When Harry Fired Sally: The Double Standard in Punishing Misconduct

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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 punishments despite engaging in misconduct which is 20% less costly and having a substantially lower propensity towards repeat offenses. We find no evidence that the observed gender differences are driven by productivity differences. Rather, we find supporting evidence that male advisers discriminate against female advisers. 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 male executives at a given branch tend to punish female advisers more severely following misconduct, and also tend to hire fewer female advisers with past records of misconduct. We extend our analysis to explore discrimination against ethnic minorities and find similar patterns. Our evidence is most consistent with managers being more forgiving when punishing missteps of members from their own gender/ethnic group, which could potentially be driven by miscalibrated beliefs about misconduct or taste-based discrimination. We find evidence suggesting that distorted beliefs play a critical role in the observed discrimination.

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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. In this paper, we document how gender differences are related to punishment of undesirable activities in the context of financial adviser misconduct. We then consider different alternatives that are consistent with these facts and conclude that biased beliefs of managers best explains our facts.

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. 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 the regulator, and possibly by the discriminating employers who may be unaware of their own biases (Bertrand et al., 2005).

Another differential aspect of discrimination in punishment is that the employer knows 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[1], examining differences in treatment across groups while holding fixed the bundle of characteristics, which can be captured in a CV. During the hiring process, and during employment, the employer learns substantially more about the employee, reducing the potential for such "attention discrimination" (Bartos et al., 2016). One might therefore imagine that discrimination disappears conditional on employment. To punish an employee after several years of tenure, the employer has already invested in knowing them well past the formal characteristics captured in their CV, suggests a potentially different discrimination mechanism is at play. Methodologically, studying this type of discrimination does not lend itself toward audit

[1] For an overview, see Bertrand and Duflo (2016).

and correspondence studies, which, by design, reduce an employee to characteristics captured in a CV. We contribute to the literature by investigating this type of discrimination in the context of financial adviser misconduct.

The financial adviser industry offers a unique setting to study gender differences in punishment and leniency in the workplace. One obstacle to research is that undesirable outcomes are generally difficult to measure, especially across firms. We use novel panel data on misconduct for all financial advisers (about 1.2 million) registered in the United States from 2005 to 2015, who represent approximately 10% of total employment in the finance and insurance sector. 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 an incidence of misconduct, financial advisers face a substantial increase in the probability of job loss and face worse employment opportunities in the industry (Egan et al., 2016). In this setting, we can also measure the extent of the misconduct costs to the employer and track employee movement across firms in the industry. This allows us to understand some features of discrimination at the level of the labor market, rather than individual employers.

Researching discrimination in this setting is also interesting per se. Finance is a large and highly compensated industry, which consistently ranks among the bottom industries in terms of gender equality. Personal financial advisers, for example, have among the largest gender earning gaps across occupations (Census, 2008). Recent survey evidence found that nearly 88% of female financial service professionals believe that gender discrimination exists within the financial services industry (Tuttle, 2013). 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. Former FDIC chairwomen Sheila Bair (2016) writes that the glass ceiling in finance is "barely cracked" for women. If women are held to a different standard than men, such as a firm's tolerance of misconduct, the differential standards inherently contribute to the glass ceiling faced by women. Such concerns about the lack of diversity and discrimination in the financial industry have become a policy issue in their own right.

The paper has two goals. First, we document key differences in the rate and punishment of misconduct across male and female financial advisers. In the second half of the paper, 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). Firms may not have an inherent prejudice against female advisers. Rather, they punish female advisers more severely because misconduct by female advisers is predictive of worse outcomes or more frequent misconduct, or because female advisers are less costly to fire. On the other hand, the observed discrimination could be taste-based (Becker, 1957) or due to miscalibrated/incorrect beliefs about misconduct across the two groups (Bordalo 2016). The financial advisory industry, customers, or regulators could simply prefer male over female advisers or perhaps industry players systematically over-estimate the rate of recidivism among female advisers. We want to distinguish between these broad types of discrimination, and see who drives discrimination in this market.

We find that women face more severe punishment for misconduct. Male financial advisers make up 75% of the financial advisory industry, and are responsible for a disproportionately large amount of the misconduct in that 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 are, thus, more than three times as likely to engage in misconduct. One possible reason for these gender differences would be if there is gender segregation across firms, markets, or types of products that male and female advisers sell. 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). 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 at both the firm and industry level following an incidence of misconduct. Female advisers are 50% more likely to experience job separation following misconduct. Conditional on being fired, female advisers face longer unemployment spells and are 30% less likely to find a new position in the industry within one year. We again 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), as well as conditioning on extensive adviser characteristics. The difference is particularly pronounced, because we find no gender differences in job turnover rates for advisers *without* misconduct. However, 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 also initiate a misconduct complaint. We find that a disproportionate share of complaints initiated against female advisers comes 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 are consistent with the recent survey evidence which suggests that a large majority of women believe there is gender discrimination within firms (Tuttle 2013). Indeed, we document large variation in patterns of discrimination within 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 proposal to limit discrimination in firms is to increase the share of women in positions of power. The idea is that decision makers in organizations can directly affect policies leading to discrimination, and that members from the discriminated group, i.e., women, are more likely to recognize discrimination and less likely to support discriminatory practices. We examine whether the gender composition of the decision-making team in a firm explains some of the differences we find across firms. Financial advising is a male dominated financial industry. Male advisers represent 75% of employment, 83% of firm managers,[2] and 83% of firm executives/owners. Important for our setting, 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 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 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 had 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. One advantage of the financial industry is that the productivity of financial advisers can be broadly encapsulated as the amount of assets they manage to 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. As we show in extensive robustness tests, which we discuss at the end of the introduction, it is unlikely that differences in characteristics drive the gender differences in punishment. From the perspective of statistical discrimination, it is also interesting that we find gender differences in punishment across the range of adviser experience as well as firm tenure. In other words, discrimination occurs even for advisers whose ability is well known, both to the firm and to the market.

[2]We define a manager as an adviser who holds a Series 24 exam which qualifies an adviser to supervise/manage branch activities.

To recap, female advisers are less likely to engage in misconduct than their male counterparts at the same firm, time, and location, and with the same qualifications and experience, and we find no evidence that females are substantially less productive employees. Female misconduct is less costly, and female advisers are less likely to be repeat offenders. Nevertheless, female advisers' job separation rates are higher than mens' following misconduct, females suffer longer unemployment spells, and are less likely to be hired by other firms following misconduct even after being employed for several years. Overall, the evidence suggests that differences in characteristics, or statistical discrimination, are not a likely reason for gender differences in misconduct punishment in the industry.

Given the set empirical facts we observe in the data, we examine the underlying mechanism behind gender discrimination. On potential explanation, is that what we observe in the data could be a result of statistical discrimination rather than some inherent bias or prejudice (Phelps 1972; Arrow, 1973). However a model of pure statistical discrimination would predict that the rates of recidivism should be the same among male and female advisers. We find the rates of recidivism are twice as high among male advisers which is inconsistent with a model of pure statistical discrimination. We argue that our evidence is most consistent with managers being more forgiving when punishing missteps of members from their own gender/ethnic group, which could potentially be driven by miscalibrated beliefs about misconduct or taste-based discrimination. The timing of the discrimination suggests that what we observe in the data is driven by miscalibrated beliefs rather than taste-based discrimination. We find that observed discrimination in punishment between male and female advisers dissipates over time as the adviser's tenor with his/her firm increases. This suggests that the observed discrimination occurring early on in an advisers' tenor with a firm has to do with firm beliefs, which evolve over time, rather than some inherent characteristic of the firm. Similarly, it is difficult to rationalize a firm's dynamic decision to engage in taste-based discrimination at the firing stage when it hired these female advisers in the first place. Our facts suggest that observed discrimination is driven by miscalibrated beliefs where male managers systematically underestimate a female adviser's propensity to engage in misconduct and consequently overreact to observed misconduct.

