + \mu_{lg} + \mu_{tg} + \varepsilon_{it} \tag{12}$$

The vector of adviser controls X_{it} includes the adviser's experience and licenses (series 6, 7, 63, 24, etc.). We also include firm, year, and county fixed effects. Furthermore, we allow the parameters to vary flexibly across genders to allow the differential treatment of men and women to vary across firms, regions, and over time. We use the predicted values from our employment separation regression (eq 12) to calculate an adviser's propensity to experience an employment separation, $\hat{p}$.

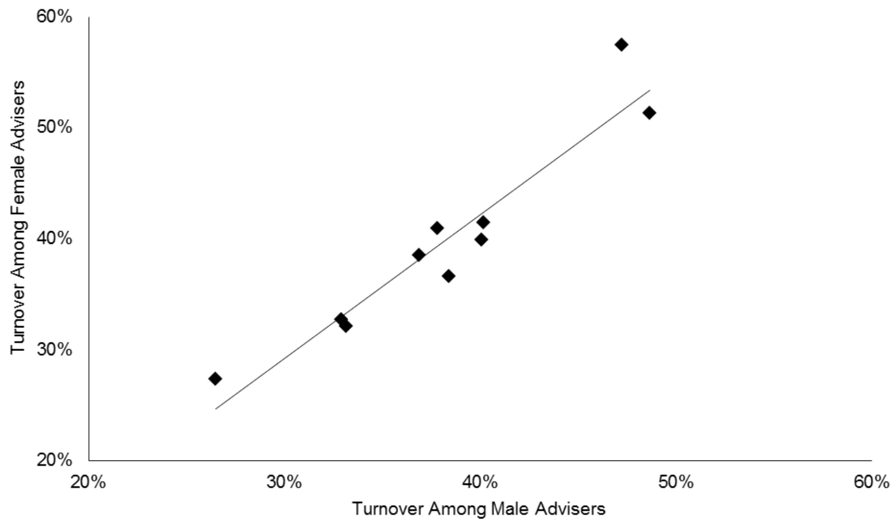
We then re-estimate using our recidivism specification (eq. 10) where include a fourth order polynomial of $\hat{p}$ as a control function. Estimating the sample selection model semi-parametrically requires an exclusion restriction. We use the adviser's past characteristics at the time of the offense (experience, employer, location, licenses, etc.) as an exclusion restriction. This exclusion restriction requires that conditional on the adviser's current observable characteristics, the past observable characteristics that help determine whether he/she was fired following misconduct such as experience, firm, or location, are uncorrelated with recidivism.

$$Misconduct_{ijlt} = \beta X_{it} + \mu_j + \mu_l + \mu_g + \sum_{k=1}^{4} \phi_k \hat{p}_i^k + \eta_{ijlt} \tag{13}$$

In our analysis, we restrict our observations to those advisers who initially engaged in misconduct and did not experience an employment separation following the previous misconduct. Table A6 displays the corresponding estimates where use a semi-parametric control function to address the potential selection issues. Consistent with the selection model, we restrict the data set to those advisers who engaged in misconduct but remained with their employer the following year. In each specification we estimate a negative and significant relationship between gender and misconduct. In column (4) we also interact gender with the propensity to experience an employment separation $\hat{p}$. The interaction term helps us recover the distribution of recidivism across male and female advisers similar to Heckman, Urzua, and Vytlacil (2006). We continue to estimate a negative relationship between recidivism and female across the support of $\hat{p}$.

A4: Additional Figures and Tables

Figure A1: Job Displacement - Male vs. Female Advisers



Note: Figure A1 plots the annual job turnover among male and female advisers at distressed firms over the period 2005-2014. We define distressed firms as firms that reduce the number of financial advisers they employ by 10% or more in a given year.

