When Harry Fired Sally: The Double Standard in Punishing Misconduct

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December 2017

First Version: September 2016

Abstract

We examine gender discrimination in misconduct punishment in the financial advisory industry. Following an incidence 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. For females, a disproportionate share of misconduct complaints are initiated by the firm rather than by customers or regulators. Moreover, firms with a greater percentage of female executives at the firm or at the local branch discriminate less in both separation and hiring. There is no evidence that the observed gender differences proxy for other adviser characteristics, such as productivity or behavior such as career interruptions. We extend our analysis to explore discrimination against ethnic minorities among male advisers and find similar patterns of "in-group" tolerance. Our evidence is inconsistent with statistical discrimination and suggests that managers are more forgiving of missteps among members of their own gender/ethnic group. We explore whether this bias arises from miscalibrated beliefs about misconduct or from taste-based discrimination. The observed discrimination appears to be context-dependent since it diminishes with adviser's tenure within the firm, suggesting that miscalibrated beliefs due to stereotyping may play a critical role in the observed discrimination.

JEL: J71, G24, G28, D18

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

*We thank Jonathan Berk, Marianne Bertrand, Jules van Binsbergen, Kerwin Charles, Darrell Duffie, Elena Espinoza, Matt Gentzkow, Christopher Hennesey, Laurie Hodrick, Emir Kamenica, Crystal Lam, Edward Lazear, Sendhil Mullainathan, Chris Palmer, Chris Parsons, Joshua Rauh, 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 seminar participants at Berkeley-Stanford and HBS-MIT Financial Economics conference.

1 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 issue of whether, and why discrimination – i.e., unequal treatment of equals, or equal treatment of unequals – exists across gender in the labor market remains hotly debated among academics and policymakers. The existing research on gender discrimination 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 gender discrimination carries over to punishment of undesirable activities as well. In other words, are labor markets more forgiving of missteps by men than women? Anecdotal evidence certainly suggests this is the case. Systematic evidence, on the other hand, is very scarce. This paper documents gender differences in punishment of undesirable activities in the context of financial adviser misconduct and explores mechanisms driving this discrimination.

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 discrimination has received little attention in academia or in policy relative to discrimination in hiring and compensation. One possible reason is that such discrimination is less likely to draw attention than the wage gap. When we observe a financial adviser losing her job following misconduct, the appeal that the termination was unfair or discriminatory sounds 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 discrimination. In such cases, discrimination may be a priori more difficult to detect, both by the legal system and regulators, and possibly by the discriminating employers who themselves may be unaware of their own biases (Bertrand et al., 2005).

Discrimination in punishment also differs from discrimination in hiring and compensation in the information that the employer has about the employee. One view is that discrimination 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 discrimination (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 gender differences among employees with several years of tenure, suggesting a potentially different discrimination mechanism is at play. Moreover, methodologically, studying this type of discrimination 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 gender discrimination in punishment and leniency in an important setting, the financial adviser industry. One obstacle to this research question is that 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. In this setting: we measure misconduct and its timing at the employee level, the nature and allegations related to misconduct, the entity initiating the misconduct compliant (regulator, firm or customer), the extent of the misconduct costs to the employer, actions taken by the firm and the regulator consequent to the misconduct, and track employee movement across firms in the industry.[1] These features of the data allow us to understand gender discrimination in punishment and leniency after employee misconduct at the level of the labor market, in addition to individual employers.

Researching discrimination 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). In addition, recent survey evidence found that nearly 88% of female financial service professionals believe that gender discrimination exists within the financial services industry (Tuttle, 2013). Similarly, a recent report from management consultant firm Oliver Wyman (2016) finds that women face a glass ceiling in the financial services industry and lists it as the number one cause for concern for women in the industry.[2] 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.

This paper has two goals. First, we document key differences in the rate and punishment of misconduct across male and female financial advisers. Second, we examine the rationale behind the observed discrimination. On one hand, the observed discrimination could simply be a function of statistical discrimination (Phelps, 1972; Arrow, 1973). Employers may not have an inherent prejudice against female advisers; rather, firms may punish female advisers more severely because misconduct by female advisers is predictive of worse outcomes or more frequent misconduct. Alternatively, if discrimination is not statistical, then it is due to some inherent bias of market participants. Such bias can be either taste-based (Becker, 1957) or due to miscalibrated/incorrect beliefs about misconduct across the two groups (Bordalo et al., 2016; Arnold et al, 2017). In other words, the financial advisory industry, customers, or regulators could simply prefer male over female advisers, or these industry players could systematically over-estimate the rate of recidivism among female advisers. The aim of second part of our analysis is to understand if the observed discrimination is statistical or due to some inherent bias; and if so, which one.

Our analysis starts by providing several facts. We find that women face more severe punishment for

[1] As shown in Egan, Matvos, Seru (2017), misconduct is prevalent in the industry and has significant labor market consequences: roughly one in thirteen financial advisers in the U.S. has a record of misconduct. Following incidences of misconduct, financial advisers face a substantial increase in the probability of job loss and face worse employment opportunities in the industry. See www.eganmatvosseru.com for more details.

[2] Former FDIC chairwomen Sheila Bair (2016), for instance, writes that the glass ceiling in finance is “barely cracked” for women.

misconduct. 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. On average, roughly 1 in 11 male advisers has a record of past misconduct, compared to only 1 in 33 female advisers. Male advisers, thus, are more than three times as likely to engage in misconduct. One possible reason for these gender differences is gender segregation across firms, markets, or types of financial products. We therefore compare male and female advisers at the same firm, in the same location, and at the same point in time (firm $\times$ year $\times$ county fixed effect). Moreover, because the market for financial advice is regulated, advisers are required to hold a particular set of qualifications to sell certain classes of products. We control for these qualifications, as well as adviser experience, and find the same large gender differences in misconduct propensity.

Despite having a lower incidence of misconduct relative to male advisers, female advisers face more severe consequences in the labor market at both the firm and industry level following an incidence of misconduct. Female advisers are 20% more likely to experience job separation following misconduct. 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. As before, we find these results by comparing male and female advisers at the same firm, in the same location, and at the same point in time (firm $\times$ year $\times$ county fixed effect), as well as conditioning on extensive adviser characteristics. 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, exhibit substantial discrimination against women when doling out punishments following misconduct.

The observed discrimination could be driven by any one of the three players involved in the market: employers, consumers, and regulators. Each of these three groups can initiate a misconduct complaint. We find that a disproportionate share of complaints initiated against female advisers are from their employer. For male advisers, 55% of misconduct complaints are initiated by customers and 28% by their employers. For female advisers, employer-initiated instances of misconduct are almost as frequent as those initiated by consumers: 41% versus 44%. These results suggest that employers may be the primary source of gender discrimination and is consistent with the survey evidence discussed earlier. We also document large variation in discrimination across firms, with firms such as Wells Fargo disciplining female advisers at a substantially higher rate relative to male advisers.

If discrimination arises because of employer bias, it is probably driven by the bias of the decision makers in the firm. One potential proposal to limit discrimination in firms has been 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, and that members from the discriminated group; i.e., women, are more likely to recognize discrimination and less likely to support discriminatory practices. We use this notion and examine whether the gender composition of the decision-making team in a firm explains some of the differences in discrimination we find across firms.

Although financial advising is a male dominated financial industry, with male advisers representing around 80% of firm managers as well as firm executives/owners, there are large differences in the share of female owners and executives across firms. If male advisers in positions of power are driving gender discrimination, we should be able to observe this in the data. Female advisers at firms with no female representation at the executive/ownership level are 42% more likely to experience job separation than are male advisers at the same branch following an incidence of misconduct. On the other hand, firms with equal representation of male and female executives/owners discipline male and female advisers at similar rates. We find similar differences between these firms when it comes to hiring advisers with misconduct records. Firms with a larger male representation at the executive/ownership level are more forgiving of misconduct by male advisers in hiring decisions. We find similar results when exploiting within-firm variation in the share of female branch-level managers. Overall, our results suggest that gender differences in labor market outcomes following misconduct are driven by the gender composition of executives at financial advisory firms. Male executives seem to be more forgiving of misconduct by men relative to women.

One potential explanation for the observed discrimination is that gender is simply a proxy for adviser characteristics or behavior. For example, firms may find it optimal to discipline women more harshly 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. Another alternative would be that female advisers are less likely to engage in misconduct unconditionally, as we discuss above, but conditional on misconduct are more likely to be repeat offenders. Again, the opposite is true. Male advisers are more than twice as likely to be repeat offenders in the future. Both these results suggest that 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.

If female advisers are less productive than male advisers, firms may also find it optimal to punish women more severely because terminating them is less costly.[3] One advantage of the financial industry is that the productivity of financial advisers can be broadly encapsulated as the amount of assets they attract, which we observe in conjunction with other measures in Meridian IQ data. Using this additional data, we find that differences in assets under management (AUM) of advisers, as well as other measures of productivity, do not explain the differences in punishment. We find gender differences in punishment across the range of adviser experience in the industry. In other words, discrimination occurs even for advisers whose abilities are well known to the market.

To recap, female advisers' job separation rates are higher than men's following misconduct at the same firm, time, and location, and with the same qualifications and experience. We find no evidence that females are substantially less productive employees or that gender proxies for misconduct severity. In fact, female misconduct is less costly. A simple model in the Appendix illustrates that a model of pure statistical discrimination would predict that the rates of recidivism should be the same among male and female advisers.

[3]For example, Gompers et al. (2014) finds that female venture capitalists underperform their male colleagues.

We find the rates of recidivism are twice as high among male advisers. Moreover, differences in discrimination are correlated with the gender composition of the management team, making statistical discrimination even less plausible. Thus, the collage of the evidence on differences in punishment across gender are not consistent with statistical discrimination.

Before drilling down on the exact source of discrimination, we first examine whether the discrimination in punishment and patterns of "in-group" tolerance is limited to gender, or whether it extends to other groups that have traditionally faced discrimination in the labor market. We re-estimate our main results on a sample of men, and find results, which are similar to those on gender discrimination. Males with names from traditionally discriminated minorities are punished more severely following misconduct. There is also less discrimination against minority males 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 amount of gender discrimination in firms. In other words, managers only alleviate discrimination within their gender or 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.

The next part of the paper investigates the mechanism generating discrimination. As noted earlier, the difference in tolerance across gender could potentially be driven by miscalibrated beliefs about misconduct propensities of genders, or taste-based discrimination. These two sources of discrimination are generally difficult to differentiate outside of a lab. In fact, both types of bias are consistent with most of our results. A simple model in the Appendix suggests that the one difference between the two explanations is that the effect of miscalibrated beliefs should be context-dependent and decline with employee tenure in a firm. Disutility from working with a person of a different gender (taste based discrimination), on the other hand, should not depend on the tenure of the co-worker. In the data, we observe a decline in gender discrimination as advisers' tenure with their firm increases. In addition, it is also difficult to rationalize a firm's dynamic decision to engage in taste-based discrimination at the separation stage when it hired these female advisers in the first place. Together, our findings suggest that the discrimination we are documenting is arising from miscalibrated beliefs due to stereotyping (Bordalo et al. 2016).

We conduct a battery of tests to assess the robustness of our inferences. The first set of tests reject the alternative that gender is simply a proxy for adviser characteristics. In our analysis, we control for much of the productivity differences among financial advisers by controlling for each adviser's qualifications, experience, the firm and location at which he or she works, and other characteristics. Moreover, the fact that we observe gender discrimination in firms with a larger share of men on the managerial team suggests that it is unlikely that some unobserved adviser characteristic, such as productivity, is driving our results. Nevertheless, in addition to the tests we discussed above, a few deserve discussion. First, we examine job turnover of advisers who *eventually* engage in misconduct. Suppose female advisers who engage in misconduct have more undesirable characteristics relative to men who engage in misconduct. If such characteristics eventually lead to turnover, biasing our results, then we should expect higher turnover among female advisers *prior* to misconduct. The evidence points in the opposite direction. Second, given that career interruptions can explain a sizable part of the wage gap in the finance industry (Bertrand et al., 2010), we examine whether career interruptions can explain our facts. While career interruptions increase the probability of job separation and decrease reemployment prospects of advisers, they do not explain differences in misconduct punishment across genders. Finally, we also examine the employment decisions of financial advisory firms that are hit with large negative shocks. A firm that decides to downsize will find it optimal to lay off the least productive employees first. If women are less productive, then firms should lay off women at higher rates than men. We find no such differences. The overall evidence in the paper convinces us that our results do not arise because gender proxies for undesirable characteristics across advisers.

Our work contributes to the large literature on gender discrimination. We document a new type of discrimination in a large industry: discrimination in job terminations for missteps. More broadly, our results suggest that gender discrimination can arise in cases where female employees see less leniency for missteps than their male counterparts. 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 gender discrimination. Discrimination could manifest itself on the job in the form of punishment following a misstep. In establishing the mechanism driving this discrimination, we relate to the 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 discrimination in the workplace. A large literature finds gender discrimination 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 discrimination has generally focused on gender differences in the compensation of productive activities, we explore whether gender discrimination carries over to punishment of undesirable activities as well. Moreover, in the discrimination in punishment that we establish, employer knows the employee, thus reducing the potential for "attention discrimination" (Bartos et al., 2016).

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 discrimination, consistent with the findings of Beaman et al. (2012), De Paola and Scoppa (2015), and Cardoso and Winter-Ebmer (2007).

After documenting gender discrimination in the financial advisory industry, we empirically examine whether the observed discrimination is consistent with taste-based discrimination, statistical discrimination and/or miscalibrated beliefs in the spirit of Altonji and Pierret (2001), Barres (2006), Knowles et al. (2001), Charles and Guryan (2008), and Arnold et al. (2017). Our paper is related to Lavy (2008) and Beaman et al. (2009) who provide evidence of the importance of stereotypes in driving discrimination. Instead of focusing on compensation as the labor outcome, we focus on punishment of misconduct through 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).

2 Gender Composition of Financial Advisers

2.1 Data Construction

Our data set contains all 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 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 brokers (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. This panel includes 644,277 currently registered advisers and 638,528 previously registered advisers who have since left the industry. For each of the roughly 1.2 million advisers in the data set, we observe the following information:

- The adviser's registrations, licenses, and industry exams he or she has passed.
- The adviser's employment history in the financial services industry. For many advisers we observe employment history dating back substantially further than the past ten years.
- Any disclosures filed, including information about customer disputes, whether these are successful or not, disciplinary events, and other financial matters (i.e., personal bankruptcy).

FINRA requires that "all individuals registered to sell securities or provide investment advice are required to 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 across the time period of our data. A disclosure indicates any sort of dispute, disciplinary action, or other financial matters concerning the adviser. Not all disclosures are indicative of fraud or wrongdoing. We describe the broad classification of disclosure categories in detail in Appendix A-1. We classify the categories of disclosures that are indicative of fraud or wrongdoing as misconduct. We classify other categories that are less directly indicative of wrongdoing into a separate category called "Other Disclosure." A detailed analysis of misconduct classifications and additional details describing the data set are in Egan, Matvos, and Seru (2017).[4]

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 as both male and female even once, the name is classified as being unisex.[5] We are able to match 97% of names in the BrokerCheck database to names in the GenderChecker database. We are able to assign genders 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 remaining15% 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 A3). Summary statistics for

[4] Our share of advisers with disclosures over the 2005 to 2015 period, 12.7%, closely matches those by FINRA of 12.6%, estimated for currently registered advisers in March of 2016.

[5] Or one of GenderChecker's other data sources.

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.

2.2 Gender Composition of Financial Advisers

2.2.1 Gender differences

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 underrepresented among executives/owners of the financial advisory firms. Figure 2b 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. It will be important to account for these differences among male and female advisers in our analysis that assesses misconduct propensity and labor market outcomes subsequent to misconduct for the two groups.

2.2.2 Who Employs Female Advisers?

Although the percentage of female advisers in the industry has remained practically constant over the past ten years, there are substantial differences among firms in the share of female advisers they employ. Figure 2a displays the percentage of female advisers working at firms with at least 100 advisers. The percentage of female advisers within a firm varies from a minimum of nearly 0% to over 70%. Firms that employ more female advisers tend to be larger and have a larger share of female owners and executives. Among female

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

advisers, the mean and median firm size is 7,354 and 4,139. In comparison, the mean and median firm size for male advisers is 6,310 and 2,877. There are also strong geographic differences in the dispersion of female advisers. Table A1 displays the distribution of male and female advisers across states. For example, female advisers make up one in three advisers in Iowa but only one in six advisers in Utah.

2.2.3 Turnover

Only 25% of employees in this well-compensated industry are women, and this share has remained quite stable over the last decade. One might think that such a steady ratio reflects a very low turnover rate in the industry. Figure 3 plots the job turnover rates for male and female financial advisers over the past ten years. Turnover is substantial; 19% of male and female advisers per year either switched firms or left the financial advisory industry. Part of the reason the share of female advisers has remained so constant is because the job turnover rates among male and female advisers have been nearly identical over the corresponding period, exhibiting a correlation of 0.98.

2.3 Misconduct Across Genders

Approximately 7% of financial advisers have records of past misconduct (Egan, Matvos, and Seru, 2017). Here, we show that misconduct is substantially more prevalent among men than women. 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 disclosure during their career. This measure suggests that the unconditional probability that an investor will encounter a dishonest adviser is three times as high among male advisers.[7]

Because male financial advisers have longer tenures, the differences in past misconduct records may be driven by tenure, rather than the propensity to engage in new misconduct. Therefore, we also measure the amount of new misconduct, that is, how many financial advisers engage in misconduct during a given period of time. Columns (1) and (2) of Table 1a show that the probability that an adviser engages in 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. As a result, males account for 92% of all misconduct among financial advisers.

Table 2 displays additional details on the misconduct disclosures received by male and female advisers. Table 2a displays the most commonly reported types of allegations in the misconduct disclosures. In general, the distribution of type of complaints received by male and female advisers is comparable, although there is more variation in the complaints received by female advisers. Similarly, Table 2b shows that the types of financial products reported in misconduct disclosures are comparable across male and female advisers. These simple summary statistics suggest that male and female advisers engage in similar types of misconduct even

[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%.

though the incidence of misconduct is substantially 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. The summary statistics reported in Table 1a indicate that, while male and female advisers are similar on a number of observable dimensions, male advisers tend to hold more qualifications and are more experienced. We first examine this hypothesis using simple cuts of the data. Different qualifications allow advisers to provide different services, as well as perform different supervisory activities. Figure 4a displays the incidence of misconduct among male and female advisers conditional on having completed some of the most popular exams: the Series 63, 7, 6, 65/66, and/or 24. These exams are indicative of the type of services a given adviser might be providing. The incidence of misconduct among male advisers is 2-3 times higher than the incidence of misconduct among female advisers across these exams.

Figure 4b displays the percentage of male and female advisers with a record of misconduct conditional on their experience. The figure indicates that, conditional on experience, male advisers are more than twice as likely to engage in misconduct relative to female advisers across all experience levels. This is the case for very experienced advisers, those with over 20 years of experience, as well as entry-level advisers with just 2-3 years of experience. Therefore, gender differences in misconduct do not arise because the career paths of female and male advisers evolve differently over time. We separately investigate gender differences in misconduct among less and more experienced advisers in Section 4.2.3.