We devote the last section of the paper to further rejecting the alternative that male advisers differ from female advisers on characteristics other than gender, and that these characteristics lead to greater punishment of misconduct. 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. 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. To explain our results, firms with female executives and managers would have to employ female advisers who are more productive on unobservable dimensions than firms with predominantly male executive teams. To explain a 50% increase in terminations, these differences would have to be large – which is far from obvious. We find the same discriminatory patterns hold for less experienced advisers, suggesting that the observed discrimination is not due to unobserved productivity differences, which might be harder to gauge at the start of an adviser's tenure. We also find gender differences for more experienced advisers, which suggests that the observed discrimination is also not due to expectations about future productivity formed at the start of an advisers' career.

We also 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. Given that career interruptions can explain a sizable part of the wage gap in the finance industry (Bertrand et al., 2010), we next 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.

Additionally, 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. Our empirical findings indicate that firms lay off male and female advisers at similar rates during times of distress, which suggests that female advisers are not less costly to lay off/fire. This collage of evidence convinces us that our results are not driven by differences in productivity or other undesirable characteristics across advisers.

We find that the unequal treatment of male and female advisers following misconduct extends beyond a firm's hiring/firing practices. We examine how past misconduct impacts future promotion prospects of female and male advisers. While both male and female advisers with recent misconduct are less likely to be promoted, the career punishment in terms of promotion prospects is substantially larger for women relative to men. Female advisers with recent misconduct are 67% less likely to be promoted relative to other female advisers. In comparison, male advisers with recent misconduct are 19% less likely to be promoted relative to other male advisers.

We conclude our analysis by documenting that regional differences in how discrimination might be perceived by the community (including customers) also explain some of the variation in discrimination. We find modest evidence suggesting that regional differences explain discrimination. Female advisers are more likely to experience discrimination in areas with high wage and participation gaps.

Our work contributes to the 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 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 that gender discrimination is absent. It could manifest itself on the job in the form of punishment following a misstep.

Our paper relates to the vast literature on discrimination dating back to the theoretical work of Becker (1957; rev. 1971), Phelps (1972), Arrow (1973), and Aigner and Cain (1977). Our paper also contributes to empirical literature documenting gender discrimination in the workplace. Previous audit and correspondence studies, such as Neumark (1996), Goldin and Rouse (2000), and Carlsson (2011), find that women face discrimination in hiring decisions. Neumark (1996) finds that relative to men, women are less likely to receive job offers at high-end restaurants, while Goldin and Rouse (2000) find that women face discrimination in symphony orchestra auditions. 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. Another differential aspect of discrimination in punishment that sets us apart is that the employer knows the employee reducing the potential for "attention discrimination" (Bartos et al., 2016).

Our paper also contributes to the growing literature documenting that significant male/female participation and wage gaps exist in competitive, high paying jobs (Bertrand and Hallock, 2001; 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 a high compensation, rather than the tail of the population represented by CEOs or directions of corporate boards.

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 Arnold et al. (2017), Knowles et al (2001), Charles and Guryan (2008), and Altonji and Pierret (2001). Instead of focusing on compensation as the labor outcome, we focus on punishment of misconduct through job separations.

Our work also relates to a literature on financial misconduct and punishment. The framework of our analysis relates closely back 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, 2016; 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 (2016). 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. Brokers (or stockbrokers) are registered with FINRA and the SEC and are 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 the FINRA terminology 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.

The data set 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 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. Central to our purposes, 15% of male advisers and 8% of female advisers in our data set have a disclosure on his/her record.[3] 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 disclosure, which 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 (2016).

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[4] as both male and female even once, the name is classified as being unisex. 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

[3]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.

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

data set are classified as male, 20% are classified as female, 15% are classified as unisex, and the remaining 3% are 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).

2.2 Gender Composition of Financial Advisers

2.2.1 Gender differences

The advisers in our data account for roughly 10% of employment of 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 panels (a) and (b) 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 1b reports the share of advisers who have passed any of the six most popular qualification exams taken by investment professionals.[5] 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 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. Given these differences among male and female advisers, it will be important to account for them in our analysis.

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 firm differences in the share of female advisers they employ. Figure 2a

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

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 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 2 displays the distribution of male and female advisers across states. For example, female advisers make up one in three advisers in Iowa while 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, 2016). Here we show that misconduct is substantially more prevalent among men than women. Table 3, 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.[6]

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 3 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 4 displays additional details on the misconduct disclosures received by male and female advisers. Table 4a displays the most commonly reported customer complaints in the misconduct disclosures. In general, the distribution of complaints received by male and female advisers is comparable, although there is more

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

variation in the complaints received by female advisers. Similarly, Table 4b 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 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 1 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 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 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×year ×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 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, and the adviser's experience in the industry in the vector X_{it}.

Table 5 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 female advisers within the same firm at the same time in the same county (column 3), male advisers are more than twice as likely (0.72pp) to engage in misconduct. These results suggest that men engage in more misconduct. 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, has a record of misconduct. Egan, Matvos, and Seru (2016) 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 female advisers face higher job separation prospects following misconduct. We start with a simple cut of the data in Table 6a. Both male and female advisers are likely to experience a job separation following misconduct, but female advisers face harsher consequences. While 46% of male advisers experience a job separation following misconduct, 55% of female advisers do so. In other words, female advisers are 20% more likely to lose their job 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 his/her firm in a given year. Figure 3 reaffirms these results, showing that 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. In other words, on average, without misconduct male and female financial advisers face similar job turnover rates. However, female advisers are substantially more likely to lose their job following misconduct.

The extremely similar turnover rates of male and female advisers in absence of misconduct strongly suggests 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, which 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, at the same point in time, by estimating the following linear probability model:

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

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×year ×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 6b. 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×year ×county fixed effects μ_{jlt}. Following Oster (2016) and Altonji, Elder, and Taber (2005a, 2005b, 2008) work on unobservable selection, we calculate the lower bound of our estimated coefficient on $Misconduct_{ijlt} \times Female_{ijlt}$ to be 4.5. 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 6b column 3). 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 job following a misconduct disclosure. These results suggest that firms are more tolerant of misconduct among male advisers.

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 termination decisions, they may also be more tolerant of their misconduct in hiring decisions as well. The distinction between hiring and firing is important, because firms fire advisers for misconduct committed at the 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 an offense 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 firing decisions than in rehiring decisions.

Simple cuts of the data displayed in Table 6a indicate that women face worse reemployment prospects following misconduct. Almost one half (47%) of male advisers who lose their job following misconduct find a new job in the industry within a year. Only one third (33%) of female advisers are reemployed in the same period. Partially, this difference in reemployment 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 6a indicate female advisers are 8pp less likely[7] to find new employment following misconduct relative to male advisers.

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 job in the previous year. $New\_Employment_{ijlt+1}$ is equal to one if the adviser i who had been employed at firm j 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

[7] $-8\% = (33\% - 48\%) - (47\% - 54\%)$

in misconduct.

The corresponding results are reported in Table 6c. 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 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 the unemployment spells for male advisers. This is the case both for advisers with misconduct in the past year and 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:

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

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 7a 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 7a 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 7a column 1).