Figure A2: Job Turnover by Experience

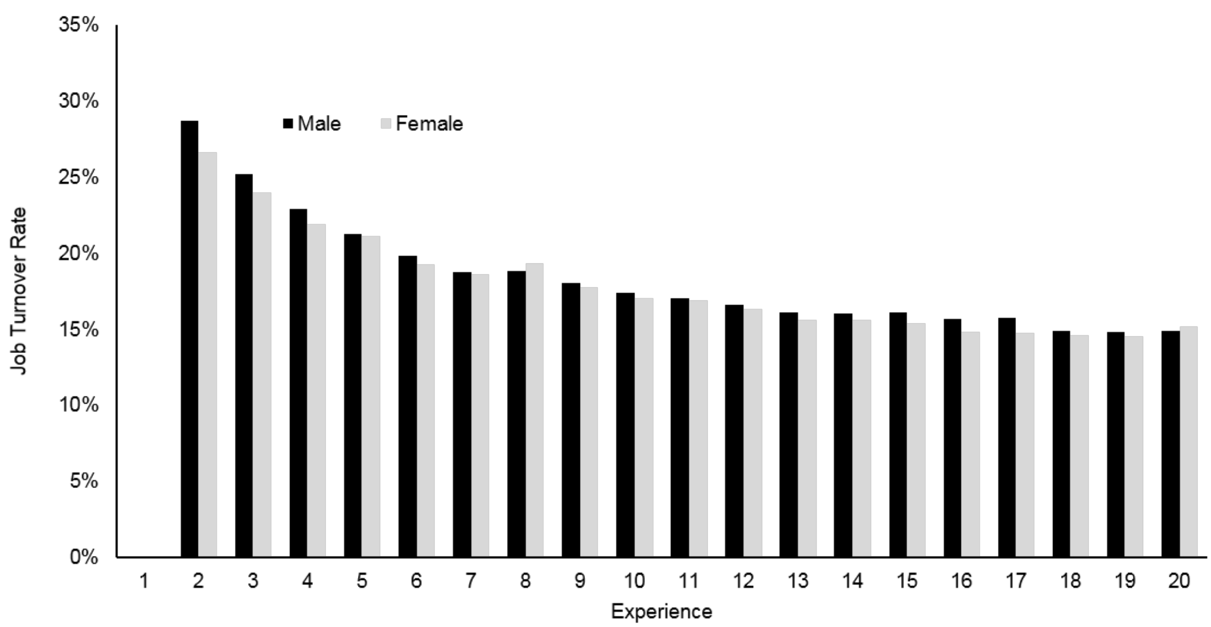


Figure A2 displays job turnover among male and female advisers conditional on the advisers' experience. Observations are at the adviser-by-year level over the period 2005-2015.