The results displayed in Figures 4a and 4b suggest that male and female advisers differ in their propensity for misconduct, and that these differences are not driven by experience and qualifications among male and female advisers. Differences between genders could nevertheless arise, either because female advisers work at firms which engage in more misconduct, or because they are exposed to different regulatory or market conditions. To account for these concerns, we examine gender differences in misconduct more systematically using the following linear probability model:

$$Misconduct_{ijlt} = \alpha Female_{ijlt} + \beta X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \tag{1}$$

Observations are at the adviser-by-year level; i indexes an adviser who worked for firm j, at time t, and in county l. The dependent variable $Misconduct_{ijlt}$ is a dummy variable indicating that adviser i received a misconduct disclosure at time t. The independent variable of interest is the dummy variable $Female_{ijlt}$, which indicates the gender of the adviser. We control for firm $\times$ year $\times$ county fixed effects μ_{jlt}. Doing so accounts for differences across firms and branches, such as the firm clientele and/or the products the firm branch is selling. The fixed effects also account for aggregate shocks such as the financial crisis and variation in regulatory conditions (subsuming any state- or county-level regulatory variation). That is, we identify the effects by looking within the same firm, in the same location, and in the same period of time. We also control for the qualifications held by an adviser (Series 7, Series 63, etc.), the number of states an adviser is registered in, which proxies for whether or not and adviser is client facing (see Egan et al. 2017), and the adviser's experience in the industry in the vector X_{it}.

Table 2d displays the results. In each specification, we estimate a negative and statistically significant relationship between the adviser's gender and the probability the adviser engages in misconduct at time t. The estimates in column (1) indicate that the probability a female adviser engages in misconduct in a given year is 0.42pp lower than that of a male adviser. Therefore, relative to male advisers (0.72pp from Table 1b), female advisers within the same firm at the same time in the same county (column 3) are less than half as likely to engage in misconduct. These results suggest that men engage in more misconduct and gender differences in misconduct are not simply a function of the types of firms male and female advisers work for, or their roles within the firm.

3 Labor Market Consequence of Misconduct across Genders

Roughly one in eleven male advisers and one in thirty-three female advisers have records of misconduct. 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 examine whether the punishment for misconduct is meted out evenly across genders.

3.1 Job Separation, Misconduct, and Gender

We first examine whether, relative to male advisers, female advisers face differential 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. These differences do 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.[8] In other words, on average, without misconduct, male and female financial advisers face similar job turnover rates. Female advisers, however, are substantially more likely to lose their jobs following misconduct.

The extremely similar turnover rates of male and female advisers in absence of misconduct strongly suggest that the increased job loss of female advisers following misconduct is not likely driven by sorting of advisers across 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 in the same location, and at the same point in time, by estimating the following linear probability model:

[8]As shown in Figure 3, and discussed earlier, despite turnover fluctuations year to year, turnover rates among male and female advisers are nearly identical over the period 2005-2015, with a correlation of 0.98.

$$Separation_{ijlt+1} = \beta_1 Female_{ijlt} + \beta_2 Misc._{ijlt} + \beta_3 Misc._{ijlt} \times Female_{ijlt} + \beta_4 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \quad (2)$$

Observations are at the adviser-by-year level; i indexes an adviser who worked for firm j at time t in county l. The dependent variable $Separation_{ijlt+1}$ is a dummy variable indicating that the adviser is *not* employed at firm j in year $t+1$. The independent variable $Misconduct_{ijlt}$, is a dummy variable indicating that the adviser received a misconduct disclosure in year t. The independent variable of interest is $Misconduct_{ijlt} \times Female_{ijlt}$, which measures the differential punishment of male and female advisers. We control for advisers' characteristics such as experience and qualifications in X_{it}. To control for differences in firms' attitudes towards misconduct or different turnover rates, demographics differences, and local labor market conditions, we include firm$\times$ year $\times$ county fixed effects μ_{jlt}. That is, as before, our effects will be identified by comparing advisers within the same firm, operating in the same location, and in the same period of time.

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. For example, the coefficient of 29 reported in column (2) implies that, all else equal, misconduct is associated with a 29pp-higher chance of a job separation among male advisers. In each specification, we estimate a positive and statistically significant coefficient on $Misconduct_{ijlt} \times Female_{ijlt}$ between 8 and 10, which changes little as we include the firm $\times$ year $\times$ county fixed effects μ_{jlt}.[9] The coefficient of 8 implies that female advisers have an 8pp higher probability of experiencing a job separation following misconduct relative to male advisers. 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 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.[10]

3.2 Gender Differences in Labor Market Costs of Misconduct

3.2.1 Reemployment

If firms are more tolerant of misconduct by male financial advisers in separation decisions, they may also be more tolerant of their misconduct in hiring decisions. The distinction between hiring and separation of advisors with misconduct records is important, because firms fire advisers for misconduct committed at the

[9] Following Oster (2016) and Altonji, Elder, and Taber (2005a, 2005b, 2008) on unobservable selection, we calculate the lower bound of our estimated coefficient on $Misconduct_{ijlt} \times Female_{ijlt}$ to be 4.5. In particular, following Oster (2016), we calculate the lower bound using $R^2_{max} = 1.3 \times \tilde{R}^2$, where $\tilde{R}^2 = 0.33$ (Table 3b column 3).

[10] As an extension, in Table A2 we show that female advisers are also less likely to be promoted following misconduct.

same firm, but rehire advisers based on misconduct committed at other firms. Firms may be willing to discipline an adviser who engages in misconduct, even if the adviser is not going to engage in misconduct in the future, simply to deter future misconduct by other advisers at the firm. Refusing to hire advisers with misconduct records, however, is not about punishing them for offenses committed at another firm. Firms would refrain from such hires because these advisers are more likely to engage in future misconduct, or because customers do not want to do business with firms who hire such advisers. Therefore, gender differences may play a different role in separation decisions than they do in rehiring decisions.

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 8pp less likely to find new employment following misconduct relative to male advisers.[11]

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

$$New\_Employment_{ijlt+1} = \beta_1 Female_{ijlt} + \beta_2 Misc._{ijlt} + \beta_3 Misc._{ijlt} \times Female_{ijlt} + \beta_4 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \quad (3)$$

We restrict the sample to financial advisers who were separated from their jobs in the previous year. $New\_Employment_{ijlt+1}$ is equal to one if the adviser i who had been employed at firm j in location l has found new employment in the industry between time t and $t+1$. The independent variable of interest is $Misconduct_{ijlt} \times Female_{ijlt}$, which measures the differential punishment of male and female advisers. We again control for adviser characteristics in X_{it} and firm (original firm at time t) $\times$ year $\times$ county fixed effects μ_{jlt}. 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, and 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 $Misconduct \times Female$ 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

[11] $-8\% = (33\% - 48\%) - (47\% - 54\%)$

advisers who are disciplined at time t are $8-12$pp less likely to find a new job in the next year, this magnitude is substantial. Relative to male advisers', female advisers' decline in reemployment opportunities following misconduct is 30% larger.

Another way to measure differences in reemployment prospects across genders is through the duration of unemployment. Figure 5 displays the unemployment 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 unemployment 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 unemployed after 24 months, while only 44% of male advisers remain unemployed after 24 months. More relevant to differential punishment across genders is the increase in unemployment duration from misconduct. The probability of long-term unemployment following misconduct increases substantially more for female advisers than for their male counterparts.

The simple non-parametric survival analysis in Figure 5 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:

$$\lambda_{it}(\tau) = \lambda_0(\tau) exp\left(\gamma_1 Female_{it} + \gamma_2 Misc._{it-1} \times Male_{it} + \gamma_3 Misc._{it-1} \times Female_{it} + \beta X_{it} + \mu_t\right), \qquad (4)$$

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 3d 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 5. The results indicate that female advisers face longer unemployment 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 unemployment spells for both male and female advisers, but the effect is much larger for female advisers. An unemployed 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 3d column 1). Conversely, an unemployed 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 3a column 1). The results from this section suggest that firms are more tolerant of misconduct by male financial advisers in their hiring decisions.

3.3 Initiating Misconduct: Employers, Customers, or Regulators?

Firms are less tolerant of misconduct by female financial advisers in separation decisions as well as in hiring decisions. Here we delve deeper into the source of these differences. We first cast a wide net and investigate which parties initiate misconduct claims against male and female advisers. We then focus more narrowly on the role of firms and the gender composition of decision makers in firms.

Recent survey evidence suggests that a large majority of women believe that gender discrimination persists within their firms. 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). The fact that firms are less tolerant of misconduct by female advisers , however, need not be caused by firms themselves. Firms could be responding to gender preferences or beliefs of customers, or even regulators. To shed some light on this issue, we examine who triggers the allegation of misconduct: customers, regulators, or advisory firms themselves. Customers can do so for a variety of reasons, ranging from fraud to violations of fiduciary or suitability standards. Similarly, regulators pursue regulatory violations and advisory firms can trigger misconduct allegations as the result of misconduct accusations or if the adviser violated the firms' internal policies.

Table 4a breaks down the share of misconduct originating from each category by the gender of the adviser .[12] The share of misconduct originated by consumers is higher for male advisers (58%) relative to female advisers (46%). Likewise, the share of regulator originated complaints is slightly higher for male advisers (21%) relative to female advisers (17%). However, female advisers are more likely to have misconduct initiated by their firm (41%) relative to male advisers (28%). In other words, firm-initiated misconduct is substantially more common among female financial advisers, suggesting that the source of differential treatment of female advisers may lie with the employer.

To ensure our results are not driven by heterogeneity in experience, qualifications, or firm characteristics, we examine the source of misconduct allegations more formally using the following specification:

$$Firm\_Initiated\_Misconduct_{ijlt} = \beta_1 Female_{ijlt} + \beta_2 X_{it} + \mu_j + \mu_l + \mu_t + \varepsilon_{ijlt}. \tag{5}$$

We restrict our data set to observations in which an adviser has new misconduct disclosure on his/her record. The dependent variable $Firm\_Initiated\_Misconduct_{ijlt}$ is a dummy variable that indicates whether the firm initiated the misconduct proceedings rather than a customer or regulator. The dependent variable

[12] We classify the originating source based on the disclosure categories reported by FINRA. Customer originated disclsoures include "Customer Dispute - Settled", "Customer Dispute - Award", and "Civil - Final" disclosures. Regulator originated disclosures include "Regulatory - Final" and "Criminal - Final Dispoosition" disclosures. Lastly, firm originated disclosures include "Employment Separation after Allegations" disclosures. In Table 4b we display the most frequently reported allegations corresponding to these disclosures.

of interest is the gender of the adviser, $Female_{ijlt}$. We also control for adviser characteristics in X_{it} and include firm, county, and year fixed effects. The results in Table 4c confirm the summary statistics results that, conditional on having a misconduct event, female advisers are substantially more likely (3-14pp) to have a claim initiated by their firm relative to male advisers. The results suggest that the differential punishment across genders may originate within the firm itself, rather than outside the firm.

3.4 Gender Differences in Tolerance after Misconduct Across Firms

If the source of gender differences in tolerance after misconduct 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 explore whether differences between firms, such as the gender composition of management, can explain differences across firms in how female advisers are treated relative to male advisers following misconduct.

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

$$Separation_{ijlt+1} = \beta_{j0} + \beta_{j1} Female_{ijlt} + \beta_{j2} Misc._{ijlt} + \beta_{j3} Misc._{ijlt} \times Female_{ijlt} + \beta_4 X_{it} + \varepsilon_{ijlt}. \quad (6)$$

The firm-specific coefficients of interest β_{j3} measures 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 allow firms to differ in both the extent of misconduct as well as the turnover rate for female advisers without misconduct, by including firm specific coefficients β_{j1} and β_{j1}. Figure 8a displays the dispersion in gender discrimination (β_{j3}) across firms. 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 tolerance after misconduct across firms. We report the firms where female advisers with misconduct face the highest separation rates relative to male advisers in Figure 8b. Three firms with the highest rates are Wells Fargo Advisers, Wells Fargo Investments, and AG Edwards & Sons. Note that all three firms are now affiliated with Wells Fargo & Company. In terms of magnitudes, estimates indicate that relative to the average firm, female advisers at Wells Fargo Advisers are 18pp more likely to experience an employment separation following misconduct relative to male advisers.[13] Overall, the results suggest that gender differences in tolerance after misconduct varies substantially across firms.

3.4.1 Do Female Managers Alleviate Discrimination?

If gender differences we document arise 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

[13] The results displayed in Table 3a indicate that, on average, female advisers are 9pp more likely to experience employment separations following misconduct relative to male advisers. The results displayed in Figure 8b indicate that female advisers at Wells Fargo are 27pp more likely to experience employment separations following misconduct relative to male advisers.

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 9a illustrates the substantial differences in gender composition of firm executives in our sample as of May 2015. We first examine whether differences in the gender composition of executive teams across firms can explain across-firm differences in discrimination. We then look within firms and see whether the gender composition of branch managers can explain differences in discrimination across branches.

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

$$\begin{aligned} Separation_{ijlt+1} &= \beta_1 Misc._{ijlt} + \beta_2 Female_{ijlt} + \beta_4 Misc._{ijlt} \times Female_{ijlt} \\ &\quad + \beta_5 Misc._{ijlt} \times Female_{ijlt} \times Pct\,Female\,Exec_j \\ &\quad + \beta_4 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \end{aligned} \tag{7}$$

Observations are at the adviser-by-year level; i indexes an adviser who worked for firm j at time t in county l. The dependent variable $Separation_{ijlt+1}$ 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 is absorbed by the fixed effect μ_{jlt}. The independent variable of interest is $Misconduct_{ijlt} \times Female_{ijlt} \times Pct\,Female\,Exec_j$, which measures how the differences in punishment across genders depends on the share of female executives. We control for advisers' characteristics such as experience and qualifications in X_{it}. To control for differences in firms' attitudes towards misconduct or turnover rates, demographics differences, and local labor market conditions, we include firm $\times$ year $\times$ county fixed effects (μ_{jlt}).

Table 5a displays the corresponding estimates. Firms with a greater share of female executives are substantially less likely to discriminate. 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 16pp more likely to experience employment separations relative to their male counterparts following misconduct (Table 5a, 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 gender discrimination. 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 $\times$ county $\times$ year level. 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)

[14] The results in column (2) of Table 5a indicate that estimated coefficient on the interaction term $Misconduct \times Female \times Pct\_Female\_Exec$ is -41.0 and estimated coefficient on the term $Misconduct \times Female$ is 14.1. There is no differential in job separation probabilities for male and female advisers following misconduct if $Pct\_Female\_Exec = \frac{14.1}{41.0} = 0.34$.

that are female at the firm $\times$ county $\times$ year level. Figures 9b and 9c display the variation in the variables $Pct\,Female\,Mgmt_{jlt}$ and $Pct\,Female_{jlt}$. We re-estimate specification eq. (7), and separately include and interact the branch-level characteristics $Pct\,Female\,Mgmt_{jlt}$ and $Pct\,Female_{jlt.}$

Tables 5b and 5c display the estimation results corresponding to eq. (7). The results indicate that female advisers employed 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 14pp 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 5c indicate that female and male advisers experience similar outcomes following misconduct when male and female advisers are roughly equally represented at the firm branch.[15]

3.4.2 Female Managers and Misconduct Tolerance in Hiring

Are female executives also more tolerant of female adviser misconduct when considering new hires? Recall that misconduct decreases female advisers' chances of reemployment relative to male counterparts'. We therefore estimate the following specification:

$$New\,Female\,Hires\,Disciplined_{jt+1} = \beta_1 Female\,Mgmt_{jt} + \beta_2 X_{jt} + \mu_s + \mu_t + \varepsilon_{jt}. \quad (8)$$

Observations are at the firm $\times$ 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.

The estimation results are reported in Table 5d. 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 3.6pp 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 is correlated with an 11% 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.

Overall, our results suggest that gender differences in labor market outcomes following misconduct are likely driven by discrimination by male executives of financial advisory firms. Male executives seem to be

[15]The coefficient on the interaction term $Misconduct \times Female \times Pct\,Female$ is -16.9 and estimated coefficient on the term $Misconduct \times Pct\,Female$ is 10.6 (column (2), Table 5c). Thus, there is no differential in job separation probabilities for male and female advisers following misconduct if $Pct\,Female = \frac{10.6}{16.9} = 0.62$.

more forgiving of misconduct by men relative to women. The correlation between discrimination and the share of female executives also deceases the likelihood that our results are driven by unobserved differences in productivity across advisors with misconduct that varies with gender. To explain the striking differences in discrimination across firms and branches within firms, offices with a larger share of women executives would have to employ morewomen with misconduct who who are productive on unobservables than firms with predominantly male executive teams, and do so to a large extent. While this alternative seems unlikely, we will assess it (and other alternative arguments) further in the next section.

4 Gender: A Proxy for Adviser Characteristics?

In this section, we examine whether gender is simply a proxy for adviser characteristics or behavior, which also drive differential labor market outcomes following misconduct. Recall that 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. Nevertheless there could still be two broad alternative reasons as to why a firm may punish misconduct more severely among female advisers. Both these alternatives would be consistent with statistical discrimination. First, gender could be indicative of future misconduct and misconduct costs. If female advisers have higher rates of recidivism or engage in more costly misconduct, then a firm may find it optimal to punish female advisers more severely. Second, gender could be indicative of productivity. If male advisers' productivity differs from that of female advisers, then firms may want to be more tolerant of male misconduct.

Average gender differences in misconduct and productivity across genders, even if unmeasured, are not sufficient to explain our results. We find less discrimination in firms as well as branches within firms with a larger share of female executives, i.e., we find more "in-group" tolerance. To explain the striking differences in discrimination across offices, it is not sufficient that men and women differ in (unobserved) productivity on average. The productivity of women relative to men has to be higher in firms or offices with a larger share of female executives. Alternatively, the extent of misconduct severity of female advisers relative to male advisers' has to be smaller in firms with a larger share of women executives. We therefore feel that the scope for such alternative explanations is quite limited.

Nevertheless, in this section we more directly examine the idea that gender proxies for the extent of misconduct and productivity. We first examine whether female advisers engage in more costly misconduct, are more likely to be repeat offenders, or engage in different types of misconduct. We then examine whether female advisers are less productive, either directly by producing less output, or indirectly through career interruptions or human capital accumulation.

In the last part of this section, we examine the idea that female advisers differ from their male counterparts on dimensions other than productivity or misconduct, for example, risk aversion. It is worth repeating that the risk aversion differences could explain our results only if risk aversion of women relative to men were different in firms and offices within firms with a larger share of female executives. However, to more directly reject the idea that our results are driven by differences in gender specific characteristics, we limit our analysis to men, and find similar patterns of in-group tolerance among minorities.