3.3 Initiating Misconduct: Employers, Customers, or Regulators?

Women face substantially harsher punishments both by the firms that employ them and other potential employers in the industry. 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 punish female advisers more harshly, 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. Regulators pursue regulatory violations. Advisory firms can trigger misconduct allegations as the result of misconduct accusations, or if the adviser violated the firms' internal policies.

Table 8a breaks down the share of misconduct originating from each category by the gender of the adviser and Table 8b reports the corresponding allegations. The share of misconduct originated by consumers is higher for male advisers (55%) relative to female advisers (45%). Likewise, the share of regulatory complaints is slightly higher for male advisers (17%) relative to female advisers (13%). 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 discrimination 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:

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

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 or not the firm initiated the misconduct proceedings rather than a customer or regulator. The dependent variable 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 8c 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 Punishment Differences Across Firms

If the source of gender differences in punishment is indeed the firm, then it is plausible that firms differ in how they treat male and female advisers following misconduct. We first document that firms differences exist. Then we explore whether differences between firms, such as the gender composition of management, can explain differences in discrimination across firms.

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.[8] Figure 8a displays the dispersion in gender discrimination (β_{j3}) across firms.[9] The estimated distribution of firm coefficients (β_3) are jointly significantly different from each other, confirming differences in discrimination 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[10] more likely to experience an employment separation following misconduct relative to male advisers. Overall, the results suggest that gender discrimination varies substantially across firms.

3.4.1 Do Female Managers Alleviate Discrimination?

If discrimination arises because of employer bias, it is probably driven by the bias of the decision makers in the firm. One proposal to limit discrimination in firms is to increase the share of women in positions of power. The idea is that decision makers in organizations can directly affect policies leading to discrimination.

[8] 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}.

[9] To improve statistical power, we restrict our analysis to firms in which at least twenty female advisers receive misconduct disclosures.

[10] The results displayed in Table 6a indicate that, on average, female advisers are 9pp more likely to experience an employment separation 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 an employment separation following misconduct relative to male advisers.

The members from the discriminated group, i.e., women, are more likely to recognize discrimination and less likely to support discriminatory practices. Figure 2b 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 within firms can explain differences in discrimination across branches.

We first examine whether the gender composition of decision-making teams across firms explains some of the firm differences in discrimination. Specifically, we examine whether gender differences are smaller in firms with more female executives using the following linear probability model:

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

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 $Pct\, Female\, Exec_{jlt}$ 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 9a 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.[11] In firms without any female executives, on the other hand, female advisers are 16pp more likely to experience an employment separation relative to their male counterparts following misconduct (Table 9a, column 3).

The share of female executives at the top level of the firm's organizational structure is related to differences in discrimination across firms. Gender discrimination may also depend on more granular firm characteristics at the branch level. 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. These specifications allow us to exploit within-firm variation to examine the causes of gender discrimination. We also examine the effects of female representation at the branch

[11] The results in column (2) of Table 9a 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 $Pct\_Female\_Exec = \frac{14.1}{41.0} = 0.34$.

level more generally by constructing the variable $Pct\,Female_{jlt}$, which reflects the percentage of advisers (weighted by experience) that are female at the firm × county × year level. Figures 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 9b and 9c display the estimation results corresponding to eq. (7). The results indicate that female advisers employed are more likely to experience an employment separation after receiving a misconduct disclosure 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. Female advisers also experience less differential treatment following misconduct at branches with more female advisers. The results displayed in column (2) of Table 9c indicate that female and male advisers experience similar outcomes following misconduct when male and female advisers are roughly equally represented at the firm branch.[12]

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:

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

Observations are at the firm × year level. The dependent variable reflects the share of new employees that were hired by firm j at time t+1 that are female and have a past record of misconduct. The independent variable of interest is again the percentage of executives/owners 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 9d. 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 driven by discrimination by male executives of financial advisory firms. Male executives seem to be more

[12] 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 9c). Thus, there is no differential in job separation probabilities for male and female advisers following misconduct if $Pct\,Female = \frac{10.6}{16.9} = 0.62$.

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 genders. To explain the striking differences in discrimination across firms and offices within firms, offices with a larger share of women executives would have to employ more productive women than firms with predominantly male executive teams, and do so to a large extent.

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 labor market outcomes. In our analysis, we control 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. There are broadly two alternative reasons why misconduct could be punished more severely. First, because gender could be indicative of misconduct costs. If women engage in more misconduct, or if this misconduct is more expensive, then the punishment should be harsher. 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 offices within firms with a larger share of female executives. 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 make advisers has to be smaller in firms with a larger share of women executives. We therefore feel that the scope for alternative explanations is quite narrow.

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 discrimination among men with distinctly African names.

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, 2016). We find that unconditionally men have higher rates of misconduct. Roughly 9% of male and 3% of female advisers engaged in misconduct during their career. However, it is possible that female advisers with a misconduct record are more likely to engage in misconduct than their male counterparts. Then 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 relative to female advisers.

To ensure that gender differences in the propensity towards repeat offenses are not driven by differences in firms, or differences in 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}.

Table 10 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 women engage in more misconduct. However, the evidence presented in Figure 6a and Table 10 indicates the exact opposite; male advisers are substantially more likely to be repeat offenders relative to female advisers.

4.1.2 Cost of Misconduct?

Female advisers do not seem to engage in more misconduct than male advisers. Instead, harsher punishment may be warranted if women engage in more costly 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. Table 4c reports the corresponding summary statistics. The median settlement is $40k for male advisers and $31k for female advisers. Furthermore, the average settlement of male advisers is more than double that of female advisers ($832k versus $320k).

We examine the 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 11 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. Overall, we find evidence that male advisers engage in more misconduct and in 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, 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 4a 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. Mens' 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 allegations, which represent unsuitable investment or misrepresentation.

We re-estimate our main results, but replacing 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 12a). The results in column (3) indicate that conditional on receiving an unauthorized activity related misconduct disclosure, 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 we document in Section 3.1.

We also examine advisers' reemployment prospects conditional on receiving an unauthorized activity related misconduct disclosure. We re-estimate eq. (3) and present results in Table 12b. 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. (2016). To see whether our results could be driven by our definition of misconduct, we also measure "Severe Misconduct" (Egan et al., 2016), which focuses on more severe instances of misconduct such as explicit fraud.[13] Table 13a 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 a record 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 13b. 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

[13]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.

when misconduct is severe. We re-estimate gender differences in job separation following misconduct from eq. (2). The results in column (2) of 13b 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 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. In this section use Meridian IQ data, which contains additional details on adviser productivity for a large subset of active[14] financial advisers. We observe information on the adviser's productivity (revenues brought to a firm), assets under management (AUM), and quality[15]. We report the productivity summary statistics for male and female advisers in the bottom panel of Table 1. 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 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 14 suggest that female advisers are 46%[16] less likely to receive a misconduct disclosure in a given year. The results in column (1) 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

[14] 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.

[15] 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.

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

specification (Table 5).

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 the linear probability model discussed in Section 3 (eq. 2) controlling for adviser productivity. We report the corresponding estimates in column (2) of Table 14. Even controlling for productivity differences, we still find evidence that female advisers are substantially more likely to experience an employment separation following misconduct. The results in column (2) indicate that female advisers are 5pp more likely to experience a job separation following misconduct relative to male advisers. Advisers that are more productive, manage more assets, and that have a high quality rating are less likely to experience an employment separation, 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 a career interruption. After controlling for observable characteristics, female advisers are 1.26pp more likely to experience a career interruption. We replicate our main analysis for Section 3 to examine whether the discrimination we observe is robust to career interruptions.

Table 15 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.