Figure A3: Unemployment and Misconduct

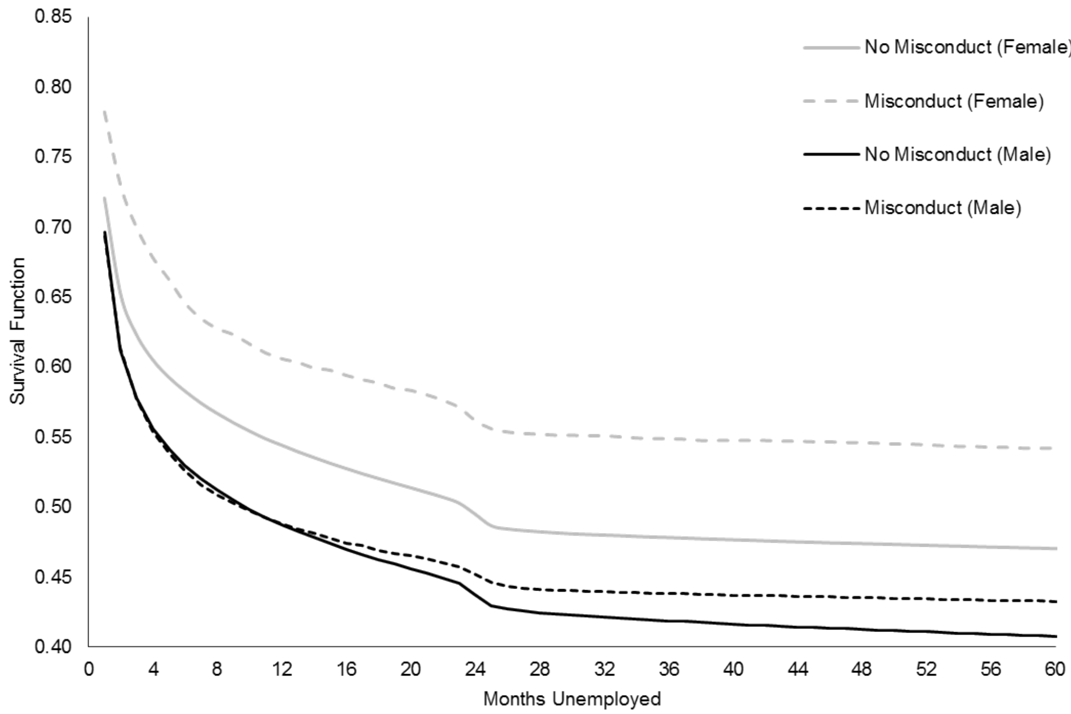


Figure A3 displays the duration out of the industry survival functions for all adviser out of the industry spells over the period 2005-2015. The solid black and gray lines display the duration out of the industry survival functions for male and female advisers did not receive a misconduct disclosure in the year prior to their spell. The dashed lines display the the duration out of the industry survival functions for male and female advisers who were reprimanded for misconduct in the year prior to the adviser's spell.

Table A1: Financial Advisers by State

Rank	State	Pct Female	Number of Observations	Female Turnover	Male Turnover
1	Iowa	32.30%	74,940	16.57%	15.78%
2	New Mexico	29.89%	15,383	14.17%	13.68%
3	Alaska	29.70%	4,788	13.07%	11.15%
4	Puerto Rico	28.46%	9,116	17.39%	15.21%
5	Wyoming	28.28%	5,028	11.92%	12.37%
6	Hawaii	27.95%	13,966	13.87%	14.69%
7	Washington	27.70%	89,201	16.38%	15.57%
8	Colorado	27.66%	153,124	16.13%	16.72%
9	Missouri	27.43%	132,450	17.33%	19.28%
10	Delaware	27.42%	15,948	19.14%	19.38%
11	North Dakota	27.37%	10,336	15.86%	13.89%
12	Arizona	27.33%	126,564	18.75%	19.61%
13	Rhode Island	26.99%	33,819	21.69%	19.50%
14	Minnesota	26.89%	174,716	23.06%	23.24%
15	Florida	26.71%	350,989	17.81%	18.64%
16	Kentucky	26.67%	50,509	15.92%	14.59%
17	Montana	26.67%	11,947	11.49%	11.95%
18	Wisconsin	26.53%	111,672	15.51%	15.31%
19	California	26.45%	601,664	19.38%	19.14%
20	Nebraska	26.37%	57,875	17.26%	18.94%
21	Texas	26.22%	367,645	18.75%	18.07%
22	Georgia	25.93%	168,652	24.49%	23.08%
23	Oklahoma	25.90%	40,419	15.87%	13.18%
24	Indiana	25.81%	91,892	18.87%	17.02%
25	Ohio	25.78%	212,704	18.52%	17.38%
26	Oregon	25.66%	52,675	17.08%	16.37%
27	Michigan	25.46%	138,815	16.79%	15.46%
28	Virginia	25.33%	106,954	16.42%	16.44%
29	Nevada	25.32%	28,493	20.04%	19.80%
30	Kansas	25.27%	52,437	15.28%	15.69%
31	Vermont	25.17%	9,590	16.28%	18.25%
32	Maryland	25.15%	96,829	17.54%	17.37%
33	New Hampshire	25.14%	33,289	17.78%	16.25%
34	North Carolina	25.02%	155,334	16.50%	16.08%
35	Louisiana	24.53%	43,942	17.69%	15.16%
36	Connecticut	24.37%	145,698	19.82%	19.94%
37	Maine	24.11%	14,236	18.59%	17.37%
38	South Dakota	24.04%	11,250	14.59%	13.20%
39	Illinois	23.91%	430,477	17.11%	16.26%
40	Pennsylvania	23.54%	256,151	15.35%	15.32%
41	Tennessee	23.10%	79,351	17.80%	16.07%
42	Massachusetts	22.59%	193,717	22.04%	19.89%
43	West Virginia	22.33%	11,686	17.13%	13.62%
44	Alabama	22.28%	45,115	20.37%	17.73%
45	Arkansas	21.97%	24,257	12.27%	14.45%
46	New York	21.74%	1,223,637	21.18%	22.29%
47	South Carolina	21.59%	38,491	16.17%	15.02%
48	New Jersey	21.37%	265,635	18.39%	18.69%
49	Idaho	21.13%	16,396	17.45%	15.95%
50	Mississippi	20.01%	22,150	19.20%	18.63%
51	Utah	16.26%	49,928	18.33%	16.89%