4.1 Gender: Proxy for Misconduct?

4.1.1 Future Misconduct?

One reason for firms to fire advisers following misconduct is that such advisers are likely to engage in misconduct again in the future (Egan, Matvos, and Seru, 2017). We find that men unconditionally have higher rates of misconduct. Roughly 9% of male and 3% of female advisers engaged in misconduct during their careers. However, it is possible that female advisers with misconduct records are more likely to re-engage in misconduct than their male counterparts. In this case, firms would find it optimal to fire female advisers with a higher probability. Figure 6a displays the share of male and female repeat offenders. 41% of men with misconduct records are repeat offenders, having two or more disclosures of misconduct. Conversely, only 22% of female advisers are repeat offenders. Male advisers are roughly twice as likely to be repeat offenders than female advisers.

To ensure that gender differences in the propensity towards repeat offenses are not driven by differences in firms or qualifications, we more formally examine the propensity of male and female advisers to commit future offenses using a linear probability model. Consider the probability that adviser i, at firm j, in county l engages in misconduct at time t. We estimate the following linear probability model:

$$Misc._{ijlt} = \beta_1 Female_{ijlt} + \beta_2 PriorMisc._{ijlt} + \beta_3 PriorMisc._{ijlt} \times Female_{ijlt} + \beta X_{ijlt} + \mu_{jlt} + \eta_{ijlt}. \quad (9)$$

The dependent variable $Misconduct_{ijlt}$ is a dummy variable indicating that the adviser was disciplined for misconduct at time t. The variable $PriorMisconduct_{ijlt}$ is a dummy variable indicating whether the adviser was ever reprimanded for misconduct prior to time t. The main independent variable of interest is $PriorMisconduct_{ijlt} \times Female_{ijlt}$. 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. To ensure that the correlation between past and future misconduct is robust, we control for firm $\times$ year $\times$ county fixed effects μ_{jlt}. In other words, the fixed effects ensure we compare advisers in the same firm, in the same county, at the same point in time. We also control for the adviser's characteristics in X_{ijlt}.

Columns (1)-(3) in Table 6a displays the corresponding estimates. The $PriorMisconduct_{ijlt}$ 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. The negative coefficient of $-0.7pp$ on $PriorMisconduct_{ijlt} \times Female_{ijlt}$, suggests the tendency of women to engage in repeat offenses is smaller. In other words, women are 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 misconduct. However, the evidence presented in Figure 6a and Table 6a indicates the exact opposite; male advisers are substantially more likely to be repeat offenders than female advisers.

We also examine the rates of recidivism among advisers who not only previously engaged in misconduct but also faced discipline at the firm level for misconduct. Building on our previous specification (eq. 9), we estimate

$$\begin{aligned} Misc._{ijlt} &= \beta_1 Female_{ijlt} + \beta_2 PriorMisc._{ijlt} + \beta_3 PriorMisc._{ijlt} \times Female_{ijlt}. \\ &+ \beta_4 PriorDiscipline_{ijlt} + \beta_5 PriorDiscipline_{ijlt} \times Female_{ijlt} \\ &+ \beta X_{ijlt} + \mu_{jlt} + \eta_{ijlt} \end{aligned}$$

The independent variable $PriorDiscipline_{ijlt}$ is an indicator variable that indicates whether an adviser ever experienced an employment separation following a misconduct event in the past. The main independent variable of interest is the interaction $PriorDiscipline_{ijlt} \times Female_{ijlt}$ which measures the differential rates of recidivism among female and male advisers who were previously disciplined for misconduct. Columns (4)-(6) in Table 6a display the corresponding estimates. The results suggest that firms are disciplining and shedding advisers that are more likely to engage in misconduct in the future. Among male advisers with past records of misconduct, the results in column (4) indicate that those advisers who were fired for misconduct are 3.94pp more likely to engage in misconduct in a given year relative to male advisers who were not fired for misconduct. The results suggest that rates of recidivism for female advisers who either were or were not disciplined for misconduct are substantially lower than their male counterparts'. Among those who faced discipline for misconduct, male advisers are roughly 2pp more likely to engage in misconduct in a given year than female advisers. Similarly, among those who were not disciplined for misconduct, male advisers are roughly 1pp more likely to engage in misconduct than female advisers. We can also use the estimates to compare female advisers who were disciplined for misconduct relative to male advisers who were not disciplined for misconduct. Male advisers who were retained after engaging in misconduct are 0.68pp more likely to engage in new misconduct relative to female advisers who lost their job after previously engaging in misconduct (column 4).[16] The results suggest firms are shedding relatively clean female advisers while retaining male advisers with a higher propensity for misconduct.

4.1.2 Cost of Misconduct?

Female advisers do not seem to engage in more misconduct than male advisers. Neither do they have a higher rate of recidivism. However, harsher punishment may be warranted if women engage in more costly

[16] The probability a male adviser, who was retained after previously engaging in misconduct, engages in new misconduct is equal to the baseline misconduct rate plus $\hat{\beta}_2 = 2.09\%$. The probability a female adviser, who lost her job after previously engaging in misconduct, engages in new misconduct is equal to the baseline misconduct rate plus $(\hat{\beta}_1 + \hat{\beta}_3 + \hat{\beta}_4 + \hat{\beta}_5) = 1.41\%$. Thus, male advisers who were retained after previously engaging in misconduct are 0.68pp (2.09%-1.41%=0.68pp) more likely to engage in new misconduct relative to female advisers who lost their jobs after previously engaging in misconduct.

misconduct. We examine the settlements and damages firms paid to investors as a result of misconduct. Figure 7 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 (see Table 2c). Furthermore, the average settlement of male advisers is more than double that of female advisers (\$832k versus \$320k).

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

$$\ln(Damages)_{ijlt} = \alpha Female_{ijlt} + \beta X_{it} + \mu_j + \phi_l + \psi_t + \varepsilon_{ijlt}. \tag{10}$$

The sample is restricted to instances of misconduct in which settlements or damages were paid to the customer. The dependent variable is $\ln(Damages_{ijlt})$, which measures the damages paid out on behalf of advisers following an incidence of misconduct. The key independent variable of interest is the dummy variable $Female_{ijlt}$. We control for adviser characteristics in X_{it}, firm (original firm at time t), year, and county fixed effects μ_j, ϕ_l, ψ_t. In effect, we compare the outcomes of female and male financial advisers who engaged in misconduct at the same firm, at the same time, in the same county, with the same characteristics.

The results in Table 6b confirm that misconduct committed by male advisers is more costly than misconduct committed by female advisers. On average, damages from female adviser misconduct are $15-20\%$ lower than damages from comparable male advisers. Thus, putting evidence across tests, we find evidence that male advisers engage in more and more costly misconduct. These results are at odds with the idea that more tolerance for male misconduct is warranted because their misconduct is less costly. Instead, firms should punish male advisers *more severely* than female advisers. In other words, even if job separation rates following misconduct were identical, and they are not, these results would still suggest that punishment of misconduct is biased against women.

4.1.3 Type and Classification of Misconduct?

Type of Misconduct: Unauthorized Activity Although female advisers engage in less misconduct and less costly misconduct in terms of settlements, female advisers may still engage in different types of misconduct. The summary statistics displayed in Table 2a suggest that the types of misconduct men and women engage in are roughly comparable in terms of the associated allegations. However, there are some notable differences. Men's misconduct allegations are more likely related to unsuitable investments, misrepresentation, and/or omission of key facts. Firms, and the industry as a whole, may wish to discipline advisers differently depending on the underling allegations.

To alleviate this concern, we 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, so its definition is more precise than that of allegations, which represent unsuitable investment or misrepresentation.

We re-estimate our main results, but replace our definition of misconduct with a narrower definition of misconduct based on unauthorized activity. We first reexamine the probability an adviser experiences an employment separation in eq. (2). We estimate a positive and significant coefficient on the interaction term $Unauthorized\,Activity \times Female$ in each specification (Table 7a). 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. These results suggest that the composition of misconduct does not drive gender differences in punishment that we document in Section 3.1.

We also examine advisers' reemployment prospects conditional on receiving unauthorized activity related misconduct disclosures. We re-estimate eq. (3) and present results in Table 7b. The negative and significant coefficient on the interaction term indicates female advisers are less likely to find new employment relative to their male counterparts following a unauthorized activity misconduct disclosure. Although male and female advisers engage in different types of misconduct on average, these results suggest that differences in the type of misconduct are not the driving force behind our results.

Alternative Misconduct Classifications We define misconduct disclosures using a subset of the 23 disclosure classifications as reported by FINRA following Egan et al. (2017). To see whether our results could be driven by our definition of misconduct, we also measure "Severe Misconduct" using allegations (see Egan et al., 2017), which focuses on more severe instances of misconduct such as explicit fraud.[17] Table 8a reports the incidence of severe misconduct among male and female advisers. Because severe misconduct is a strict subset of misconduct, the incidence of severe misconduct is lower than the incidence of misconduct. Roughly 3.6% of male advisers and 1.1% of female advisers have records of severe misconduct. The results indicate that male advisers are roughly three times as likely to engage in both misconduct and severe misconduct relative to female advisers. We re-estimate our baseline specifications using the severe misconduct definition and present the results in Table 8b. In column (1) we re-estimate eq. (1) to illustrate that male advisers are almost three times as likely to engage in severe misconduct relative to female advisers even after we control for differences across advisers, firms, and time.

We then test whether the labor market is more forgiving of misconduct by male financial advisers even when misconduct is severe. We re-estimate gender differences in job separation following misconduct from eq. (2). The results in column (2) of 8b show that severe misconduct leads to elevated termination for both male and female advisers. However, the punishment is more severe for female advisers, whose probability of

[17] Severe misconduct is defined as any settled regulatory, civil, or customer dispute involving: unauthorized activity, fraud, forgery, churning, selling unregistered securities, misrepresentation, and/or omission of material/key facts. We also include as severe misconduct any finalized criminal cases involving investment-related activities, fraud, and/or forgery.

job termination rises by 24pp relative to 17pp for their male counterparts. In other words, firms are more forgiving of male advisers' misconduct committed on their premises, even when such misconduct is quite severe. Advisory firms are also more tolerant of male financial advisers who engaged in severe misconduct at their previous employer. Female advisers who engage in severe misconduct are 4pp less likely to find new employment relative to male advisers who engage in severe misconduct. These results reaffirm our initial finding that the financial services industry is less tolerant of misconduct among female advisers.

4.2 Gender: A Proxy for Productivity Differences?

4.2.1 Measures of Productivity?

Firms may find it optimal to punish women more severely if it is less costly to punish female advisers relative to male advisers. For example, it would be more costly to fire an adviser that generates $1mm in revenue relative to an adviser who generates $100k in revenue. Firms would optimally be more tolerant of misconduct among their more productive employees.

In our analysis, we control for much of the productivity differences among financial advisers by controlling for each adviser's qualifications, experience, the firm and location at which they work, and other characteristics. As well, in this section use Meridian IQ data, which contains additional details on adviser productivity for a large subset of active financial advisers.[18] We observe information on the adviser's productivity (revenues brought to a firm), assets under management (AUM), and quality[19]. 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.

We examine whether these small observable productivity differences can explain the gender differences we document in Section 3. We first reexamine the probability that male and female advisers engage in misconduct. We re-estimate the linear probability model discussed in Section 2.3 (eq. 1), controlling for adviser productivity. The results in column (1) of Table 9a suggest that female advisers are 46% less likely to receive misconduct disclosures in a given year.[20] The results in column (1) also suggest that more productive advisers are more likely to receive misconduct disclosures: a 100% increase in assets under management is associated with a small, 6% increase in the probability of receiving a misconduct disclosure in a given year. Controlling for productivity leaves the estimates comparable to those corresponding to our baseline specification (Table 2d).

Differences in productivity do not explain our finding that male advisers are more likely to engage in misconduct, but can it explain the differences in firm discipline across male and female advisers? We re-estimate

[18] We only observe productivity information for currently active advisers. This limits our ability to conduct the same reemployment analysis discussed in Section 3.2 since all of the advisers with productivity data are currently employed in the industry.

[19] Meridian IQ has a proprietary success-likelihood measure for a large subset of the advisers in the data set. We control for whether or not the adviser has a "high" or "low" success likelihood.

[20] On average, 0.72% of male financial advisers receive misconduct disclosures in a given year.

the linear probability model discussed in Section 3 (eq. 2) controlling for adviser productivity. We report the corresponding estimates in column (2) of Table 9a. Even controlling for productivity differences, we still find evidence that female advisers are substantially more likely to experience employment separations following misconduct. The results in column (2) indicate that female advisers are 5pp more likely to experience job separations following misconduct relative to male advisers. Advisers that are more productive, manage more assets, and have high quality ratings are less likely to experience employment separations, validating our productivity measures do offset turnover. Overall, the results suggest that the observed differences in productivity do not explain the differences in firm discipline across male and female advisers.

4.2.2 Career Interruptions?

Bertrand et al. (2010) find that career interruptions explain about one-third of the gender wage gap in young professionals in the financial and corporate sectors. We examine whether the differential treatment among male and female advisers can be explained by career interruptions. As in Bertrand et al. (2010), we define a career interruption as an unemployment 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.

Next, we replicate our main analysis for Section 3 to examine whether the discrimination we observe is robust to career interruptions.

Table 9b displays the estimation results for our baseline specifications where we now control for career interruptions. In column (1), we re-estimate eq. (1), where the dependent variable is a dummy variable indicating whether or not an adviser engages in misconduct at time t. The results indicate that after controlling for career interruptions, male advisers are still more than twice as likely to engage in misconduct. More central to our analysis, we reexamine how firms and the industry discipline misconduct after controlling for career separations. In columns (2) and (3) we re-estimate the effect of gender on the probability of job loss and rehiring following misconduct, eq. (2) and (3). Career interruptions do little to explain the different treatment of genders following misconduct: our main results are robust and essentially remain unchanged after controlling for career interruptions. This does not imply that career interruptions have no effect on labor market outcomes. An interruption is correlated with a 5pp increase in job separation rate and a 4pp decrease in reemployment rates, which is consistent with observations in Bertrand et al. (2010).

4.2.3 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 on the job at different rates, or female advisers may be more likely than male advisers to experience career interruptions. Here, we separately examine financial advisers based on different 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 same discriminatory patterns hold for advisers with little experience, this suggests that the observed discrimination is not due to differences in human capital acquisition. Similarly, after 15 years in the industry, the difference between realized and future productivity should be small. If we find that the same discriminatory patterns hold for more experienced advisers, this suggests that the observed discrimination is not due to expectations of higher future productivity growth.

We separately re-estimate our baseline misconduct (eq. 1), employment separation (eq. 2), and reemployment (eq. 3) linear probability models based on the adviser's level of experience in the industry. The corresponding estimates are displayed in Tables 10a and 10b. The results in Table 10a indicate that the same discriminatory patterns hold for less experienced advisers: relative to male advisers, female advisers are 49% less likely to engage in misconduct, 9pp more likely to experience employment separations following misconduct, and 2pp less likely to find new jobs following misconduct relative to male advisers.[21] We find similar patterns for more experienced advisers. Among those advisers with fifteen years experience, female advisers are 50%[22] less likely to engage in misconduct and 4pp 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 issue, given the smaller sample sizes. The discriminatory patterns documented in Section 3 are persistent regardless of the female adviser's level of experience.

4.2.4 Turnover following Large Shocks

Here, we present another test of potential unobserved productivity differences among male and female advisers. We examine the employment decisions of financial advisory firms that are hit with a negative shock. A firm that decides to downsize will find it optimal to lay off the least productive employees first. If women are less productive, then firms should lay off women at a higher rate than men.

We examine firms in our data that experienced large declines in their labor force. We first measure if female advisers are displaced at a higher rate than male advisers among these distressed firms – defined as those with a large reduction in advisor workfoce relative to previous year – by plotting displacement rates in Figure A1. The two series are highly correlated (0.95) and nearly identical. The figure suggests that female employees do not seem to be marginal. We examine these differences more systematically by estimating the following linear probability to compare the displacement rates across male and female advisers:

$$Separation_{ijlt} = \alpha_1 Female_{ijlt-1} + \alpha_2 Female_{ijlt-1} \times Downsize_{ijtl-1} + \beta X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \qquad (11)$$

The dependent variable $Separation_{ijlt}$ is an dummy variable indicating whether adviser i working for firm j in county l at time t experiences a job separation. The independent variable $Downsize_{ijlt-1}$ is a dummy variable indicating that firm j downsized its workforce; the level effect is absorbed by the fixed effect. The

[21] On average, 0.38% of male advisers with five or fewer years of experience receive misconduct disclosures in a given year.
[22] On average, 1.01% of male advisers with fifteen or more years of experience receive misconduct disclosures in a given year.

key independent variable of interest is the interaction between $Female_{ijlt-1}$ and $Downsize_{ijlt-1}$. If female advisers are less productive employees, then we would expect to estimate a positive and significant coefficient for the interaction term $Female_{ijlt-1} \times Downsize_{ijtl-1}$.[23]

Table 11 reports the estimation results across three different definitions of firm downsizing. We define downsizing as a year over year decline in the adviser workforce of 5%, 10%, or 25%. For example, roughly 13% of our data set (in terms of adviser-by-year observations) experiences 10% declines. The average displacement rate at these distressed firms is 45%. When we compare male and female advisers within the same firm at the same time in the same county, we find no evidence that distressed firms downsize more extensively among females; in fact, the coefficient on $Female \times Distressed$ is negative. We find similar results across different definitions of downsizing.

4.2.5 Job Turnover

Another potential alternative explanation for our findings is that the type of female advisers who engage in misconduct have higher rates of turnover, in general, relative to their male counterparts. For example, there could be some omitted variable/characteristic that is correlated with misconduct and turnover for female advisers but not male advisers. We examine this alternative by examining job turnover among male and female advisers before they engage in misconduct.

We reestimate our job separation model (eq. 2) where we restrict the data set to advisers without records of misconduct prior to time t but who eventually receive one or more misconduct disclosure. Table 12 displays the corresponding estimates. The coefficient of interest is the gender of the adviser. In each specification, we estimate a negative and significant relationship between the female dummy variable and employment separation. The results in column (3) indicate that among advisers who engage in misconduct at a latter point in their career, female advisers are 1.45% less likely to experience an employment separation in a given year. The results suggest that the types of female advisers who engage in misconduct do not have higher rates of turnover relative to their male counterparts. In fact, the evidence here is the exact opposite. Female adviser who eventually engage in misconduct historically have lower rates of turnover than comparable male advisers.

4.3 Discrimination and Minorities

In this section we first examine whether the discrimination in punishment and patterns of "in-group" toleranace is limited to gender, or whether it extends to other groups that have traditionally faced discrimination in the labor market.There are several reaons for this analysis. First, we do so to narrow the scope of theories

[23] As additional support for our empirical specification, we first examine the specification

$$Separation_{ijlt} = \alpha_1 Downsize_{ijlt-1} + \alpha_2 Manager_{ijlt-1} \times Downsize_{ijtl-1} + \beta X_{it} + \mu_{jlt} + \varepsilon_{ijlt}.$$

The independent variable $Manager_{ijlt-1}$ indicates whether adviser i holds a General Securities Principal Examination license, which allows the adviser to operate in supervisory capacity. As reported in the Appendix, we find that distressed firms are less likely to lay off managers. This suggest that firms lay off less productive employees during times of distress.

of discrimination that are consistent with out facts. 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).[24] Gender identity norms (Bertrand and Kamenica, 2015) could also drive behavior. If we find that discrimination extends beyond gender, then the theory cannot be gender specific. Second, if the discrimination we observe is driven by miscalibrated beliefs (Bordalo et al, 2016), then this evidence can limit the type of belief distortions that can explain our results.