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 financial advisers different experience levels. Previous research suggests that gender differences in pre-market human capital among men and women are negligible (Blau 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 16a and 16b. The results in Table 16a indicate that the same discriminatory patterns hold for less experienced advisers: relative to male advisers, female advisers are 49%[17] less likely to engage in misconduct, 9pp more likely to experience an employment separation following misconduct, and 2pp less likely to find a new job following misconduct relative to male advisers. We find similar patterns for more experienced advisers. Among those advisers with fifteen years experience, female advisers are 50%[18] less likely to engage in misconduct and 4pp more likely to experience an employment separation following misconduct. In both sub-samples we find less 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 throughout a female adviser's career.

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 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 independent variable indicating whether adviser i working for

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

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 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 $Female_{ijlt-1} \times Downsize_{ijtl-1}$. [19]

Table 17 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.

4.3 Discrimination and Minorities

In this section we first examine whether the discrimination in punishment is limited to gender, or whether it extends to other groups, which have traditionally faced discrimination in the labor market. We do so to narrow the scope of theories 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, risk aversion, which can explain several important phenomena that might look like discrimination across gender (Bertrand et al. 2010).[20] Gender identity norms govern (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). The Ambekar et al. (2009) name-ethnicity classifier uses a hidden Markov models and decision trees to classify names into thirteen different ethnic groups. [21] 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

[19] 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.

[20] 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.

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

origins and 2% are classified as 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 a misconduct disclosure in a given year relative to other male advisers (Table 18c). 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 after observing misconduct. Recall that such updating is not necessarily in line with future offenses of female advisers. However, miscalibrated updating based on low rates could still be a possibility. If this is the case, however, then we should not find harsher 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 18a, the estimated coefficient on the interaction terms $Misconduct \times African\,Origins$ and $Misconduct \times Hispanic\,Origins$ are positive and significant, suggesting African and Hispanic advisers are more likely to experience a job separation following misconduct. In other words, minority men experience similar punishment to female advisers. We find similar results for reemployment following misconduct (Table 18b). Results suggest that Hispanic advisers face relatively worse employment prospects following misconduct relative to non-African and -Hispanic advisers. We do not find any evidence suggesting that African advisers face worse reemployment prospects following misconduct relative to non-African and -Hispanic advisers. Overall, the results suggest that following misconduct, African advisers face more severe punishment at the firm level but not at the industry level while Hispanic advisers face more severe punishment at both the firm and industry level.

4.3.1 Minority Managers

We find less gender discrimination of misconduct punishment in firms with a larger share of female managers. Here, we explore if 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) 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 19a suggest that minority advisers working at a branch with no African representation at the branch management level are 10pp more likely to experience an employment separation following misconduct. However, minority advisers working at a branch where 42% of the branch managers are of their minority are equally likely to experience an employment separation following misconduct relative to non-minority advisers. These results suggest that differences in labor market outcomes following misconduct are driven by discrimination of executives of financial advisory firms.

Male executives seem to be more forgiving of misconduct by men relative to 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 being members of a discriminated group they understand the phenomenon of discrimination better, and seek to avoid it. Then 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. 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:

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

The estimates in Table 19c indicate that female advisers with recent misconduct are 10pp more likely to experience an employment separation 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 plays an important role in understanding the differential treatment of advisers across different genders and ethnicities.

5 Discussion: What Drives Discrimination

In this section, we argue that the gender discrimination in punishment we observe is best explained by mangers exhibiting more forgiveness towards members of their own group. This increased level of forgives can arise either because of miscalibrated beliefs (Bordalo et al, 2017), or taste differences (Becker, 1957) across the groups. In the appendix, we present a simple model of discrimination based on biased male managers. The bias can either arise because of miscalibrated beliefs about the probability of repeat offenses across genders or because of taste-based discrimination. For ease of exposition we discuss the model in terms of miscalibrated beliefs and then discuss why our findings are more consistent with miscalibrated beliefs rather than taste-based discrimination. Firms' firing and hiring decisions across gender are based on expected misconduct and productivity across genders. Male managers can have miscalibrated beliefs about the probability of repeat offenses across genders. Specifically, male manage believe that conditional on observing misconduct, female advisers have a higher hazard of repeat offenses than male offenders. We contrast the predictions of the miscalibrated model to a benchmark model without miscalibrated beliefs–a pure statistical discrimination model (Phelps, 1972; Arrow, 1973). We show that the pure statistical discrimination model can explain several facts; however, it is rejected on dimensions in which its predictions differ from the miscalibrated beliefs model. Last, we discuss which types of miscalibration beliefs are consistent with our evidence.

5.1 Statistical Discrimination vs. Manager Bias

First, consider the benchmark, a pure statistical discrimination model without manager bias (either miscalibrated beliefs or taste-based discrimination). We first 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 the marginal male adviser. Recall that on average, female advisers have lower rates of misconduct. The model predicts that because female advisers have lower rates of misconduct on average, firms are willing to hire them at a lower productivity, all else equal. Therefore, as misconduct is detected, this lower productivity results in more termination among female advisers. This result only holds up as long as the true underlying 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, which can more directly differentiate between the pure statistical discrimination model, and that of biased managers.

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 statically 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 the recidivism is substantially higher for male advisers than female advisers on average. On the other hand, the miscalibration model suggests that female advisers will have lower rates of repeat offenses. The idea is the following: if male managers believe that males are less likely to engage in repeat misconduct offenses than females, then they will fire female advisers with a higher probability of recidivism upon observing misconduct. This behavior will result in a lower measured recidivism among female advisers, as we show in the Appendix. The intuition for repeat behavior is as follows: if managers are biased, they impose a stricter threshold for female advisers. Then 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 probability of repeat offenses between the genders are the same.[22] The results in 4.1.1 reject the baseline statistical discrimination model: female advisers are less likely to engage in repeat offenses.

Second, the pure statistical discrimination model cannot explain why gender differences are most present in firms with male management. The intuition of the miscalculated beliefs model is straightforward. Male managers are those with biased beliefs; more male managers leads to more discrimination. In sum, the model without belief miscalibration is rejected in the data, which is consistent with a model in which male managers believe that female advisers are more prone to repeat offenses than male advisers conditional on observing misconduct. Note that male advisers can still believe that female advisers engage in less misconduct; the only miscalibration that is required is that they believe that conditional on observed misconduct, female advisers are more likely to repeat. In other words, female bad apples are worse than male bad apples.

A model with a simple miscalibration can rationalize the results we document: a manager believes that members of his / her group have a lower propensity to engage in repeat offenses, i.e. they "deserve another shot." We next discuss an alternative plausible miscalibration of beliefs, which would be a different small departure from the statistical discrimination model. Suppose, male advisers believe that female advisers are on average less prone to misconduct–this belief is consistent with the data. Just as in a pure statistical discrimination model, the manger is Bayesian, and updates that probability of future misconduct for female advisers conditional on discovery is higher. As we show, such updating is not consistent with the data, and would therefore represent a miscalibrated model. Recall that, unlike female advisers, male minority advisers have a higher average rate of misconduct than male non-minority advisers. The fact that discrimination of minority men in firms with non-minority management suggests that this form of miscalibration is not responsible for gender discrimination either. Overall, our data suggest that the simplest model, which explains the facts across gender and minority discrimination in punishment of misconduct is one in which managers are more lenient towards members of their own group, possibly because they believe that the possibility of repeat misconduct is smallest.