Note: Table A1 displays the summary statistics corresponding to our panel of male and female financial advisers at the state level. Turnover reflects the percentage of advisers who leave their firms in a given year. Observations are at the adviser by year level over the period 2005-2015.

Table A2: Alternative Gender Data

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.29***	-0.65***	-1.12***
	(0.031)	(0.15)	(0.20)
Misconduct		11.5***	0.16
		(0.76)	(0.44)
Misconduct × Female		3.37***	-2.06
		(1.27)	(1.60)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	3,787,172	3,359,568	340,136
R-squared	0.113	0.435	0.240
Mean of Dependent Variable	0.5%	11.3 %	92%

Note: Table A2 displays the regression results for three linear probability models. The dependent variable in column (1) is a dummy variable indicating whether or not the adviser received a misconduct disclosure in year t (eq. 1). The dependent variable in column (2) is a dummy variable indicating whether or not a financial adviser left his firm (eq. 3). The dependent variable in column (3) is a dummy variable indicating whether or not a financial adviser joined a new firm within one year (eq. 4). In column (3), we restrict the sample to advisers who left their firms in a given year. Here we identify the gender of each adviser using data from Meridian IQ. Meridian IQ contains data on the gender of active advisers as of 2016. Because we only observe the gender for active advisers in Meridian IQ, our ability to identify the impact of misconduct on an adviser's reemployment prospects is limited (all of the advisers in the Meridian IQ data set are active and employed as of 2016 by construction). Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Gender Gap in Promotions

	(1)	(2)	(3)
Misconduct	-0.17**	-0.13**	-0.10
	(0.075)	(0.065)	(0.065)
Misconduct × Female	-0.25**	-0.18*	-0.14
	(0.11)	(0.10)	(0.11)
Female	-0.25***	-0.22***	-0.082***
	(0.030)	(0.035)	(0.023)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	5,657,813	5,657,813	5,351,741
R-squared	0.000	0.008	0.094
Mean of Dependent Variable	0.8%	0.8%	0.8%

Note: Table A3 displays the regression results corresponding to a linear probability model. The dependent variable is a dummy variable indicating whether or not a financial adviser passed the general securities principal exam (Series 24) at time t. Coefficients are expressed in percentage points. Observations are at the financial adviser by year level over the period 2005-2015. We restrict our sample to those financial advisers that are not general securities principals prior to time t. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, and investment adviser exams), and number of other qualifications. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Gender Punishment Gap In Reemployment: Duration Analysis

	(1)	(2)
Misconduct (Male)	0.84***	0.85***
	(0.0075)	(0.0076)
Misconduct (Female)	0.74***	0.75***
	(0.019)	(0.020)
Female	0.96***	0.96***
	(0.0029)	(0.0029)
Adviser Controls	X	X
Year F.E.		X
Observations	1,109,210	1,109,210