We examine the labor market consequences 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).[25] We focus our attention to African and Hispanic ethnic origins. 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.

The first difference between female advisers and minority advisers is in the incidence of misconduct. Recall that 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 13a). One potential reason why female advisers could be treated more harshly following misconduct is precisely because of their low average rates of misconduct. In response to low average rates, the market may update more about them after observing misconduct. Recall that such updating not consistent with the data: men have higher rates of recidivism. However, miscalibrated updating based on low rates could still be a possibility. Such miscalibration would suggest milder punishment for minority men, whose base rates of misconduct are higher.

We examine the probability a male adviser experiences an employment separation following misconduct in eq. (2). We include additional controls for the adviser's ethnicity (African or Hispanic) and the interaction of misconduct and the adviser's ethnicity. In each specification in Table 13b, 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 bias in punishment similar female advisers. We find similar results for reemployment following misconduct (Table 13c). 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

[24]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.

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

the industry level while Hispanic advisers face more severe punishment at both the firm and industry level.

4.3.1 Minority Managers: In-group Tolerance

We find less gender discrimination of misconduct punishment in firms with a larger share of female managers. Here, we explore whether minority managers mitigate large punishments of minority men following misconduct. Specifically, we re-estimate the analog of eq. (7) 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 14a suggest that minority advisers working at a branch with no African origin representation at the branch management level are 10pp more likely to experience employment separations following misconduct. However, the estimates also imply that there would be no discrimination in branches where 42% of the branch managers are of the same minority as the adviser. These results suggest that differences in labor market outcomes following misconduct are driven by 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.

4.3.2 Minority Male Managers and Female Advisers

Given that female managers alleviate discrimination against female advisers and minority male managers alleviate discrimination against minority male managers, it is natural to ask whether managers from discriminated groups discriminate less in general. Firms with minority managers (ethnic or gender) could discriminate less because they understand the phenomenon of discrimination better and seek to avoid it. In this framework we would expect minority managers to reduce gender discrimination. If, on the other hand, minority managers do not alleviate gender discrimination, then the mechanism driving discrimination is likely linked to more specific group membership. That is, members of a specific group can then undo discrimination of the members of their own group, but not other discriminated groups. This would arise either because they only understand that the stereotypes about their own group are incorrect but share stereotypes about other groups, or because of simple in-group favoritism. We examine how genders discrimination varies with the ethnic composition of branch management:

$$
\begin{aligned}
Separation_{ijlt+1} \quad = \quad & \beta_1 Misc._{ijlt} + \beta_2 Female_{ijlt} + \beta_4 Misc._{ijlt} \times Female_{ijlt} \\
& + \beta_5 Misc._{ijlt} \times Female_{ijlt} \times Pct\,African\,Mgmt_{jlt} \qquad (12) \\
& + \beta_4 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}.
\end{aligned}
$$

The estimates in Table 14c indicate that female advisers with recent misconduct are 10pp more likely to experience employment separations relative to male advisers with recent misconduct. The estimates suggest that the differential treatment of male and female advisers does not vary with the ethnic composition of the firm's branch management. The estimated coefficient on the triple interaction term $Misc._{ijlt} \times Female_{ijlt} \times Pct\,African\,Mgmt_{jlt}$ is insignificant in each specification, and is positive and small when we include the fixed effects. The results suggest that while managers can alleviate discrimination, they do so within their gender or ethnic group. Group membership seems to play an important role in understanding the differential treatment of advisers across different genders and ethnicities.

5 Discussion: What Drives Discrimination?

We find that female and minority advisers face more severe punishment for misconduct relative to their male and non-minority counterparts at the firm level. A poignant feature of the data is that there is substantial heterogeneity in the observed gender and ethnic discrimination across firms and within firms across firm branches. The empirical evidence indicates that managers are more forgiving of misconduct caused by advisers of their gender or ethnicity. For example, male managers are more forgiving of male advisers who engage in misconduct and are less forgiving of female advisers.

In the Appendix (A.3) we develop a model of gender discrimination in misconduct punishments. The model allows us to more formally map the predictions of different types of discrimination into our empirical results. The model allows for three different types of discrimination. First, managers may be statistically discriminating across male and female advisers (Phelps, 1972; Arrow, 1973). Under this benchmark, managers do not have an inherent prejudice against female adviser. They punish female advisers more severely because misconduct by female advisers is predictive of more frequent misconduct. Second, male managers may engage in taste-based discrimination and have a prejudice against female advisers (Becker 1957). In other words, male managers experience lower utility from employing female advisers. Last, male managers may have miscalibrated beliefs about female advisers due to stereotyping (Bordalo et al. 2016). Managers punish advisers believing they they do so in a profit maximizing way, but use incorrect beliefs based on gender. As result of stereotypes, managers will "assume the worst" and over-estimate the probability of recidivism when they observe misconduct by female advisers early on in the adviser's career.

Each of the three types of discrimination offer different predictions about the nature of discrimination in the data. We contrast the predictions of a pure-statistical discrimination model to one with taste-based discrimination and one with miscalibrated beliefs due to stereotyping. We show that the pure statistical discrimination model can explain several facts; however, it is rejected when its predictions differ from a model with manager bias, either due to miscalculated beliefs or taste-based discrimination. Both models with manager bias, miscalibrated beliefs and taste-based discrimination, offer similar predictions and are consistent with the main discriminatory firing patterns in the data. One key distinction between the miscalibrated beliefs model and taste-based discrimination is that miscalibrated beliefs and stereotypes are context-dependent while taste-based discrimination is not. We show that the observed discrimination in the data is context-dependent, suggesting that miscalibrated beliefs due to stereotypes may be an important factor driving our findings.

5.1 Statistical Discrimination or Manager Bias?

First, we consider the benchmark model, a pure statistical discrimination model without manager bias (either miscalibrated beliefs or taste-based discrimination). We discuss which facts are consistent with this benchmark and then which facts reject it. If female misconduct is punished more, it is because upon observing misconduct, firms rationally update that female advisers have a higher propensity for repeat misconduct or lower productivity than a comparable male adviser.

With respect to productivity, recall that, on average, female advisers have lower rates of misconduct. One possibility is that because female advisers have lower rates of misconduct on average, firms are willing to hire less productive female advisers, all else equal. Therefore, as misconduct is detected, this lower productivity results in more termination among female advisers. This result only holds up if the unobserved productivity of female advisers is lower than that of men – i.e. productivity is poorly measured by the researcher. In Section 4.2 we argue that this is not likely the case, especially for experienced advisers for whom productivity is well known. Nevertheless, the possibility of mis-measurement is always present. Therefore we turn to other predictions that can more directly differentiate between the pure statistical discrimination model and the manager bias models.

The first difference is in repeat offenses. Following the work of Becker's (1957) model of discrimination and, more recently, Arnold et al. (2017), if firms are statistically discriminating across male and female advisers, we would expect the rate of recidivism among male and female advisers to be the same on the margin. In our baseline analysis, we show that recidivism is substantially higher for male advisers than for female advisers on average. Average and marginal misconduct are likely highly correlated. Nevertheless, in Appendix Table A4 we show that this fact is also true for the marginal male and female adviser following the IV method developed in Arnold et al. (2017). The results in 4.1.1 therefore reject the baseline statistical discrimination model since female advisers are less likely to engage in repeat offenses.

Conversely, the miscalibrated beliefs and taste-based discrimination models suggest that female advisers will have lower rates of recidivism. The intuition for the lower rates of recidivism among female advisers in the miscalibrated beliefs model is the following: if male managers incorrectly believe that females are more likely to engage in repeat offenses than males, then managers will fire female advisers with a lower true probability of recidivism relative to comparable male advisers. This behavior will result in lower measured recidivism among female advisers, as we show in the Appendix (A.3.1). The intuition for the lower rates of recidivism among female advisers in the taste-based model is the following: if managers are biased, they impose a stricter threshold for female advisers. Consequently, the marginal female adviser will be less likely to engage in misconduct than the marginal male adviser. This will be the case even if underlying probabilities of repeat offenses between the genders are the same. This test is similar to that employed by Arnold, Dobbie, and Yang (2017) who compare recidivism across racial groups to measure racial bias in bail decisions.[26]

Second, the pure statistical discrimination model have a difficult time explain why gender differences are most present in firms with male management. The intuition of the miscalibrated beliefs and taste-based models are straightforward. Male managers are those with biased beliefs/preferences; more male managers leads to more discrimination. In sum, the model without belief miscalibration or taste-based discrimination is rejected in the data. A more formal discussion is available in Appendix A.3.2.

5.2 Bias: Miscalibrated Beliefs or Taste-Based Discrimination?

Given that our facts reject statistical discrimination, we now discuss whether our results can differentiate between models of managerial bias. In many respects the miscalibrated beliefs due to stereotyping and taste-based discrimination models are observationally equivalent in the data. A firm manager may be more likely to fire a female adviser because (a) the manager's preferences or (b) the manager has biased beliefs about recidivism among female advisers. One way to differentiate between taste-based discrimination and miscalibrated beliefs is that beliefs rely on the information structure. Recall that miscalibrated beliefs due to stereotyping are context dependent and vary with the information structure. As as show in the Appendix (A.3.1), stereotyping causes a male manger to overreact when a female adviser engages in misconduct early on in her tenure with the firm. The manager will be less biased, and may even under-react when a female adviser engages in misconduct later on in her tenure. Taste-based discrimination, on the other hand, is not context dependent and does not depend on the timing of the misconduct (Appendix A.3.2). .

We reexamine the relationship between misconduct and discipline based on the adviser's tenure with his/her firm. Figure 10a displays the coefficients for our baseline employment separation specifications (2) where we separately estimate the regression based on the adviser's experience *within the firm* (Table A5a). The black line plots the change in the probability a male adviser experiences an employment separation following misconduct. The gray line plots the change in the probability a female adviser experiences an employment separation following misconduct.

The probability a female adviser with less than five years tenure within her firm experiences an employment separation increases by 36pp following misconduct. Conversely, the probability a male adviser with less than five years tenure within his firm experiences an employment separation increases by 24pp following misconduct. Although female advisers face disproportionately more punishment when they have limited experience within their firm, Figure 10a illustrates that the differential treatment between male and female advisers decreases with firm tenure. Among advisers with 15-20 years experience within their firms, male and female advisers experience similar levels of discipline following misconduct. Notice that discipline for male advisers remains relatively constant as a function of the adviser's tenure within the firm. The

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decline in discrimination is primarily due to firms holding established female advisers to the same standard as established male advisers rather than an overall decline in discipline.

We find that discrimination in punishment between male and female advisers dissipates over time as the adviser's tenure with his/her firm increases. Contrasting these results with our earlier results from Section 4.2.3, the decline in discrimination is not due to an adviser's total amount of experience in the industry, but is due to an adviser's experience within his/her firm. Figure 10b mirrors Figure 10a and illustrates how the differential punishment between male and female advisers changes with adviser experience rather than firm tenure. Contrary to our findings with firm tenure, gender discrimination does not decrease with an adviser's total experience in the industry. In other words, discrimination is negatively correlated with a female adviser's tenure within her firm but not her overall level of experience. These results are consistent with the notion that the observed discrimination occurring early on in an adviser's tenure within a firm is related to firm beliefs, which evolve over time, rather than some inherent characteristic of the firm.

6 Conclusion

We document large and pervasive differences in the treatment of male and female advisers. Female financial advisers face more severe consequences at both the firm and industry level for engaging in misconduct relative to male advisers. While male advisers are more than two times as likely to engage in misconduct, female advisers are 20% more likely to be fired for engaging in misconduct. Female advisers are also 30% less likely to find new employment and face longer unemployment spells as a result of misconduct.

The observed discrimination could simply be statistical discrimination. Firms may find it optimal to punish women more severely if female advisers engage in more costly misconduct or if female employees are less costly to replace. The empirical evidence suggests the exact opposite. Male advisers tend to engage in more costly misconduct and are twice as likely to be repeat offenders. Conversely, we find evidence suggesting that the observed discrimination is driven by firm biases. Firms initiate relatively more complaints against female advisers. Moreover, there is significant heterogeneity among firms and firms in which males comprise a greater percentage of executives/owners are more likely to punish female advisers more severely and hire fewer female advisers with records of past misconduct. We also find that discrimination dissipates as an adviser's tenure with her firm increases. The dynamic evolution of discrimination is consistent with these patterns being driven by initially miscalibrated/stereotyped beliefs which evolve over time.

Our findings provide new insight into gender discrimination in the workplace. We examine an inconspicuous and potentially costly channel of discrimination: punishment following cause. The financial advisory industry is willing to give male advisers a second chance, while female advisers are less likely to be promoted within the firm, and more likely to be cast from the industry. The narrower margin for error faced by female advisers could also be partially responsible for the glass ceiling observed in the industry.

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

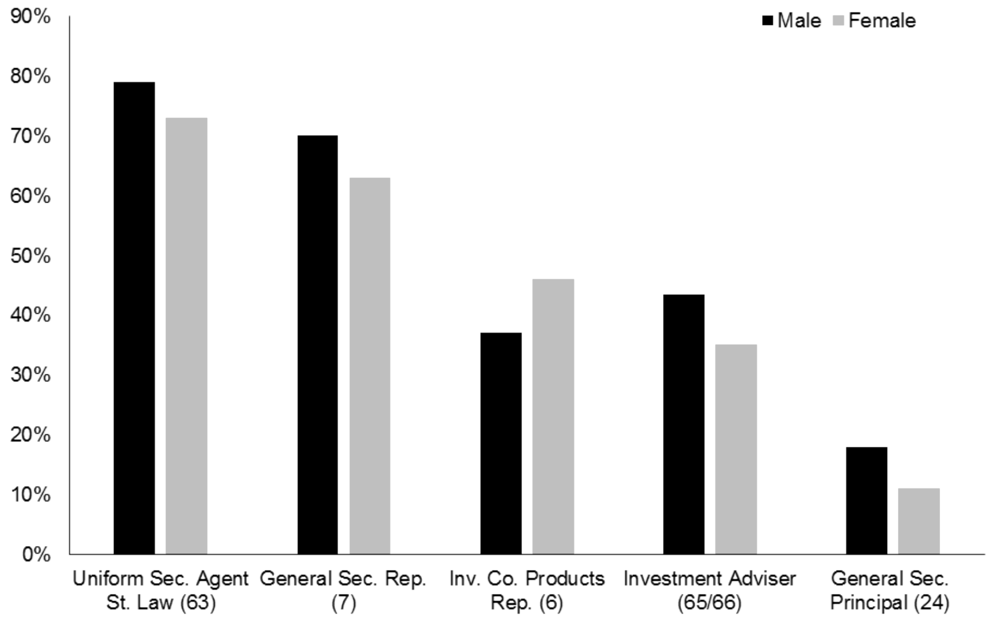
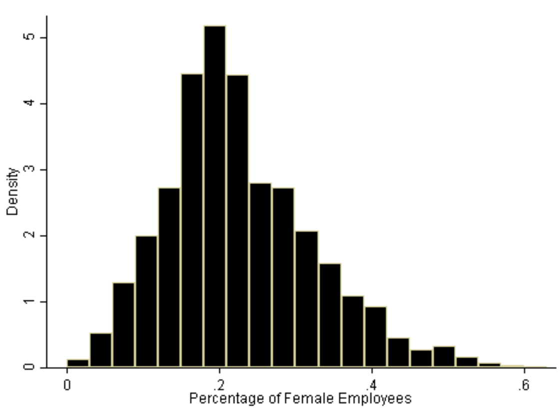


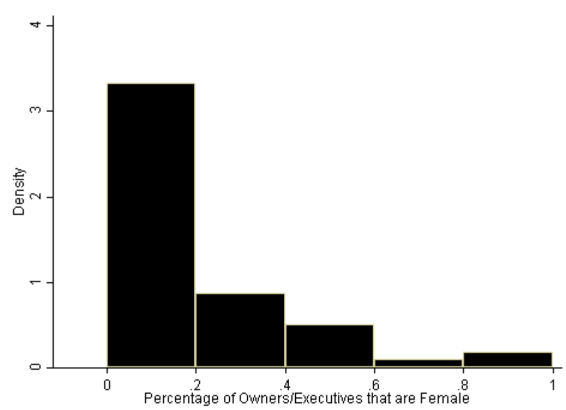
Figure 1 displays the percentage of female and male advisers that hold a particular qualification. We examine the six most popular qualifications. Observations are at the adviser-by-year level over the period 2005-2015.

Figure 2: Distribution of Female Advisors Across Firms

(a) Percentage of Female Advisers

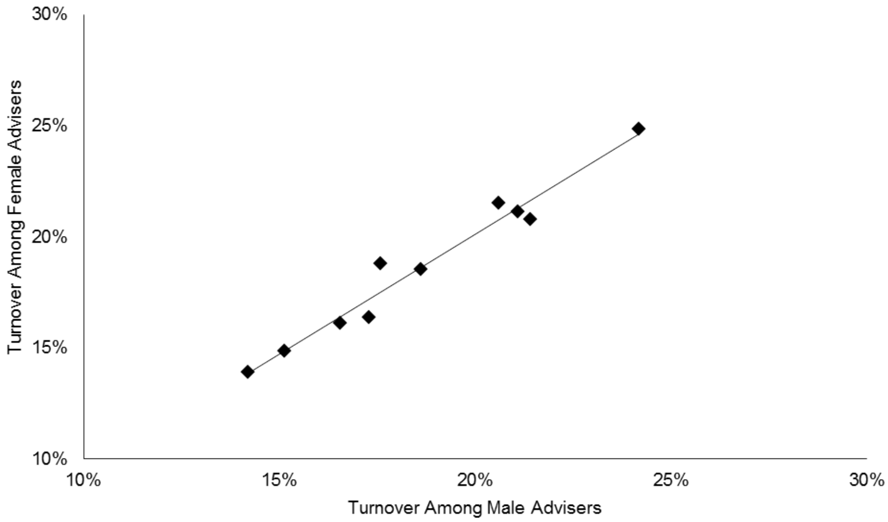


(b) Percentage of Female Executives/Owners



Note: Figure 2a displays a histogram of the percentage of advisers that are female for each firm in our data set with at least 100 advisers. Observations are at the firm by year level over the period 2005-2015. Figure 2b displays the percentage of executives/owners in our sample that are female as of 2015, for each firm in our data set with at least 100 advisers.