5.2 Bias: Miscalibrated Beliefs vs. Taste-Based Discrimination.

Our empirical facts are best explained by a model of manager bias, either miscalibrated beliefs or taste-based discrimination. In the model, miscalibrated beliefs and taste-based discrimination are observationally equivalent with respect to a firm's firing decision and recidivism. 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. We exploit variation in the information structure by examining advisers with different firm level experience. As a manager learns more about an individual

[22] Arnold, Dobbie, and Yang (2017) apply a similar test of recidivism across racial groups to measure racial bias in bail decisions.

adviser over time, the manager's beliefs will shift from his original potentially biased prior beliefs to the manager's personal experience. Conversely, a manager's preferences over genders will not change with an individual adviser's firm tenor.

We reexamine the relationship between misconduct and discipline based on the adviser's level of experience within his/her firm. In Tables 16c and 16d we report the estimation results for our baseline specifications for those advisers with five years or less experience and fifteen or more years experience within his/her firm. We find the same patterns hold for less experienced advisers (within a firm). The results displayed in column (2) of Table 16c indicate that female advisers are 12pp more likely to experience an employment separation following misconduct and are 3pp less likely to find a new job following misconduct relative to male advisers. In contrast to our previous results, we do not find evidence suggesting that female advisers with fifteen or more years of experience face differential treatment following misconduct relative to male advisers (16d). We find that discrimination in punishment between male and female advisers dissipates over time as the adviser's tenor with his/her firm increases. These results suggests that the observed discrimination occurring early on in an advisers' tenor with a firm has to do with firm beliefs, which evolve over time, rather than some inherent characteristic of the firm.

6 Other Results

6.1 Promotions

Our main analysis focuses on how a firm disciplines misconduct in terms of the firm's firing/hiring practices. Another dimension firms could use to discipline misconduct is through promotion. Here, we examine how a past record of misconduct impacts the promotion prospects of male and female advisers.

We examine the probability an adviser is promoted in a given year. Our measure of promotion is whether or not the financial adviser is promoted to a general securities principal. A general securities principal must pass the Series 24 exam, which qualifies an individual to supervise or manage employees at a general securities broker dealer. We estimate the corresponding linear probability model

$$Promotion_{ijlt} = \beta_1 Female_{ijlt} + \beta_2 Misc._{ijlt} + \beta_3 Misc._{ijlt} \times Female_{ijlt} + \beta_4 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \tag{13}$$

The dependent variable, $Promotion_{ijlt}$, indicates whether or not adviser i passed the general securities principal exam at time t. Our unit of observation is at the adviser-by-year level, where we restrict our analysis to the full set of financial advisers who were not general securities principals prior to time t. The independent variables of interest are the variables $Misconduct$ and the interaction term $Misconduct \times Female$. The interaction term tells us if and how the promotion prospects of male and female advisers differ after he/she receives a misconduct disclosure.

The corresponding estimates for our promotion linear probability model are reported in Table A1. In each specification, we find a negative relationship between misconduct and the probability an adviser is promoted in a given year. The results in column (1) of Table A1 indicate that those male advisers who recently received a misconduct disclosure are 17bps less likely to be promoted. To put this number in perspective, 0.91% of male advisers in the sample are promoted each year. Thus, those male advisers who recently received misconduct disclosures are 19% less likely to be promoted relative to other male advisers. The results also indicate that female advisers are disproportionately punished for misconduct. We estimate a negative relationship between promotion and the interaction term $Misconduct \times Female$ in each specification and the estimated coefficient is statistically significant in two out of three specifications. The results in column (1) of Table A1 indicate that female advisers recently disciplined for misconduct are 67% less likely to be promoted relative to other female advisers. The results suggest that firms not only discriminate across male and female advisers in terms of their hiring/firing practices following misconduct, but also in their promotion decisions.

6.2 Regional Differences

We find that there is substantial variation in discriminatory practices across firms but how about across regions? In this section, we examine regional differences in discriminatory hiring/firing practices and how they relate to other measures of gender inequality. Using spatial variation allows us to ask if the regional differences in gender outcomes, which represents the tolerance of the community (including customers of the firm), might explain some of the differences we document. Specifically, we examine how our measures of discrimination relate to wage and participation gender gaps in the finance sector. We supplement our data set with data from the American Community Survey on wage and participation gender gaps in the financial sector[23] at the county-by-year level over the period 2010-2015. One might expect that women would face harsher discipline relative to men in areas with larger gender gaps, regardless of whether or not the underlying discrimination is taste-based or statistical.

We re-estimate our baseline employment separation and reemployment regressions (eq. 2 and 3), where we fully interact our misconduct and gender variables with our measure of gender wage and participation gaps:

$$\begin{aligned} Separation_{ijlt+1} = {} & \beta_1 Female_{ijlt} + \beta_2 Misc._{ijlt} + \beta_3 Wage\_Gap_{lt} + \beta_4 Misc._{ijlt} \times Female_{ijlt} \\ & + \beta_5 Gender\_Gap_{lt} \times Misc._{ijlt} + \beta_6 Gender\_Gap_{lt} \times Female_{ijlt} \\ & + \beta_7 Gender\_Gap_{lt} \times Misc._{ijlt} \times Female_{ijlt} + \beta_8 X_{it} + \mu_{jlt} + \varepsilon_{ijlt}. \end{aligned} \tag{14}$$

The dependent variable indicates whether or not adviser i experienced an employment separation at time t. We construct four different measures of the variable $Gender\_Gap_{lt}$ at the year-by-county level. First,

[23] We examine the median wages earned by males and females in "Management, business, science, and arts occupations: Management, business, and financial occupations: Business and financial operations occupations."

we construct $Gender\_Gap_{lt}$ as a dummy variable equal to one if county $l's$ wage gap is above the median wage gap in the sample. We define the wage gap in the financial sector and across all sectors such that $Wage\_Gap_{lt} = \frac{Median\_Male\_Wages_{lt} - Median\_Female\_Wages_{lt}}{Median\_Male\_Wages_{lt}}$. Second, we construct $Gender\_Gap_{lt}$ as a dummy variable equal to one if county $l's$ participation gap is above the median participation gap in the sample. We define the participation gap in the financial sector and across all sectors such that $Participation\_Gap_{lt} = \frac{\#Male\_Employees_{lt}}{\#Female\_Employees_{lt} + \#Male\_Employees_{lt}}$. The independent variable of interest is the triple interaction term $Gender\_Gap_{lt} \times Misconduct_{ijlt} \times Female_{ijlt}$. A positive coefficient on the triple interaction term indicates that female advisers experience more discrimination in areas with large gender gaps. We also estimate the corresponding specification where the dependent variable is whether or not the adviser was reemployed following an employment separation.

The corresponding estimation results are displayed in Tables A2a and A2b. We report the results corresponding to our employment separation regressions (eq. 2) in Table A2a. We find modest evidence suggesting that female advisers face more discrimination in areas with relatively large wage and participation gender gaps. In all four specifications, we estimate a positive coefficient on the triple interaction term $Gender\_Gap_{lt} \times Misconduct_{ijlt} \times Female_{ijlt}$. The estimated coefficients are statistically significant at the 10% level in column (1) and are marginally significant in columns (2) and (3) (p values of 0.10 and 0.11 respectively). The estimates in column (1) indicate that female advisers with recent misconduct in regions with relatively large wage gaps (above the median) are roughly 20pp[24] more likely to experience an employment separation relative to male advisers in those regions with recent misconduct. Conversely, female advisers with recent misconduct in regions with relatively low wage gaps are roughly 16pp more likely to experience an employment separation relative to male advisers in those regions with recent misconduct.