Note: Table A4 displays the estimation results corresponding to a Cox proportional hazard model (eq. 11). The dependent variable is the length of an out of the industry spell in months. The key independent variable of interest, Misconduct, is a dummy variable indicating whether or not the adviser received a misconduct disclosure in the year prior to his/her unemployment spell. We interact Misconduct with the gender of the adviser to allow the effect to be different for male and female advisers. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24 and investment adviser exam), and number of other qualifications. The coefficients are reported in terms of proportional hazards such that a coefficient less than one indicates that it takes longer for an adviser to find a new job. Observations are at the financial adviser by out of the industry spell level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A5: Job Turnover Among Advisers Who Eventually Engage in Misconduct

	(1)	(2)	(3)
Female	-1.72***	-1.79***	-1.58***
	(0.65)	(0.59)	(0.35)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	102,915	102,915	63,124
R-squared	0.000	0.013	0.596
Mean of Dependent Variable	15.9%	15.9%	17.8%

Note: Table A5 displays the regression results corresponding to a linear probability model (eq. 3). The dependent variable is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). Observations are at the financial adviser-by-year level over the period 2005-2015. We restrict the sample to observations corresponding to advisers who had not yet received a misconduct disclosure but who will ultimately receive one or more misconduct disclosures over the course of his/her career. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Coefficients are in percentage points. Standard errors are in parentheses and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A6: Recidivism and Selection Correction

	(1)	(2)	(3)	(4)
Female	-0.59**	-0.97***	-0.51*	-0.98**
	(0.24)	(0.28)	(0.27)	(0.45)
Female×Propensity				2.88
				(2.08)
Female×Propensity^2				-4.20
				(2.87)
Adviser Controls		X	X	X
Year F.E.			X	X
Firm F.E.			X	X
County F.E.			X	X
Observations	87,088	87,088	86,753	86,753
R-squared	0.000	0.008	0.090	0.090
Mean of Dependent Variable 5.3%	5.3%	5.3%	5.3%	

Note: Table A6 displays the regression results for a linear probability model (eq. 13). The dependent variable is whether or not a financial adviser received a misconduct disclosure at time t. We restrict our observations to those advisers who initially engaged in misconduct and did not experience an employment separation following misconduct. Because our sample represents a "selected" sample of individuals who engaged in misconduct and did not experience an employment separation following misconduct, we correct for the potential selection using a two-step semi-parametric method as described in the Appendix. Coefficient units are percentage points. Propensity measures the adviser's probability of being fired following his/her initial misconduct disclosure (eq.12). Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Observations are at the adviser-by-year level. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Turnover in Firms that Downsize

	(1)	(2)	(3)	(4)	(5)
Downsize	22.9***	22.5***			
	(1.88)	(1.91)			
Downsize × Female	1.91	1.99*	0.32	0.21	0.59
	(1.02)	(1.00)	(0.29)	(0.22)	(0.37)
Female	-0.14	-0.86***	-0.59***	-0.61**	-0.58***
	(0.22)	(0.26)	(0.17)	(0.19)	(0.16)
Adviser Controls		X	X	X	X
Year×Firm×County×License F.E.			X	X	X
Downsize: 5%+				X	
Downsize: 25%+					X
Observations	6,002,088	6,002,088	4,093,438	4,093,438	4,093,438
R-squared	0.042	0.049	0.401	0.401	0.401
Mean of Dependent Variable	18.8%	18.8%	19.2%		
	19.2%				
	19.2%				

Note: Table A7 displays the results for a linear probability model (eq. 3). The dependent variable is a dummy variable indicating whether or not the adviser experienced a job separation between time t and $t+1$. The key independent variable of interest is the dummy variable $Downsize_{ijt}$, which indicates whether or not firm j reduced the number of advisers it employs by some percentage between time t and $t+1$. In columns (1)-(3), we define *Downsize* as a firm that reduced its number of advisers by 10% or more. In columns (4) and (5), we redefine *Downsize* as a firm that its number of advisers by 5% or more and 25% or more. Coefficients are in percentage points. Other adviser controls include the adviser's experience and dummy variables for the licenses the adviser holds (Series 6, 7, 24, etc.). Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.