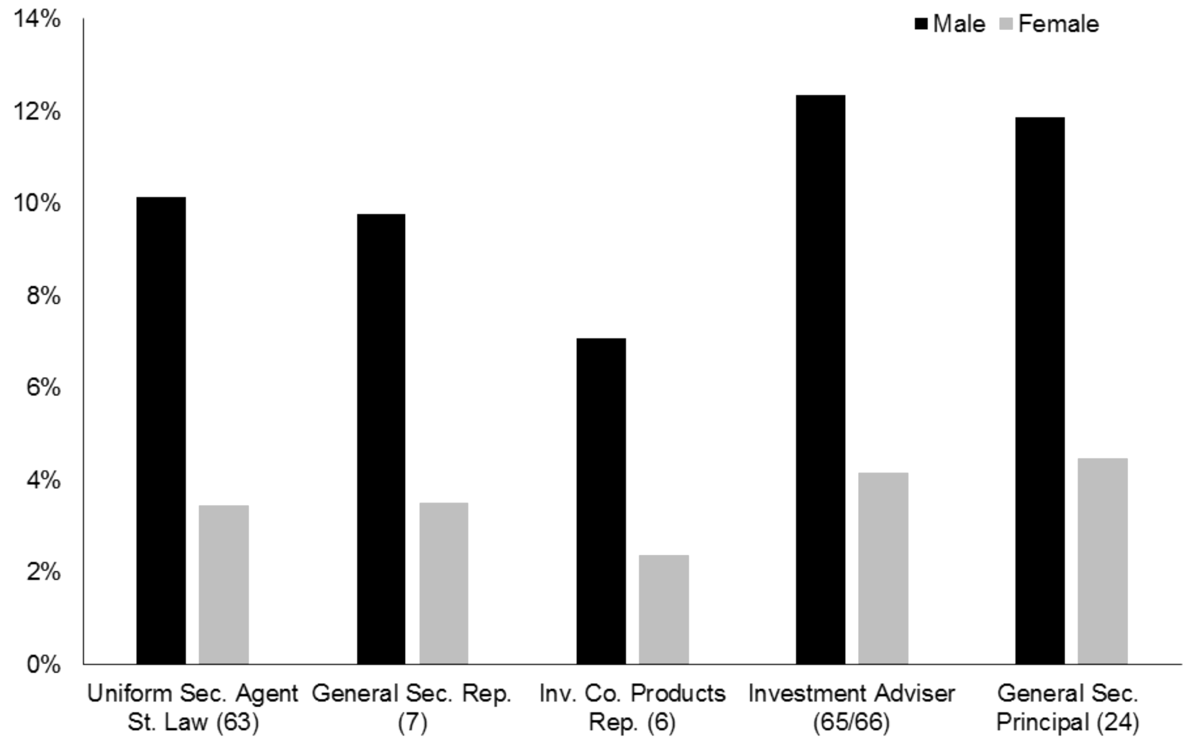
Figure 3: Job Turnover - Male vs. Female Advisers



Note: Figure 3 plots the annual job turnover among male and female advisers over the period 2005-2014.

Figure 4: Misconduct Among Male and Female Advisers

(a) Frequency of Misconduct by Qualification Exam



(b) Frequency of Misconduct by Experience

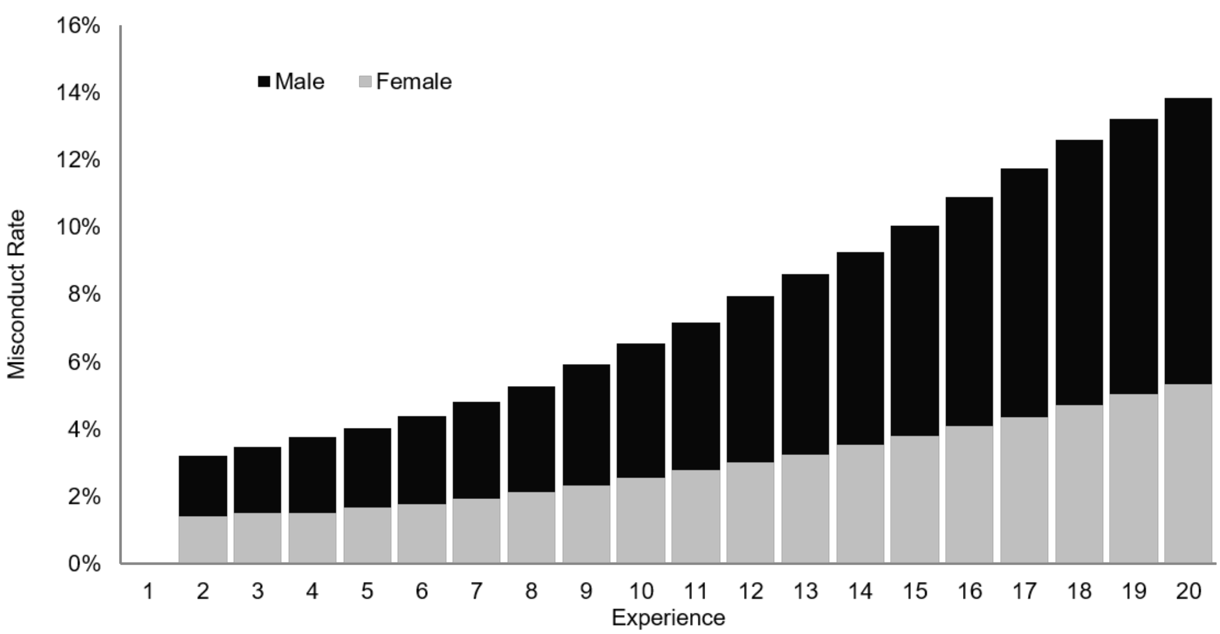


Figure 4a displays the percentage of male and female advisers with misconduct disclosures on his/her record conditional on the advisers holding the specified qualification exam. Figure 4b displays the percentage of male and female advisers with misconduct disclosures on their records conditional on the advisers' experience. Observations are at the adviser-by-year level over the period 2005-2015.

Figure 5: Unemployment and Misconduct

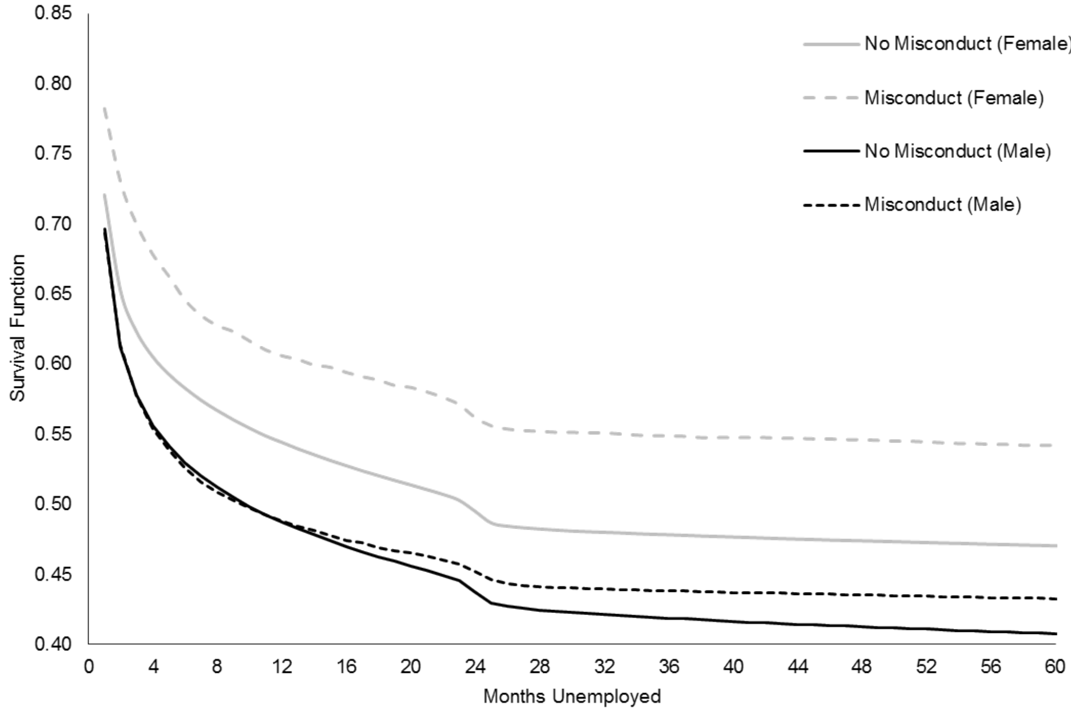
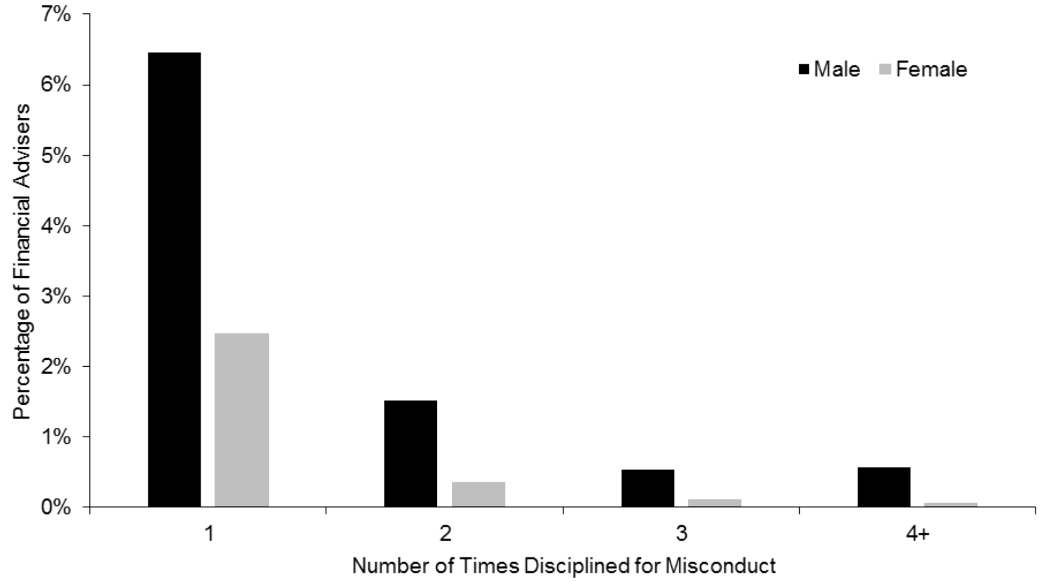


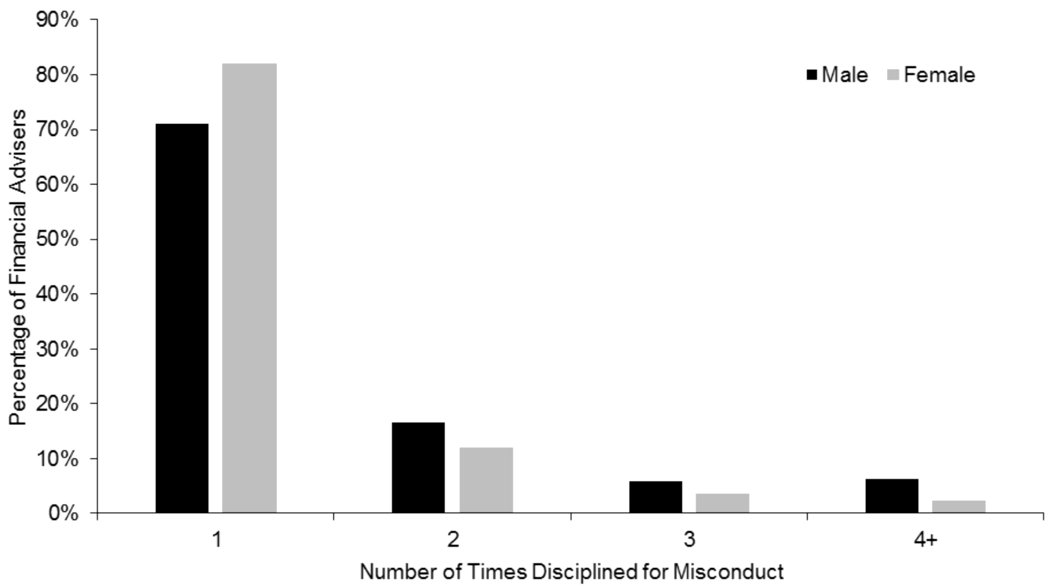
Figure 5 displays the unemployment survival function for all adviser unemployment spells over the period 2005-2015. The solid black and gray lines display the unemployment survival functions for male and female advisers who were not disciplined for misconduct in the year prior to their unemployment spell. The dashed lines display the unemployment survival functions for male and female advisers who were reprimanded for misconduct in the year prior to the adviser's unemployment spell.

Figure 6: Frequency of Misconduct

(a) Distribution of Misconduct

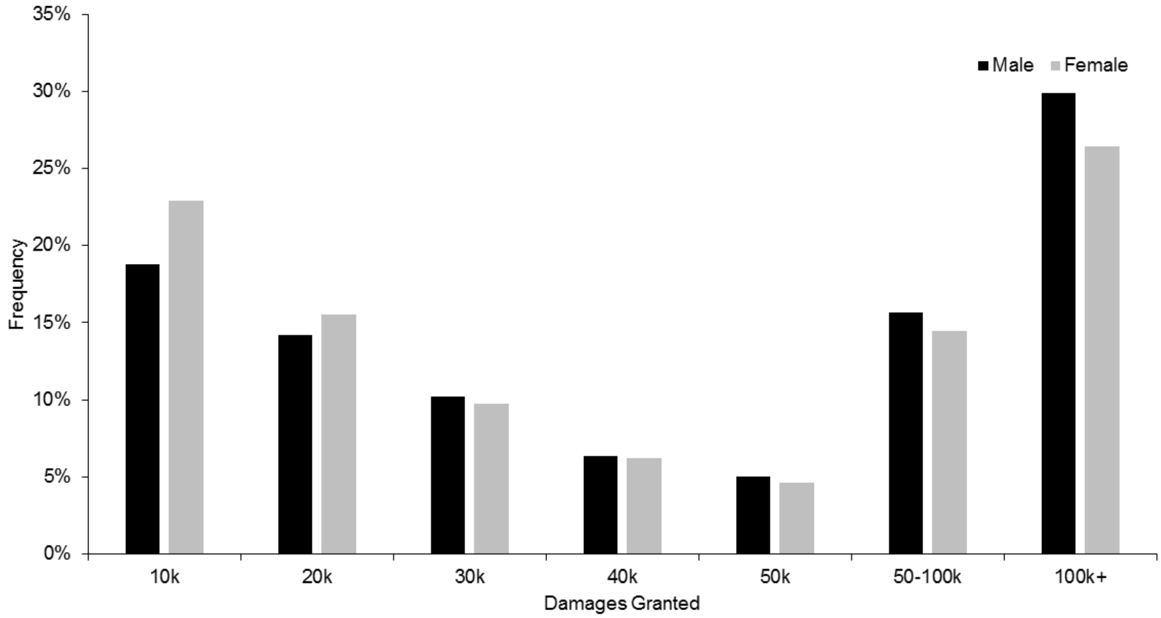


(b) Distribution of Misconduct - Repeat Offenders



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.

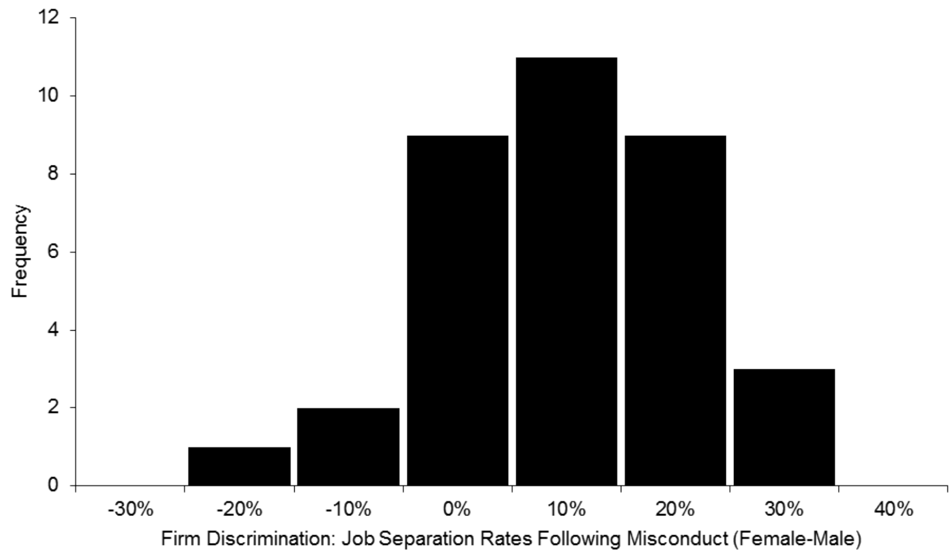
Figure 7: Distribution of Settlments/Damages



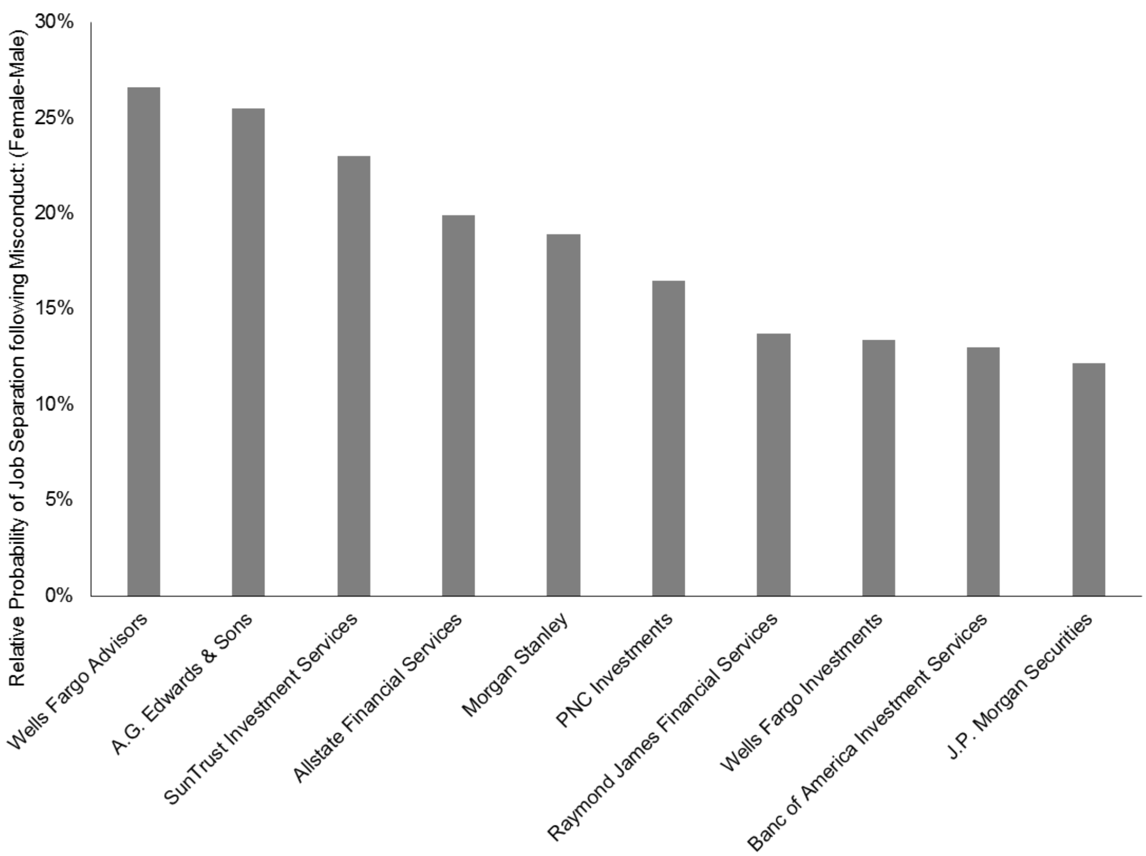
Note: Figure 7 displays the distribution of settlements/damages for male and female advisers that were granted over the period 2005-2015. In the BrokerCheck database, we observe the settlements/damages details for 45.80% of misconduct-related disclosures and 0.55% of the other types of disclosures. Observations are at the financial adviser by year level.