Table A2b displays our results corresponding to our reemployment regressions (eq. 3). The dependent variable indicates whether or not an adviser who recently experienced an employment separation was able to find new employment within a year. We again find modest evidence suggesting that female advisers face more discrimination in areas with relatively large wage and participation gender gaps. In three out of the four specifications we estimate a negative coefficient on the triple interaction term, $Gender\_Gap_{lt} \times Misconduct_{ijlt} \times Female_{ijlt}$. A negative coefficient indicates that the reemployment prospects of female advisers with recent episodes of misconduct are worse in areas with larger wage gaps. The estimates in column (4) indicate that female advisers with recent misconduct disclosures in regions with relatively large participation gaps (above the median) are 9.38pp[25] less likely to find new employment relative to male advisers in those regions with recent misconduct.

[24] 0.157+0.0401=0.1971
[25] 4.443+4.942=9.385

6.3 Which types of firms hire advisers following misconduct

Last, we examine the quality of new employment among male and female advisers recently reprimanded for misconduct. We estimate the following specification:

$$New\_Firm\_Characteristic_{ij'lt+1} = \beta_1 Misc._{ijlt} + \beta_2 Misc._{ijlt} \times Female_{ijlt} + \mu_{jlt} + \varepsilon_{ijlt}. \qquad (15)$$

The dependent variable $New\_Firm\_Characteristic_{ij't+1}$ measures the size and the amount of misconduct of the firm j' joined by adviser i who joined firm j' after leaving firm j. The independent variable of interest is the interaction term $Misconduct_{ijt} \times Female_{ijlt}$, which captures the difference in quality of new employment opportunities obtained by female advisers with recent misconduct relative to male advisers with recent misconduct. Here we include the previous firm × county × time fixed effects μ_{jlt}. In other words, we are comparing the new employment outcomes of male and female advisers with recent misconduct who were working for the same firm at the same location at the same time.

Table 7b displays the results. Both male and female advisers with recent misconduct move to firms that are smaller and firms that have a higher share of employees with past misconduct records. However, relative to male advisers with recent misconduct, female advisers with recent misconduct move to firms that have 800 fewer employees and firms that have a 1.37pp lower incidence of past misconduct. Overall, these results suggest that, relative to male advisers, female advisers experience face harsher consequences for engaging in misconduct at both the firm and industry level. Subsequent to leaving the firm after misconduct, female advisers also move to firms that are cleaner in terms of misconduct propensity of the advisers that are employed by the new firm.

7 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 male advisers 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 females with a record of past misconduct. We find that a model of miscalibrated beliefs best explains the observed discrimination in the data.

Our findings provide new insight into gender discrimination in the workplace. We examine an inconspicuous and potentially costly channel of discrimination: termination following cause. The financial advisory industry is willing to give male advisers a second chance, while female advisers are likely to be cast from the industry.

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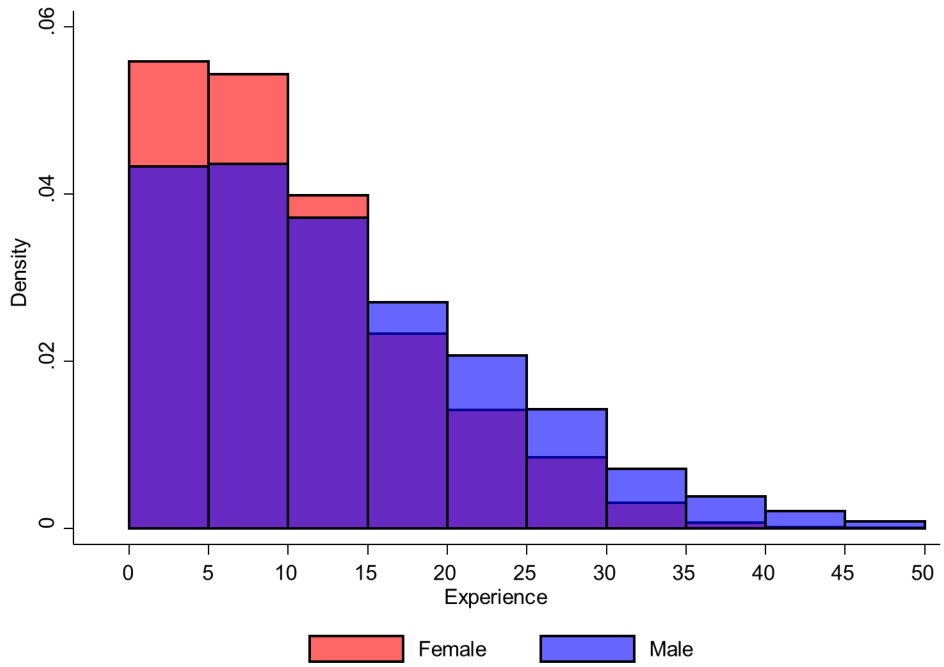
Figure 1: Characteristics of Female and Male Financial Advisers

(a) Experience



(b) Qualifications

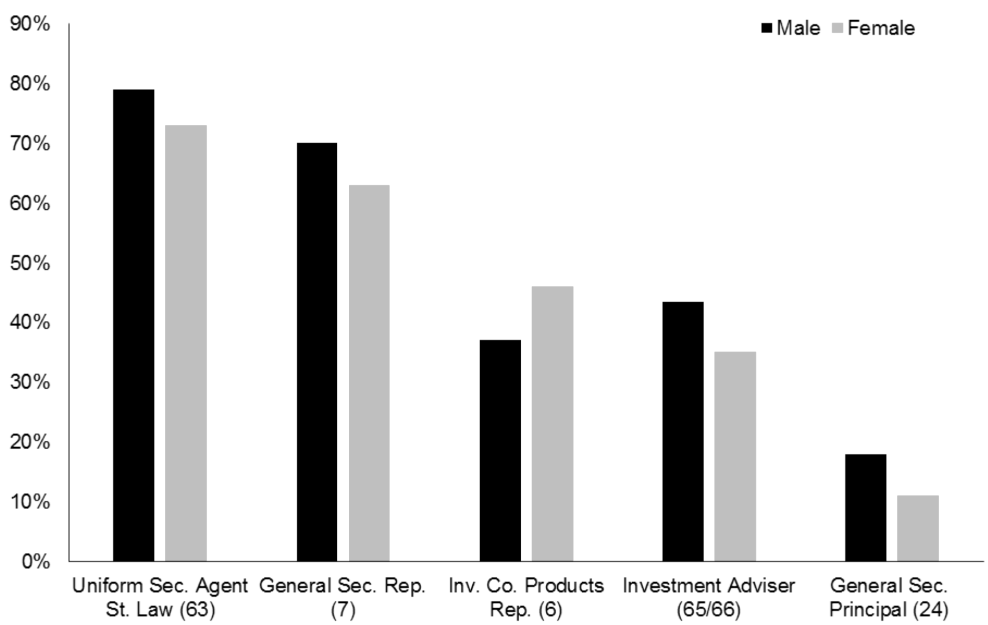
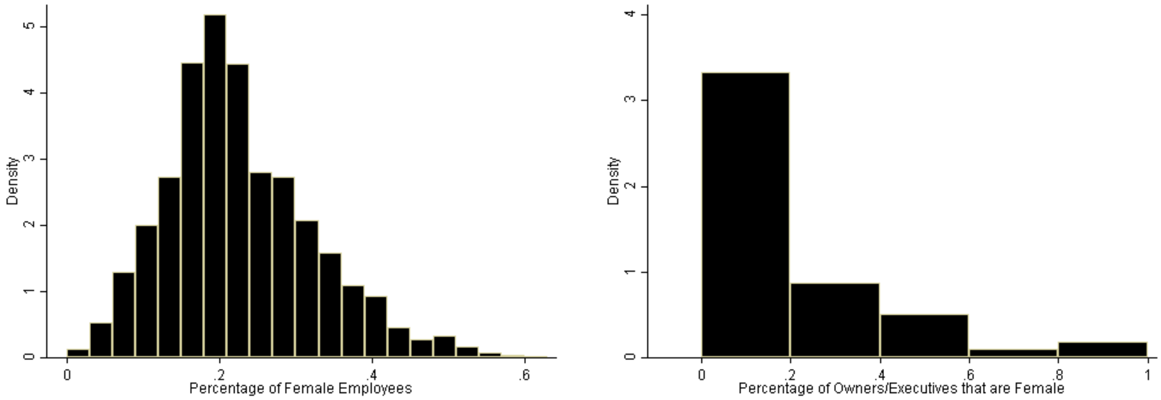