Figure 8: Firm Heterogeniety in Gender Treatment

(a) Distribution of Gender Treatment



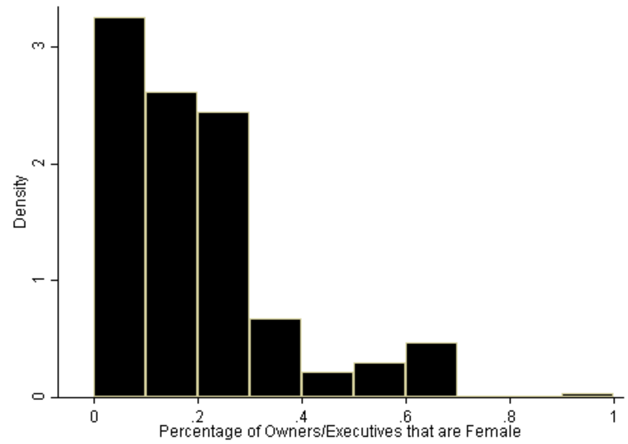
(b) Firms with Least Tolerance



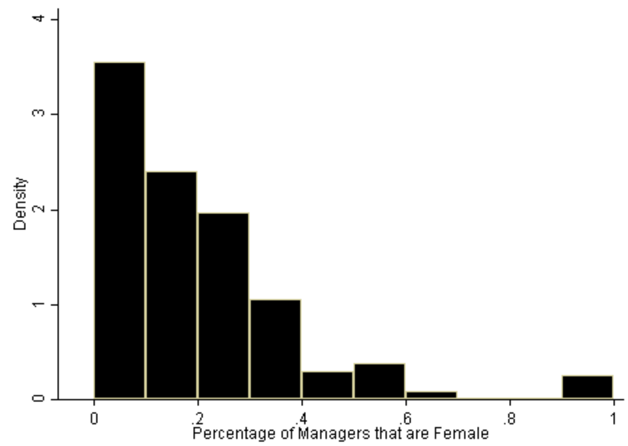
Note: Figures 8a and 8b display the distribution of gender differences in discipline across firms. The figures plot the distribution of the coefficient β_{j3} from eq. (6), which captures the differential probability that female advisers experience employment separations following misconduct relative to male advisers' (i.e., the difference in differences for female and male advisers with and without misconduct). Figure 8b 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 9: Female Representation at Financial Advisory Firms

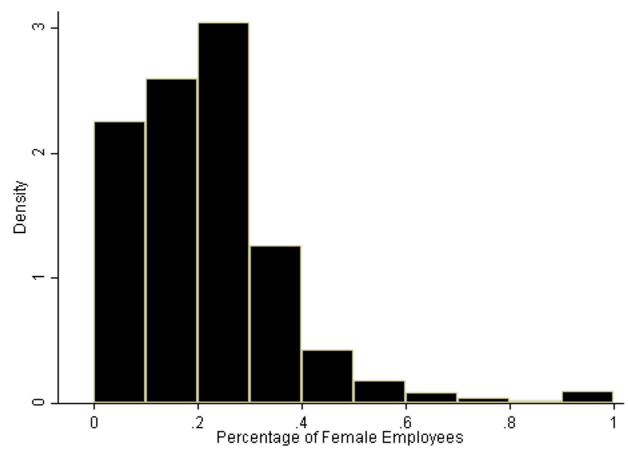
(a) Firm Executives/Ownership



(b) Branch Management



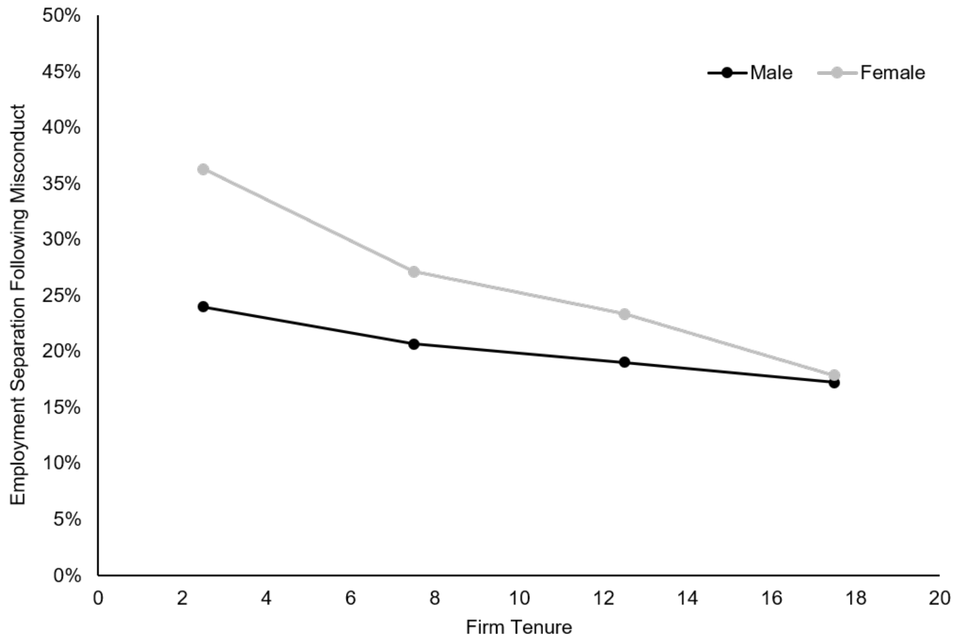
(c) Branch Adviser



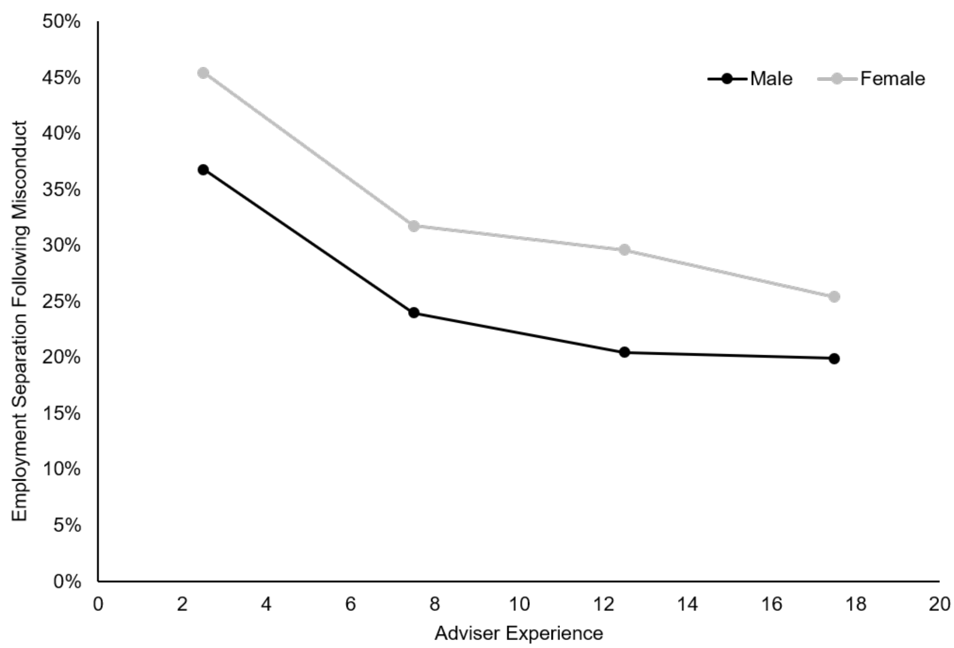
Note: Figure 9a displays the percentage of owners/executives that are female. Figure 9b displays the percentage of managers that are female at the branch level, i.e., at the firm by county by year level. Figure 9c displays the percentage of advisers (weighted by experience) that are female at the branch level, i.e., at the firm by county by year level. Observations in 9a are at the adviser-by-year level as of 2015. Observations in Figures 9b and 9c are at the adviser-by-year level over the period 2005-2015.

Figure 10: Gender Treatement by Firm Tenure and Total Industry Experience

(a) Gender Treatment by Firm Tenure



(b) Gender Treatment by Total Industry Experience



Note: Figures 10a and 10b display the coefficients corresponding to our employment separation linear probability model (2), where we separately estimate the model depending on the adviser's level of within firm and total industry experience. The dependent variable is a dummy variable indicating whether or not an adviser experienced an employment separation in a given year. The corresponding regression estimates and controls are reported in Table A5. The black line plots the increase in the probability of an employment separation following misconduct for male advisers as a function of the adviser's experience within the firm (10a) and total industry experience (10b). The gray line plots the increase in the probability of an employment separation following misconduct for female advisers as a function of the adviser's experience within the firm (10a) and total industry experience (10b) .

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	3.05	1,615,496	2.65
Uniform Sec. Agent St. Law (63)	4,932,478	0.79	1,615,496	0.73
General Sec. Rep. (7)	4,932,478	0.70	1,615,496	0.63
Inv. Co. Products Rep. (6)	4,932,478	0.37	1,615,496	0.46
Uniform Combined St. Law (66)	4,932,478	0.21	1,615,496	0.21
Uniform Inv. Adviser Law (65)	4,932,478	0.23	1,615,496	0.15
General Sec. Principal (24)	4,932,478	0.18	1,615,496	0.11
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.

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%

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.

Table 2: Misconduct Complaints, Products, Settlements/Damages and Incidence of Misconduct across Gender

(a) Reasons for Complaint

Reasons for Complaint	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%

(b) Products

Product	Gender	
	Male	Female
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%

(c) 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

(d) Incidence of Misconduct

	(1)	(2)	(3)
Female	-0.43***	-0.33***	-0.34***
	(0.025)	(0.023)	(0.030)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	6,547,974	6,547,974	6,221,173
R-squared	0.001	0.002	0.097

Table 2a displays the most frequently reported allegations corresponding to the disclosures that occurred over the period 2005-2015. We observe allegations for 91.89% of the misconduct-related disclosures. The allegation categories are not mutually exclusive. The "Other" category includes all other allegations/classifications that were reported with a frequency of less than 2%. Table 2b displays the most frequently reported financial products in the allegations. Over half of the allegations do not list specific financial products. Table 2c 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 2d displays the regression results for a linear probability model (eq. 2). The dependent variable is a dummy variable indicating whether or not the adviser was formally disciplined for misconduct in year t. Coefficients are in percentage points. 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 3: 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 Consequences: Employment Separation

	(1)	(2)	(3)
Misconduct	27.65***	29.04***	22.26***
	(1.47)	(1.40)	(1.52)
Misconduct × Female	8.32***	8.18***	10.19***
	(2.05)	(1.96)	(1.91)
Female	0.14	-0.88**	-0.75***
	(0.29)	(0.35)	(0.16)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	6,002,088	6,002,088	5,698,577
R-squared	0.004	0.011	0.331

(c) Industry Level Consequences: New Employment

	(1)	(2)	(3)
Misconduct	-7.66***	-11.70***	-8.92***
	(2.13)	(1.36)	(1.03)
Misconduct × Female	-7.22***	-5.36***	-3.46***
	(1.80)	(1.30)	(1.18)
Female	-6.22***	-1.33**	-2.91***
	(0.65)	(0.61)	(0.26)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	1,125,715	1,125,715	1,006,760
R-squared	0.003	0.125	0.379

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. 2 and 3). 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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 3: Labor Market Outcomes Following Misconduct (contd.)

(d) Unemployment Duration

	(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 3d displays the estimation results corresponding to a Cox proportional hazard model (eq. 4). The dependent variable is the length of an unemployment spell in months. The key independent variable of interest, Misconduct, is a dummy variable indicating whether or not the adviser was disciplined for misconduct 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 unemployment spell level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: Distribution of Misconduct Claims

(a) Financial Adviser Misconduct by Origination Source

Origination Source	Gender	
	Male	Female
Customer Originated	58%	46%
Firm Originated	28%	41%
Regulator Originated	21%	17%
Any Misconduct Disclosure	100%	100%

(b) Allegations related to "Employment Separation after Allegations"

Reasons for Employment Separation	Gender	
	Male	Female
Unauthorized Activity	13.0%	13.7%
Omission of Key Facts	9.4%	4.6%
Fee/Commission Related	3.1%	2.4%
Unsuitable	2.7%	1.3%
Misrepresentation	1.9%	1.3%
Fraud	1.8%	1.9%
Other	70.9%	76.4%

(c) Firm Initiated Misconduct

	(1)	(2)	(3)
Female	13.72***	7.17***	3.35***
	(2.46)	(1.26)	(0.92)
Adviser Controls		X	X
Year F.E.			X
County F.E.			X
Firm F.E.			X
Observations	40,264	40,264	38,406
R-squared	0.009	0.107	0.307

Note: Table 4a displays the conditional probability that an adviser has a type of misconduct disclosure in a given year, conditional on the adviser's engaging in misconduct in the given year. We classify the originating source based on the disclosure categories reported by FINRA. Customer originated disclosures include Customer Dispute - Settled, Customer Dispute - Award, and Civil - Final disclosures. Regulator originated disclosures include Regulatory - Final and Criminal - Final Disposition disclosures. Lastly, firm originated disclosures include Employment Separation after Allegations disclosures. Observations are at the adviser-by-year level over the period 2005-2015.
Table 4b displays the most frequently reported allegations corresponding to disclosures classifed as "Employment Separation after Allegations" over the period 2005-2015. We observe allegations for 98.6% of the misconduct related disclosures. The allegation categories are not mutually exclusive. The "Other" category includes all other allegations/classifications that were reported with a frequency of less than 1%.
Table 4c displays the regression results for a linear probability model (eq. 5). The dependent variable is a dummy variable indicating whether or not the adviser experienced a misconduct event that was initiated by his/her firm in year t. We restrict our data set to those adviser-by-year observations in which an adviser experienced a misconduct event. Standard errors are in parentheses and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Firm Characteristics and Gender Differences in Tolerance

(a) Executive Gender Composition and Firm Separation

	(1)	(2)	(3)
Misconduct	53.51***	54.08***	51.39***
	(4.86)	(4.43)	(5.29)
Misconduct × Female	14.69***	14.06***	16.41***
	(3.03)	(2.97)	(3.52)
Misconduct × (Pct Female Exec)	-24.55	-23.01	-25.49
	(15.57)	(14.32)	(16.78)
Misconduct × Female × (Pct Female Exec)	-40.74***	-41.03***	-43.32***
	(14.31)	(14.13)	(16.19)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	564,905	564,905	541,137
R-squared	0.010	0.018	0.143

(b) Branch Manager Gender Composition and Firm Separation

	(1)	(2)	(3)
Misconduct	25.24***	26.78***	19.98***
	(1.26)	(1.18)	(1.30)
Misconduct × Female	11.23***	10.86***	13.55***
	(2.68)	(2.54)	(2.35)
Misconduct × (Pct Female Mgmt)	10.09***	9.83***	11.15***
	(2.64)	(2.51)	(2.45)
Misconduct × Female × (Pct Female Mgmt)	-13.49***	-12.58***	-18.15***
	(4.65)	(4.46)	(3.74)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	4,927,304	4,927,304	4,807,888
R-squared	0.003	0.011	0.315

(c) Branch Gender Composition and Firm Separation

	(1)	(2)	(3)
Misconduct	24.27***	25.62***	16.62***
	(1.11)	(1.07)	(1.29)
Misconduct × Female	10.44***	10.57***	11.79***
	(3.23)	(3.07)	(3.11)
Misconduct × (Pct Female)	19.80**	19.87***	30.00***
	(8.28)	(7.62)	(8.81)
Misconduct × Female × (Pct Female)	-15.93*	-16.86**	-16.17**
	(8.16)	(7.61)	(6.79)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	5,990,929	5,990,929	5,695,544
R-squared	0.004	0.011	0.331

Table 5: Firm Characteristics and Gender Differences in Tolerance (contd.)

(d) Firm Hiring

	(1)	(2)	(3)
Pct Female Exec	0.0082**	0.0082**	0.0093**
	(0.0037)	(0.0037)	(0.0038)
Adviser Controls	X	X	X
Year F.E.			X
State F.E.			X
Observations	1,982	1,982	1,982
R-squared	0.012	0.012	0.049

Note: Table 5a displays the results for a linear probability model (eq. 7). 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. Observations in Table 5a are at the adviser level in 2015. Observations in Tables 5b and 5c are at the adviser-by-year level over the period 2005-2015. Standard errors are in parentheses and are clustered by firm.