Figure 1 panels (a) and (b) plot the distribution of characterstics among male and female advisers in the data set. Panel (a) plots the distribution of experience among male and female advisers. Panel (b) displays the percentage of female and male advisers that hold a particular qualification. We examine 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

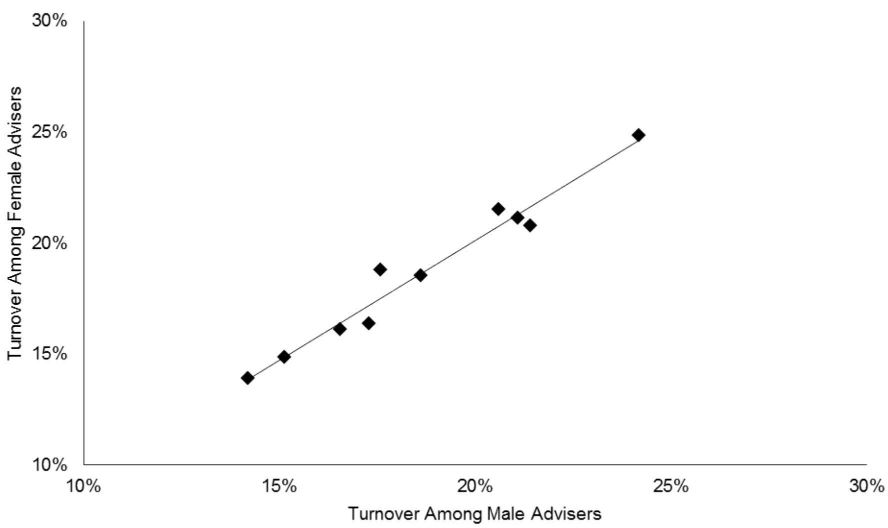
(a) Percentage of Advisers that are Female

(b) Percentage of Executives/Owners that are Female



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 firm by year over the period 2005-2015. Figure 2b displays the percentage of executives/owners in our sample that are female as of 2015.

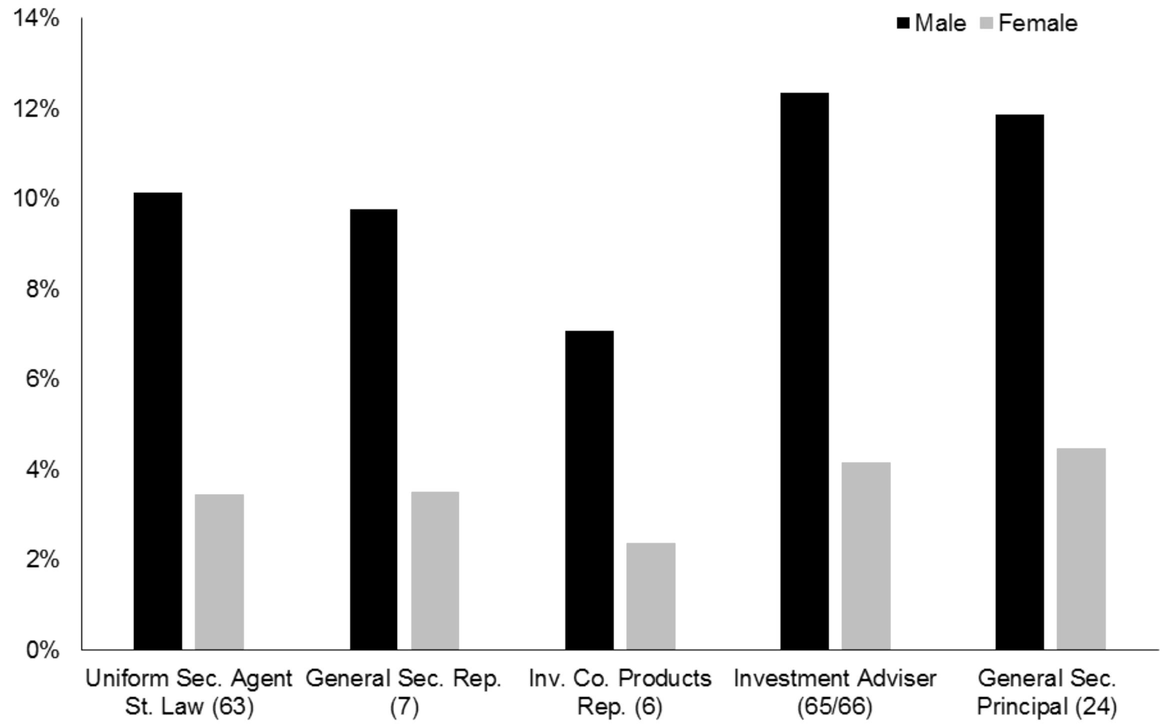
Figure 3: Job Turnover - Male vs. Female Advisers



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

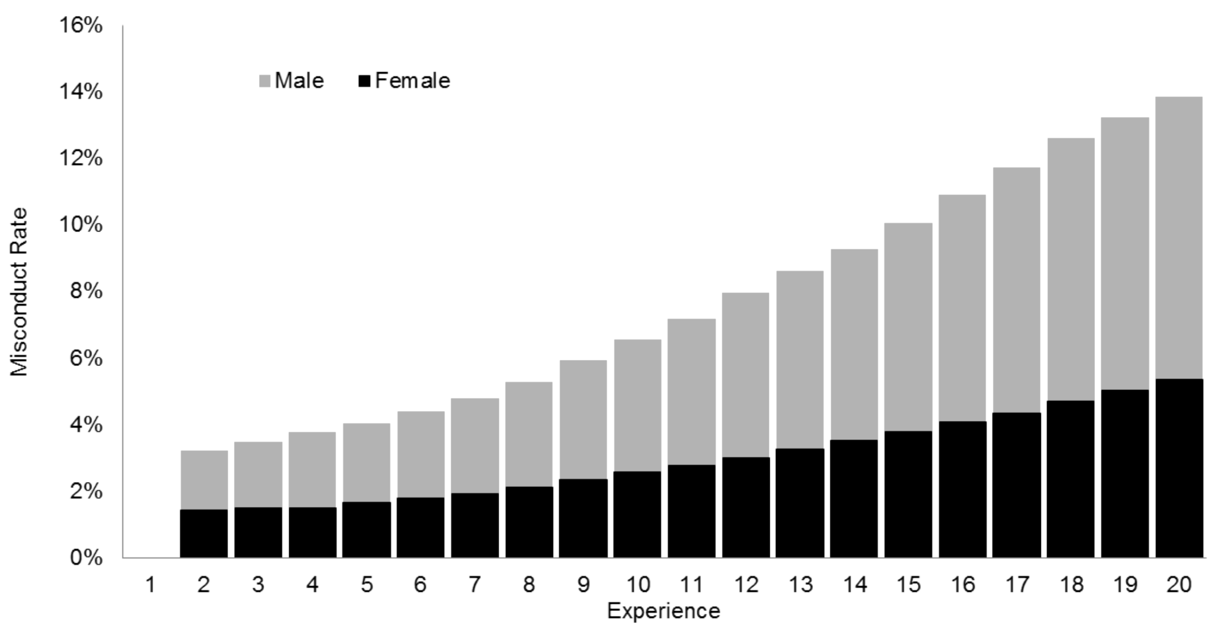


Figure 4a displays the percentage of male and female advisers with a misconduct disclosure on his/her record conditional on the adviser holding the specified qualification exam. Figure 4b displays the percentage of male and female advisers with a misconduct disclosure on his/her record conditional on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