Table 5d 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. 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 6: Expected Future Misconduct and Severity of Misconduct

(a) Recidivism

	(1)	(2)	(3)	(4)	(5)	(6)
Prior Misconduct	2.42***	2.31***	1.92***	2.09***	1.99***	1.65***
	(0.10)	(0.100)	(0.077)	(0.089)	(0.085)	(0.068)
Prior Misconduct × Female	-0.69***	-0.70***	-0.57***	-0.56***	-0.56***	-0.49***
	(0.099)	(0.099)	(0.090)	(0.095)	(0.095)	(0.086)
Prior Discipline				3.94***	3.91***	3.52***
				(0.28)	(0.28)	(0.25)
Prior Discipline × Female				-1.70***	-1.72***	-1.19***
				(0.43)	(0.43)	(0.45)
Female	-0.27***	-0.22***	-0.25***	-0.27***	-0.22***	-0.25***
	(0.017)	(0.018)	(0.026)	(0.017)	(0.018)	(0.026)
Adviser Controls		X	X		X	X
Year×Firm×County F.E.			X			X
Observations	6,547,974	6,547,974	6,221,173	6,547,974	6,547,974	6,221,173
R-squared	0.007	0.007	0.101	0.008	0.008	0.101

(b) Settlements/Damages Granted by Gender

	(1)	(2)	(3)
Female	-0.20***	-0.11**	-0.14***
	(0.052)	(0.048)	(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	0.034	0.246

Note: Table 6a displays the regression results for a linear probability model (eq. 9). 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. Table 6b displays the results for linear regression model (eq. 10). The dependent variable is the log damages paid out on behalf of a financial adviser as the result of a misconduct settlement/arbitration. 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 financial adviser by year level over the period 2005-2015. We restrict the data set to only those observations in which the adviser was disciplined for misconduct 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 7: Labor Market Outcomes Following Misconduct Disclosure related to Unauthorized Activity

(a) Employment Separation

	(1)	(2)	(3)
Unauthorized Activity	35.60***	36.81***	27.84***
	(1.57)	(1.48)	(1.86)
Unauthorized Activity × Female	10.35***	10.27***	14.46***
	(3.20)	(3.05)	(3.21)
Female	0.057	-0.94***	-0.79***
	(0.29)	(0.35)	(0.16)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	6,002,088	6,002,088	5,698,577
R-squared	0.001	0.008	0.330

(b) New Employment

	(1)	(2)	(3)
Unauthorized Activity	-11.31***	-14.58***	-10.84***
	(2.47)	(1.64)	(1.19)
Unauthorized Activity × Female	-13.44***	-11.57***	-7.227**
	(2.48)	(2.54)	(3.53)
Female	-6.21***	-1.29**	-2.88***
	(0.65)	(0.61)	(0.26)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	1,125,715	1,125,715	1,006,760
R-squared	0.003	0.124	0.379

Tables 7a and 7b display the regression results corresponding to linear probability models (eq. 2 and 3). The dependent variable in Table 7a 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 7b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 7b, we restrict the sample to those advisers who left their firm in a given year. The independent variable Unauthorized Activity indicates whether or not an adviser received a misconduct disclosure in a given year in which the plaintiff alleged the adviser engaged in unauthorized activity. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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 8: Alternative Misconduct Classification

(a) Severe Misconduct

	Frequency			
	Current		Current and Past	
Disclosure Classification	Male	Female	Male	Female
Any Disclosure	1.83%	1.08%	14.89%	7.61%
Misconduct	0.72%	0.29%	9.08%	3.01%
Severe Misconduct	0.30%	0.11%	3.68%	1.09%

(b) Severe Misconduct and Firm/Industry Separation

Dependent Variable	Severe Misconduct	Job Separation	New Employment
Female	-0.14***	-0.78***	-2.89***
	(0.014)	(0.16)	(0.26)
Severe Misconduct		17.40***	-8.89***
		(1.11)	(1.03)
Severe Misconduct × Female		6.76***	-3.69
		(1.94)	(2.27)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	6,221,173	5,698,577	1,006,760
R-squared	0.097	0.330	0.379

Note: As a robustness check we construct the classification "Severe Misconduct," which is a subset of misconduct. We define severe misconduct as any settled regulatory, civil, or customer dispute involving: unauthorized activity, fraud, forgery, churning, selling unregistered securities, misrepresentation, and/or omission of material/key facts. We also include as severe misconduct any finalized criminal cases involving investment-related activites, fraud, and/or forgery. Table 8a reports the incidence of severe misconduct among male and female advisers.

Table 8b 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 was formally disciplined for misconduct in year t. The dependent variable in column (2) 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 column (3) is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In column (3), we restrict the sample to advisers who left their firms in a given year. Coefficients are in 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 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: Productivity Differences and Career Interruptions

(a) Productivity Differences

Dependent Variable	Misconduct	Job Separation
Female	-0.33***	-0.65***
	(0.057)	(0.11)
Misconduct		8.91***
		(0.88)
Misconduct × Female		4.36***
		(1.57)
High Rating	0.011	-4.10***
	(0.060)	(0.63)
ln(AUM)	0.035**	-0.43***
	(0.016)	(0.074)
ln(Production)	0.18***	-0.25***
	(0.023)	(0.072)
Adviser Controls	X	X
Year×Firm×County F.E.	X	X
Observations	487,159	442,159
R-squared	0.181	0.627

(b) Career Interruptions

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.34***	-0.81***	-2.89***
	(0.030)	(0.16)	(0.26)
Misconduct		22.41***	-9.11***
		(1.51)	(1.02)
Misconduct × Female		10.09***	-3.33***
		(1.89)	(1.18)
Career Interruption	-0.12***	5.19***	-3.79***
	(0.018)	(0.24)	(0.21)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	6,221,173	5,698,577	1,006,760
R-squared	0.097	0.333	0.380

Note: Table 9a displays the regression results for two linear probability models (eq. 1 and 2). The dependent variable in column (1) is a dummy variable indicating whether or not the adviser was formally disciplined for misconduct in year t. The dependent variable in column (2) 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. Table 9b 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 was formally disciplined for misconduct 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. 2). 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. 3). In column (3), 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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: Stratifying on Adviser Industry Experience

(a) Advisers with 5 or Fewer Years Industry Experience

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.187***	-1.561***	-0.865***
	(0.0280)	(0.243)	(0.275)
Misconduct		37.29***	-12.00***
		(3.731)	(1.845)
Misconduct × Female		8.868***	-1.969
		(1.670)	(1.328)
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	0.388

(b) Advisers with 15 or More Years Industry Experience

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.504***	0.264**	-6.096***
	(0.0365)	(0.109)	(0.440)
Misconduct		17.87***	-7.044***
		(1.085)	(1.274)
Misconduct × Female		4.338***	0.907
		(1.510)	(2.538)
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	0.410	0.437

Note: Tables 10a-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 was formally disciplined for misconduct 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. 2). 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. 3). 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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: Displaced Advisers in Firms that Downsize

	(1)	(2)	(3)	(4)	(5)
Downsize	22.87***	22.67***			
	(1.876)	(1.905)			
Downsize × Female	1.912*	1.932*	-0.0848	-0.00331	-0.464
	(1.017)	(1.006)	(0.278)	(0.199)	(0.557)
Female	-0.142	-1.129***	-0.787***	-0.798***	-0.777***
	(0.218)	(0.265)	(0.174)	(0.187)	(0.167)
Adviser Controls		X	X	X	X
Year×Firm×County F.E.			X	X	X
Downsize: 5%+				X	
Downsize: 25%+					X
Observations	6,002,088	6,002,088	5,698,577	5,698,577	5,698,577
R-squared	0.042	0.049	0.329	0.329	0.329

Note: Table 11 displays the results for a linear probability model (eq. 11). 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, tests (series 6, 7, 63, 24, 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 12: Job Turnover Among Advisers Who Eventually Engage in Misconduct

	(1)	(2)	(3)
Female	-1.72***	-1.80***	-1.45***
	(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

Note: Table 12 displays the regression results corresponding to a linear probability model (eq. 2). 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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 13: Labor Market Outcomes Following Misconduct: Adviser Ethnicity

(a) Misconduct

	(1)	(2)	(3)
African	0.088**	0.16***	0.094***
	(0.043)	(0.043)	(0.032)
Hispanic	0.16***	0.28***	0.090***
	(0.048)	(0.047)	(0.026)
Adviser Controls		X	X
Yr×Firm×Cty F.E.			X
Observations	4,904,653	4,904,653	4,598,081
R-squared	0.000	0.002	0.110

(b) Employment Separation

	(1)	(2)	(3)
Misconduct	27.11***	28.54***	21.73***
	(1.37)	(1.31)	(1.40)
Misc. × African	8.98***	8.92***	7.60***
	(2.00)	(1.91)	(2.18)
Misc. × Hispanic	6.02**	5.55**	6.47**
	(2.50)	(2.41)	(2.75)
African	2.41***	1.51***	0.46***
	(0.32)	(0.28)	(0.15)
Hispanic	2.79***	1.60***	0.41**
	(0.62)	(0.54)	(0.20)
Adviser Controls		X	X
Yr×Firm×Cty F.E.			X
Observations	4,494,607	4,494,607	4,210,431
R-squared	0.004	0.013	0.337

(c) New Employment

	(1)	(2)	(3)
Misconduct	-7.22***	-11.69***	-8.83***
	(1.95)	(1.25)	(1.02)
Misc. × African	2.08	3.07	3.50
	(3.51)	(2.98)	(2.92)
Misc × Hispanic	-8.43***	-5.63***	-5.29***
	(2.79)	(1.98)	(1.42)
African	-2.93***	-0.76	-0.98**
	(0.75)	(0.72)	(0.38)
Hispanic	-0.62	3.11**	1.90***
	(1.22)	(1.24)	(0.28)
Adviser Controls		X	X
Yr×Firm×Cty F.E.			X
Observations	842,622	842,622	735,946
R-squared	0.001	0.125	0.378

Tables 13a, 13b, and 13c display the regression results corresponding to linear probability models (eq. 1, 2, and 3) where we examine the relationship between misconduct and ethnicity among male advisers. The dependent variable in Table 13a is a dummy variable indicating whether or not the adviser received a misconduct disclosure in a given year. The dependent variable in Table 13c 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 13c is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 13c, we restrict the sample to those advisers who left their firms in a given year. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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 14: Labor Market Outcomes Following Misconduct by Management Composition, Adviser Ethnicity

(a) Employment Separation, Male Advisers and African Male Managers

	(1)	(2)	(3)
Misconduct	26.25***	27.83***	21.42***
	(1.43)	(1.34)	(1.44)
Misconduct × African	10.26***	10.10***	9.04***
	(2.29)	(2.19)	(2.33)
Misconduct × (Pct African Mgmt)	19.65***	18.50***	14.47**
	(5.55)	(5.47)	(6.27)
Misconduct × African × (Pct African Mgmt)	-24.46**	-24.53**	-44.97***
	(10.46)	(10.11)	(10.15)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	3,680,055	3,680,055	3,571,854
R-squared	0.004	0.013	0.322

(b) Employment Separation, Male Advisers and Hispanic Male Managers

	(1)	(2)	(3)
Misconduct	(2.350)		
Misconduct × Hispanic	7.80***	7.13**	7.80**
	(3.03)	(2.87)	(3.24)
Misconduct × (Pct Hispanic Mgmt)	9.17	8.56	9.70*
	(5.65)	(5.37)	(5.57)
Misconduct × Hispanic × (Pct Hispanic Mgmt)	-22.57**	-21.90**	-18.32*
	(9.71)	(9.20)	(10.08)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	3,680,055	3,680,055	3,571,854
R-squared	0.004	0.013	0.322

(c) Employment Separation, Female Advisers and African Male Managers

	(1)	(2)	(3)
Misconduct	26.51***	28.04***	21.65***
	(1.47)	(1.37)	(1.48)
Misconduct × Female	8.92***	8.74***	10.07***
	(2.05)	(1.94)	(1.96)
Misconduct × (Pct African Mgmt)	15.35***	14.69***	8.63
	(5.07)	(4.98)	(5.84)
Misconduct × Female × (Pct African Mgmt)	-3.61	-2.76	1.49
	(14.40)	(13.87)	(13.47)
Adviser Controls	X	X	X
Year×Firm×County F.E.			X
Observations	4,927,304	4,927,304	4,807,888
R-squared	0.003	0.011	0.315

Table 14: Labor Market Outcomes Following Misconduct by Management Composition, Adviser Ethnicity (contd.)

(d) Employment Separation, Female Advisers and Hispanic Male Managers

	(1)	(2)	(3)
Misconduct	26.56***	28.11***	21.52***
	(1.427)	(1.329)	(1.437)
Misconduct × Female	9.11***	8.93***	10.55***
	(2.00)	(1.91)	(1.90)
Misconduct × (Pct Hispanic Mgmt)	4.76	4.30	7.15*
	(4.25)	(4.09)	(4.21)
Misconduct × Female × (Pct Hispanic Mgmt)	-6.57	-6.38	-10.93
	(7.74)	(7.67)	(7.40)
Adviser Controls	X	X	X
Year F.E.			X
State F.E.			X
Observations	4,927,304	4,927,304	4,807,888
R-squared	0.003	0.011	0.315

Note: Table 14 displays the results for a linear probability model (eq. 7). 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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.

Appendix

A1: Disclosure Definitions[27]

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.

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

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

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.

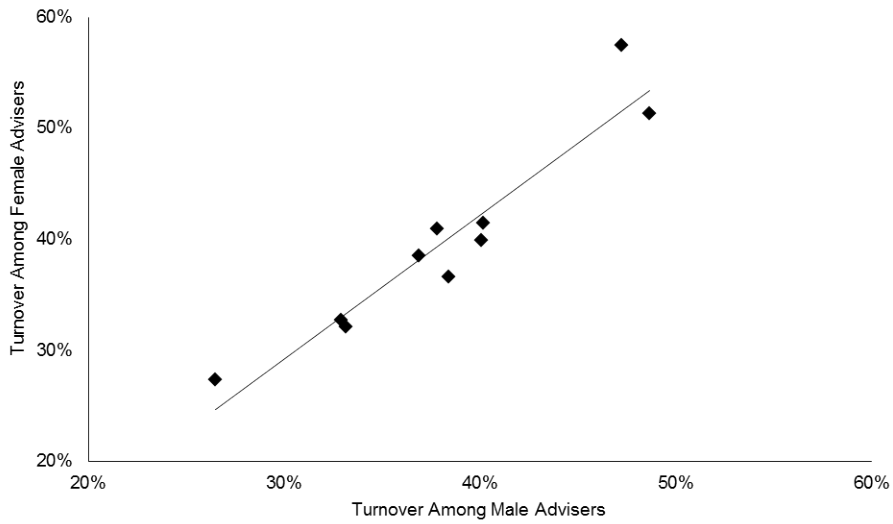
Regulatory - On Appeal: This type of disclosure event may involves (1) a formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulator such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation 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: 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

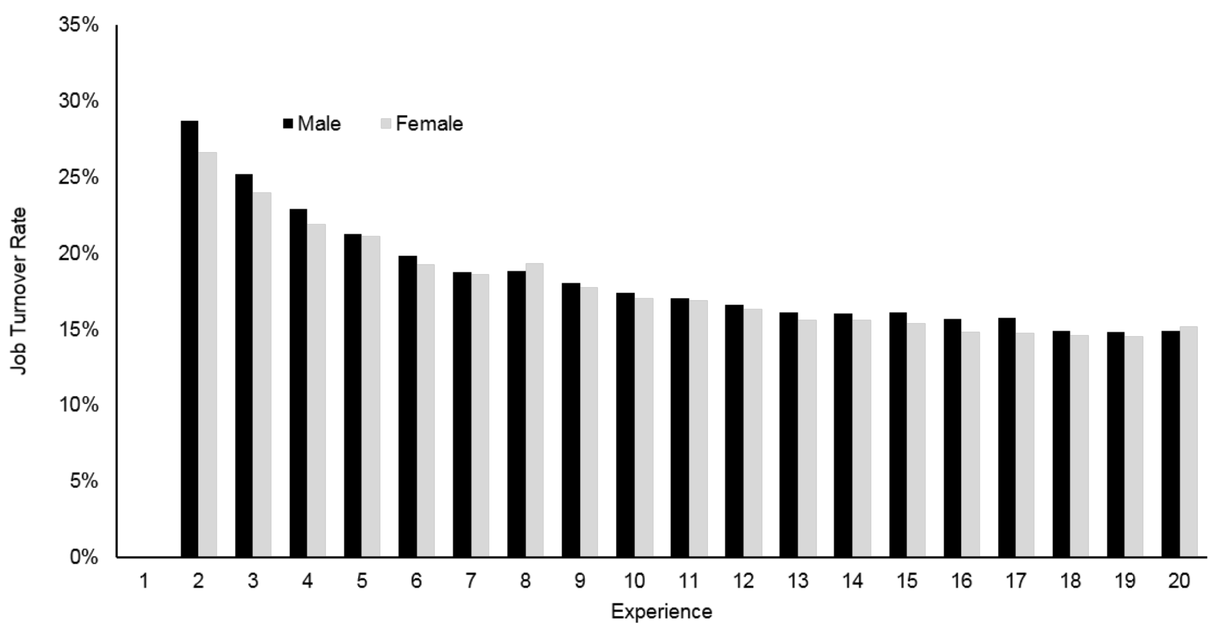


Figure A2 displays job turnover among male and female advisers conditional on the advisers' experience. Observations are at the adviser-by-year level over the period 2005-2015.

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: Promotions

	(1)	(2)	(3)
Misconduct	-0.17**	-0.145**	-0.096
	(0.075)	(0.065)	(0.065)
Misconduct × Female	-0.25**	-0.18*	-0.13
	(0.11)	(0.10)	(0.11)
Female	-0.25***	-0.20***	-0.072***
	(0.030)	(0.034)	(0.024)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	5,657,813	5,657,813	5,351,741
R-squared	0.000	0.007	0.094

Note: Table A2 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, 24, 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 A3: Alternative Gender Data

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.311***	-0.549***	-1.309***
	(0.0347)	(0.148)	(0.204)
Misconduct		11.39***	0.168
		(0.761)	(0.444)
Misconduct × Female		3.258***	-1.651
		(1.262)	(1.648)
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

Note: Table A3 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 was formally disciplined for misconduct 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. 2). 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. 3). 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 June 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, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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 A4: Recidivism: Using -Instrumental Variables

	(1)	(2)	(3)
Prior Misconduct	1.86***	1.76***	1.46***
	(0.071)	(0.067)	(0.055)
Prior Misconduct × Female	-0.53***	-0.53***	-0.45***
	(0.081)	(0.081)	(0.075)
Prior Discipline	6.40***	6.34***	6.10***
	(0.61)	(0.61)	(0.63)
Prior Discipline × Female	-2.14***	-2.20***	-1.77***
	(0.54)	(0.54)	(0.55)
Female	-0.27***	-0.22***	-0.25***
	(0.017)	(0.018)	(0.025)
Adviser Controls		X	X
Year×Firm×County F.E.			X
IV	X	X	X
Observations	6,540,621	6,540,621	6,217,572
R-squared	0.007	0.008	0.100

Note: Table A4 displays the regression results for a linear probability model (eq. 9). 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.

The regression specification is in the spirit of the statistical discrimination test proposed by Becker (1957) and employed by Arnold et al. (2017). Consistent with the model developed in Appendix A3, Becker's statistical discrimination test suggests that if firms are engaging in statistical discrimination, the rate of recidivism should be the same across male and female advisers at the margin of remaining employed/being fired following misconduct. In the context of the results reported in Table A4, the Becker test implies that the coefficient Prior Discipline×Female should be equal to zero for male/female advisers at the margin if firms are engaging statistical discrimination. A caveat of the Becker test is that the statistical discrimination recidivism/equivalence condition is only guaranteed to hold for male and female advisers at the margin rather than for the average male and female adviser. Following Arnold et al. (2017), we employ an instrumental variables estimator to recover the rate of recidivism for male and female advisers at the margin.

In our setting we need an instrument for whether or not an adviser was disciplined (Prior Discipline, Prior Discipline×Female) following misconduct in the past. We construct our instrument by using plausibly exogenous variation in the probability an adviser experienced an employment separation following his/her most recent misconduct event. Our instrumental variables strategy relies on exploiting differences across firms in their tolerance for misconduct. Egan, Matvos, and Seru (2017) show that firms with higher misconduct propensities tend to discipline misconduct less severely. Thus, we use variation in the misconduct propensity of an adviser's previous employer as an instrument for whether or not an adviser was disciplined for misconduct in the past. To construct the instrument, we first calculate a firm's propensity to engage in misconduct by averaging the estimated residuals from eq. 1 (Table 2d column 2) at the firm level. We then re-estimate an augmented version of our employment separation regression (eq. 2) where we interact a firm's propensity to engage in misconduct with the variables Female, Misconduct, and Female×Misconduct. Finally, we construct our instrument as the predicted values from the augmented employment separation regression (eq. 2). The validity of the instrument requires that the characteristics of an adviser's past employer predict whether or not he/she experienced an employment separation following misconduct; however, the characteristics of an adviser's past employer are otherwise uncorrelated with the probability that an adviser will be a repeat offender.

Table A4 displays the instrumental variables estimates. Coefficient units are percentage points. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24 and investment adviser exam), 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 A5: Employment Separations by Within Firm and Total Experience

(a) Employment Separations by Within Firm Experience

	(1)	(2)	(3)	(4)
Female	-0.880***	-0.163	0.0414	0.149
	(0.175)	(0.161)	(0.136)	(0.200)
Misconduct	23.96***	20.68***	19.01***	17.21***
	(1.880)	(1.405)	(2.294)	(2.889)
Misconduct × Female	12.33***	6.460***	4.346	-0.618
	(1.882)	(2.155)	(2.860)	(3.630)
Within Firm Experience	0-5yrs	6-10yrs	11-15yrs	16-20yrs
Adviser Controls	X	X	X	X
Experience F.E.	X	X	X	X
Firm Tenure F.E.	X	X	X	X
Year×Firm×County F.E.	X	X	X	X
Observations	3,619,393	1,022,905	439,182	173,576
R-squared	0.330	0.418	0.424	0.552

(b) Employment Separations by Total Experience

	(1)	(2)	(3)	(4)
Female	36.78***	23.97***	20.45***	19.89***
	(3.673)	(1.457)	(1.075)	(1.427)
Misconduct	36.78***	23.97***	20.45***	19.89***
	(3.673)	(1.457)	(1.075)	(1.427)
Misconduct × Female	8.657***	7.772***	9.150***	5.499*
	(1.664)	(2.396)	(2.312)	(3.303)
Total Experience	0-5yrs	6-10yrs	11-15yrs	16-20yrs
Adviser Controls	X	X	X	X
Experience F.E.	X	X	X	X
Firm Tenure F.E.	X	X	X	X
Year×Firm×County F.E.	X	X	X	X
Observations	1,818,479	1,109,748	850,260	517,019
R-squared	0.323	0.383	0.402	0.430

Note: Tables A5a and A5b display the regression results corresponding to our employment separation linear probability model (eq. 2). The dependent variable is a dummy variable indicating whether or not a financial adviser left his firm (either leaving the industry or switching firms). In Table A5a columns (1)-(4) we reestimate the model separately depending on the adviser's experience within his/her firm: 0-5yrs, 6-10yrs, 11-15yrs, and 16-20yrs. In Table A5b columns (1)-(4) we reestimate the model separately depending on the adviser's total level of experience: 0-5yrs, 6-10yrs, 11-15yrs, and 16-20yrs. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24, and investment adviser exams), and number of other qualifications. 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.

A3: A Model of Firm Discipline

We consider a simple model of a financial advisory firm's hiring and firing decisions to help understand the features of the data. Advisers differ along two dimensions: their productivity η and their propensity to engage in misconduct ν. Firms wish to employ advisers who are productive but have low propensities to engage in misconduct. Whether or not a firm 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 advisory firms but misconduct propensity ν_i is not. Firms 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.

A3.1 Differential Firm Firing Decisions Across Genders Following Misconduct: Statistical, Taste-based or Miscalibrated Beliefs?

We next consider a firm'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 $d_{it} \in \{0, 1\}$ where

$$d^*_{it} = \nu_i + \epsilon_{it}$$

$$d_{it} = \mathbf{1}\{d^*_{it} > 0\}$$

where ν_i reflects an adviser's misconduct propensity and ϵ_{it} is some idiosyncratic misconduct shock. The continuous variable d^*_{it} reflects the true underlying misconduct, and the indicator variable d_{it} is the noisy disclosure signal observed by firms. Firms use this information to update their beliefs regarding an adviser's propensity to engage in misconduct which we denote $\tilde{\nu}_g(\vec{d}_{it})$, where $\vec{d}_{it}$ is a vector of the adviser's disclosure history and g indicates gender. A firm's beliefs over an adviser's propensity to engage in misconduct could be unbiased such that $\tilde{\nu}_g(\vec{d}_{it}) = E[\nu|\vec{d}_{it}, g_i]$ or systematically biased such that the bias could vary across genders.

Suppose an adviser receives his/her first disclosure $d_{it} = 1$ at time t. We denote the time at which the adviser receives his/her first misconduct disclosure τ_d such that τ_d is a sufficient statistic for the adviser's disclosure history $\vec{d}_{it}$. A firm elects to fire an employee if the firm believes his/her net productivity is below some threshold S^*_g where g indicates the adviser's gender. An adviser who receives his first disclosure at τ_d is fired if:

$$S^*_g > \eta_i - \tilde{\nu}_g(\tau_d) + \varepsilon_{it} \tag{13}$$

where S^*_g is the threshold which potentially varies across gender, η_i is the adviser's productivity, $\tilde{\nu}_g(\tau_d)$ is the firm's updated beliefs about the adviser's propensity to engage in misconduct, and ε_{it} is some idiosyncratic shock that is independent of η, g, and ν. One could think of ε_{it} as information privately observed by the firm.

The formulation allows for three potential explanations for why female advisers might experience discrimination at the firing stage after their first offense. We briefly describe these explanations here and discuss the predictions for each of these in Section A.3.2

Statistical Discrimination

First, the discrimination could be statistical in nature. Firm managers could use information about an adviser's gender when rationally forming beliefs about future misconduct $\tilde{\nu}_g(\tau_d)$.

Taste Based Discrimination

Second, the firm may hold male and female advisers to a different standard S_g^*. Variation in the threshold S_g across genders reflects taste-based discrimination at the firing stage. Firms may simply prefer male advisers and consequently hold female advises to a higher standard.

Miscalibrated Beliefs based Discrimination

Third, the model also allows for a different type of firm bias that could result from miscalibrated beliefs based on stereotypes. We assume that mangers potentially rely on stereotypes when forming beliefs about a group of individuals as developed in Bordalo et. al (2016). The stereotypes are in the spirit of Tversky and Kahneman's (1983) representative heuristics. A firm manager wants to fire those "bad" type advisers for which $\nu_i > S_g - \eta_i$ and retain those "good" type advisers for which $\nu_i < S_g - \eta_i$. Under the formulation in Gennaioli and Shleifer (2010), the bad type is representative of those advisers who receive their first misconduct disclosure at time t if:

$$\frac{\Pr(\nu > S_g - \eta | \tau_d = t, \eta)}{\Pr(\nu > S_g - \eta | \tau_d \neq t, \eta)} > \frac{\Pr(\nu < S_g - \eta | \tau_d = t, \eta)}{\Pr(\nu < S_g - \eta | \tau_d \neq t, \eta)}$$

Note that the bad type is representative of those advisers who receive their first misconduct disclosure early on with the firm, say with $\tau_d = 1$

$$\frac{\Pr(\nu > S_g - \eta | \tau_d = 1, \eta)}{\Pr(\nu > S_g - \eta | \tau_d \neq 1, \eta)} > \frac{\Pr(\nu < S_g - \eta | \tau_d = 1, \eta)}{\Pr(\nu < S_g - \eta | \tau_d \neq 1, \eta)}$$

Following Bordalo et al. (2016) we assume that firm managers potentially rely on stereotypes such that beliefs are of the form:

$$\tilde{\rho}_g(\tau_d) = \Pr(\nu > S_g - \eta | \tau_d = t, \eta) \frac{\left(\frac{\Pr(\nu > S_g - \eta | \tau_d = t, \eta)}{\Pr(\nu > S_g - \eta | \tau_d \neq t, \eta)}\right)^\theta}{\left(\Pr(\nu > S_g - \eta | \tau_d = t, \eta) \left(\frac{\Pr(\nu > S_g - \eta | \tau_d = t, \eta)}{\Pr(\nu > S_g - \eta | \tau_d \neq t, \eta)}\right)^\theta + \Pr(\nu < S_g - \eta | \tau_d = t, \eta) \left(\frac{\Pr(\nu < S_g - \eta | \tau_d = t, \eta)}{\Pr(\nu < S_g - \eta | \tau_d \neq t, \eta)}\right)^\theta\right)}$$

Under this formulation, $\theta = 0$ if firm beliefs are rational and unbiased, and $\theta \geq 0$ if firm beliefs are miscalibrated due to stereotypes. We assume that managers have rational and correct beliefs when evaluating members of their own group (male advisers) such that $\theta_M = 0$, and assume that managers potentially rely on stereotypes when evaluating members of a different group (female advisers) such that $\theta_F > 0$. In our context, the stereotype/representative heuristic implies that firms with male managers as decision makers will overweight the probability that a female adviser is a bad type after observing a female adviser engage in misconduct early on in her career such that $\tilde{\rho}_F(1) > \Pr(\nu > S_F - \eta_i|\tau_d = 1, \eta)$. Consequently, male manager will overestimate the rate of recidivism among female advisers who engage in misconduct early on in their carrers, $\tilde{\nu}_F(1) = E[\nu|\nu > S_F - \eta]\tilde{\rho}_F(1) + E[\nu|\nu < S_F - \eta](1 - \tilde{\rho}_F(1)) > E[\nu|\tau_d = 1, Female]$ In other words, in our context, male managers will "assume the worst" when observing female advisers who engage in misconduct early on in the adviser's career.

Stereotypes of this form have two important properties as highlighted in Bordalo et al. (2016). First, stereotypes amplify differences across groups. Stereotypes about female advisers who engage in misconduct will cause firms to overreact to misconduct among female advisers early on in their careers. Second, stereotypes are context-dependent. This means that the distortions arising from stereotypes will change over time. For example, the bad type is representative of those female advisers who receive misconduct disclosures in the first period $\tau = 1$ relative to the good types. While receiving an initial misconduct disclosure early on in one's career is representative of bad advisers, receiving an initial disclosure sufficiently late in one's career is then inherently representative of good advisers. Similarly, an adviser's past record will also interact with stereotypes. Observing a new offense by an adviser with a history of past misconduct has different "representativeness" than observing a new offense by an adviser without a past history of misconduct. Hence, stereotypes about misconduct will naturally change over time.

Recidivism in the Model:

Recidivism is observed in the data conditional on the adviser's remaining employed in the industry after the initial misconduct offense. For ease of exposition, we assume that if an adviser is fired for misconduct, he/she is cast from the industry. Thus, the expected misconduct at time t conditional on an adviser who previously engaged in misconduct at time $t-1$ is given by

$$E[d_{it}|\tilde{\nu}_g(\tau_d) < \eta - S_g^*]$$

The rates of recidivism across male and female advisers will depend on the standard male/female advisers are held to, S_g, and the firm's beliefs over the probability of a repeat offense, $\tilde{\nu}_g(\tau_d)$.

A.3.2 Model Predictions

Discrimination across male and female advisers can arise in the model due to statistical discrimination, taste-based discrimination, and/or miscalibrated beliefs due to stereotyping. Each underlying cause of discrimination produces separate implications for the rates of recidivism across male and female advisers.

Statistical Discrimination

We first consider the case in which male and female advisers are held to the same standard ($S_M^* = S_F^* = S^*$) and firms have unbiased beliefs about future misconduct across genders ($\theta_M = \theta_F = 0 \implies \tilde{\nu}_g(\tau_d) =$

$E[\nu|\tau_d, g_i]$) such that firms neither engage in taste-based discrimination nor do they stereotype. Thus, the only form of potential discrimination in the data is statistical. The rate of recidivism is given by

$$E[d_{it}|E[\nu|\tau_d, g_i] < \eta - S^*]$$

The formulation implies male and female advisers at the margin ($E[\nu|\tau_d, g_i] = \eta - S^*$) will have the same rates of recidivism. Thus if we observe higher rates of recidivism among male advisers relative to female advisers on the margin, we can reject the statistical discrimination model.

If we further assume that the distribution of misconduct ν conditional on η is the same across male and female advisers, the statistical model implies that $\tilde{\nu}_F(\tau_d) = \tilde{\nu}_M(\tau_d)$, which implies further restrictions on the data. First, the rates of recidivism for male advisers relative to female advisers' should be the same on average such that $E[d_{it}|\tilde{\nu}_F(\tau_d) < \eta - S^*, Female] = E[d_{it}|\tilde{\nu}_M(\tau_d) < \eta - S^*, Male]$. Second, the firing rates following misconduct should be the same for male and female advisers following misconduct.

$$\Pr\left(S^* - \eta_i + \tilde{\nu}_F(\tau_d) > \varepsilon_{it}\right) = \Pr\left(S^* - \eta_i + \tilde{\nu}_M(\tau_d) > \varepsilon_{it}\right)$$
$$\Pr(Fired|Female) = \Pr(Fired|Male)$$

If we observe either relatively higher firing rates for female advisers or higher rates of recidivism among male advisers (assuming $F_F(\cdot|\eta) = F_M(\cdot|\eta)$), we can reject the statistical discrimination model. Such differences in recidivism or firing would necessarily be driven by taste-based discrimination or miscalibrated/stereotype beliefs.

Taste-based Discrimination

We next consider the case where firms engage in taste-based discrimination such that they hold female advisers to a higher standard than male advisers ($S_F^* > S_M^*$). Further, we assume that firms have unbiased beliefs about future misconduct across genders ($\theta_M = \theta_F = 0 \implies \tilde{\nu}_g(\tau_d) = E[\nu|\tau_d, g_i]$). If female advisers are held to a higher standard than male advisers, then the rate of recidivism will be lower among female advisers than male advisers at the margin

$$E[d_{it}|E[\nu|\tau_d, g_i] = \eta_i - S^F] = \eta_i - S^F < \eta_i - S^M = E[d_{it}|E[\nu|\tau_d, g_i] = \eta_i - S^M]$$

Provided that the distributions of ν conditional on η are the same across male and female advisers such that $E[\nu|\tau_d, Female] = E[\nu|\tau_d, Male] = E[\nu|\tau_d]$, the rates of recidivism will be higher among male advisers than female advisers' on average. The model also implies that female advisers should be fired at a higher rate than male advisers. Since $S_F^* > S_M^*$, we have that

$$\Pr\left(S_F^* - \eta_i + E[\nu|\tau_d]\right) > \varepsilon_{it}) > \Pr\left(S_M^* - \eta_i + E[\nu|\tau_d]\right) > \varepsilon_{it})$$
$$\Pr(Fired|Female) > \Pr(Fired|Male)$$

The taste-based discrimination model suggests that if female advisers are held to a higher standard than male advisers, then female advisers will be fired at a higher rate than male advisers despite having lower rates of recidivism.

Another implication of the model is that if the underlying mechanism behind discrimination is taste-based, a firm's taste-based preferences should not change over time. Similarly, discrimination is not impacted by the timing of the misconduct. If firms hold female advisers to a higher standard than male advisers ($S_F^* > S_M^*$), the relationship will not change over time.

The time invariance of firm preferences has important implications if one extends the model to allow firms to engage in taste-based discrimination at the hiring stage as well as the firing stage. Suppose that firms use the same hiring rule as their firing rule (eq. 13). A firm employs an adviser if his/her net productivity is greater than some threshold

$$S_g^* < \eta_i - E[\nu|g] + \varepsilon_{it} \tag{14}$$

Where $E[\nu|g]$ reflects the firm's beliefs about the adviser's initial propensity to engage in misconduct. For expositional ease, we assume here that the distributions of ν conditional on η are the same across male and female advisers such that $E[\nu|Female] = E[\nu|Male] = E[\nu]$. Notice that if firms hold female advisers to a higher standard than male advisers at the hiring stage ($S_F^* > S_M^*$), the expected value of the unobservable term ε_{it} will be higher for female advisers than for male advisers ($E[\varepsilon|\varepsilon > S_F - \eta_i - E[v]] > E[\varepsilon|\varepsilon > S_M - \eta_i + E[v]]$) that are employed in the industry even though ε_{it} is distributed the same across the population. Taste-based discrimination at the hiring stage will result in selection into the industry such that female advisers will have better unobservable characteristics than male advisers'.

Let's reconsider a firm's firing decision following misconduct. Given the hiring rule, the probability a female is fired following misconduct is $\Pr(S_F^* - \eta_i + E[\nu|\tau_d] > \varepsilon_{it}|S_F^* - \eta_i + E[\nu] < \varepsilon_{it})$ and for male advisers is $\Pr(S_M^* - \eta_i + E[\nu|\tau_d] > \varepsilon_{it}|S_M^* - \eta_i + E[\nu] < \varepsilon_{it})$. It is no longer the necessarily the case that female advisers are more likely to be fired following misconduct if firms engage in taste based discrimination at the hiring stage. In fact, male and female advisers at the margin of being hired ($S_g^* = \eta_i - E[\nu] + \varepsilon_{it}$) with comparable productivity (η) should face similar separation rates following misconduct. To summarize, if firms engage in taste-based discrimination at the hiring stage, then we may not observe discrimination at the firing stage.

Miscalibrated/Stereotyped Beliefs

Lastly, we consider the case where firms rely on stereotypes which results in miscalibrated beliefs. We assume that firms rely on stereotypes when evaluating female advisers ($\theta_F > 0$) and have rational unbiased beliefs when evaluating male advisers ($\theta_M = 0$). Moreover, assume that male and female advisers are held to the same standard ($S^*_M = S^*_F = S^*$). A direct implication is that firms will overestimate the probability that a female adviser will engage in a repeat offense in the future such that $\tilde{\nu}_F(1) > E[\nu|\tau_d = 1, Female]$ if female advisers engage in misconduct early on in their career. If firms rely on stereotypes when evaluating female advisers but not male advisers, this implies that the rates of recidivism will be higher among male advisers on the margin

$$E[d_{it}|\tilde{\nu}_F(1) = \eta_i - S^*] < \eta_i - S^* = E[d_{it}|\tilde{\nu}_M(1) = \eta_i - S^*]$$

Again, provided that the distribution of ν conditional on η is the same across male and female advisers, the rates of recidivism will be higher among male advisers than female advisers on average. Similarly, the model suggests that female advisers will be fired at higher rates than male advisers if they engage in misconduct early on in their careers. Since $\tilde{\nu}_F(1) > \tilde{\nu}_M(1)$ we have that

$$\Pr\left(S^* - \eta_i + \tilde{\nu}_F(1) > \varepsilon_{it}\right) > \Pr\left(S^*_M - \eta_i + E[\nu|\tau_d]) > \varepsilon_{it}\right)$$
$$\Pr(Fired|Female) > \Pr(Fired|Male)$$

Both the taste-based and stereotype mechanisms imply that the rates of recidivism will be higher among male advisers despite female advisers being fired at higher rates.

Although the stereotype and taste-based discrimination models offer similar predictions early on in an adviser's career, the models have different dynamic implications. Recall that stereotypes are context-dependent, thus the nature of stereotypes changes over time. The model formulation suggests that with sufficient time, every adviser will eventually receive some sort of misconduct disclosure. While receiving an initial misconduct disclosure early on in one's career is representative of "bad" advisers, receiving an initial disclosure sufficiently late in one's career is then inherently representative of "good" advisers. Firms will assume the worst for a female adviser who engages in misconduct early on in her career, but will assume the best for a female adviser who receives a misconduct disclosure later on in her career. Hence the observed discrimination should dissipate and evolve over time based on the adviser's experience with her firm.