Figure 5: Unemployment and Misconduct

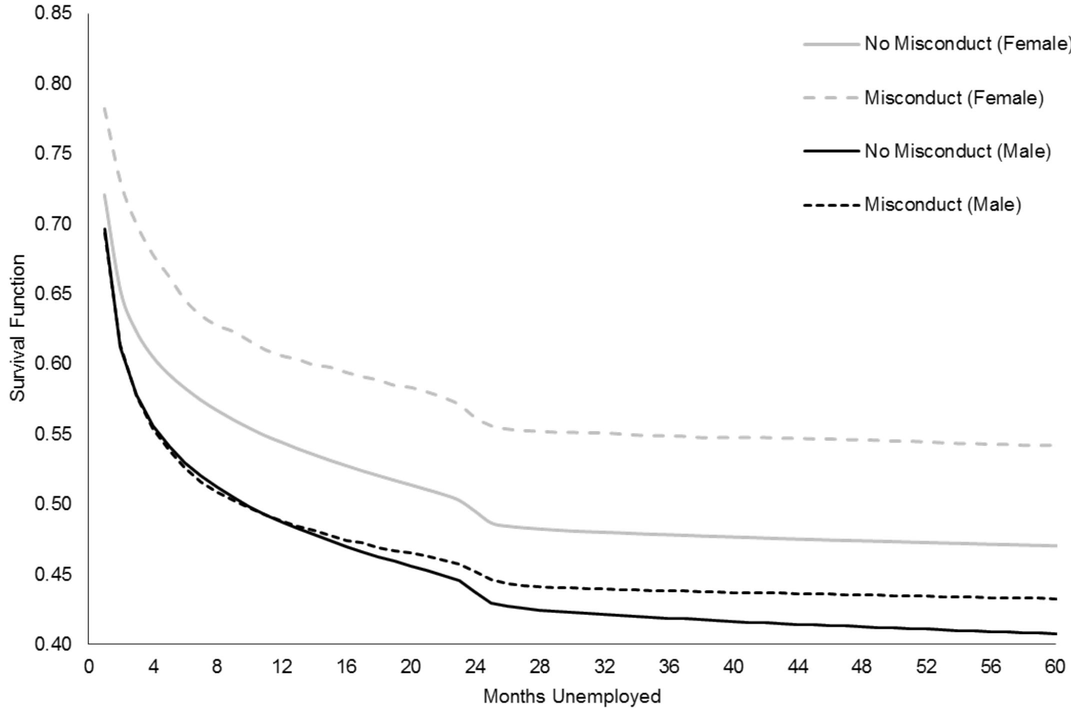
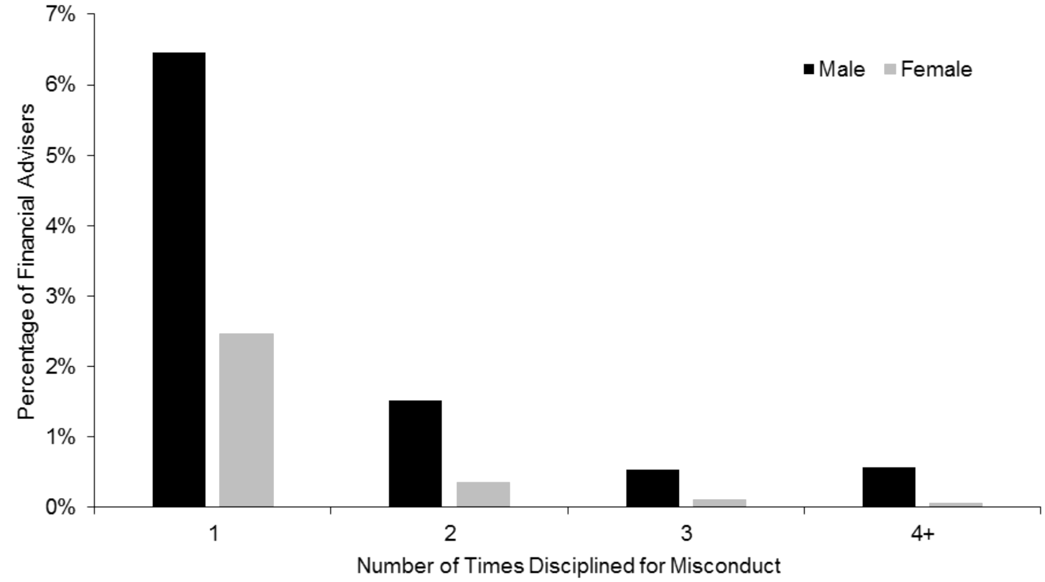


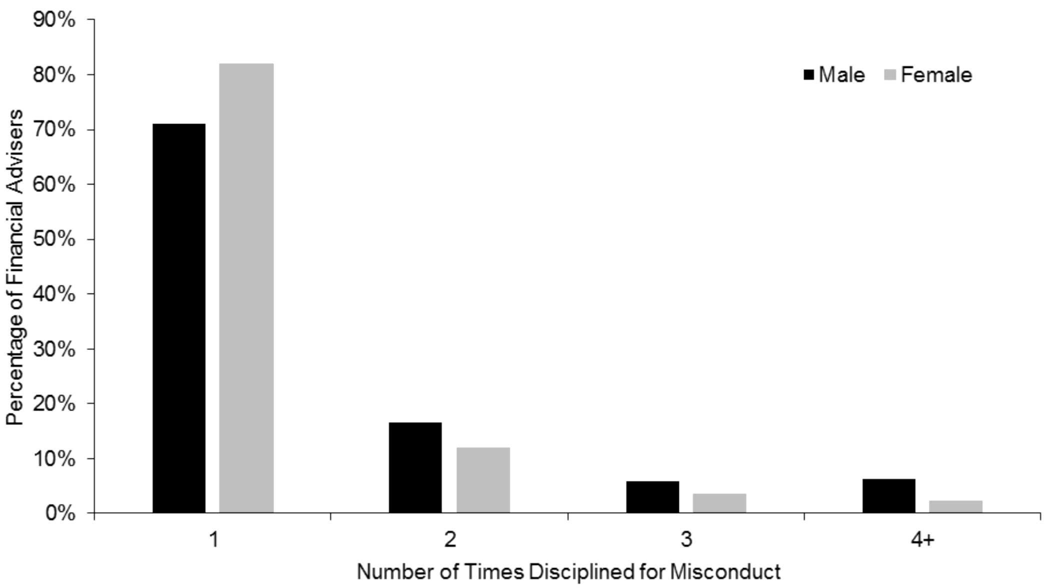
Figure 5 displays the unemployment survival function for all adviser unemployment spells over the period 2005-2015. The solid black and gray lines display the unemployment survival functions for those male and female advisers who were not disciplined for misconduct in the year prior to their unemployment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

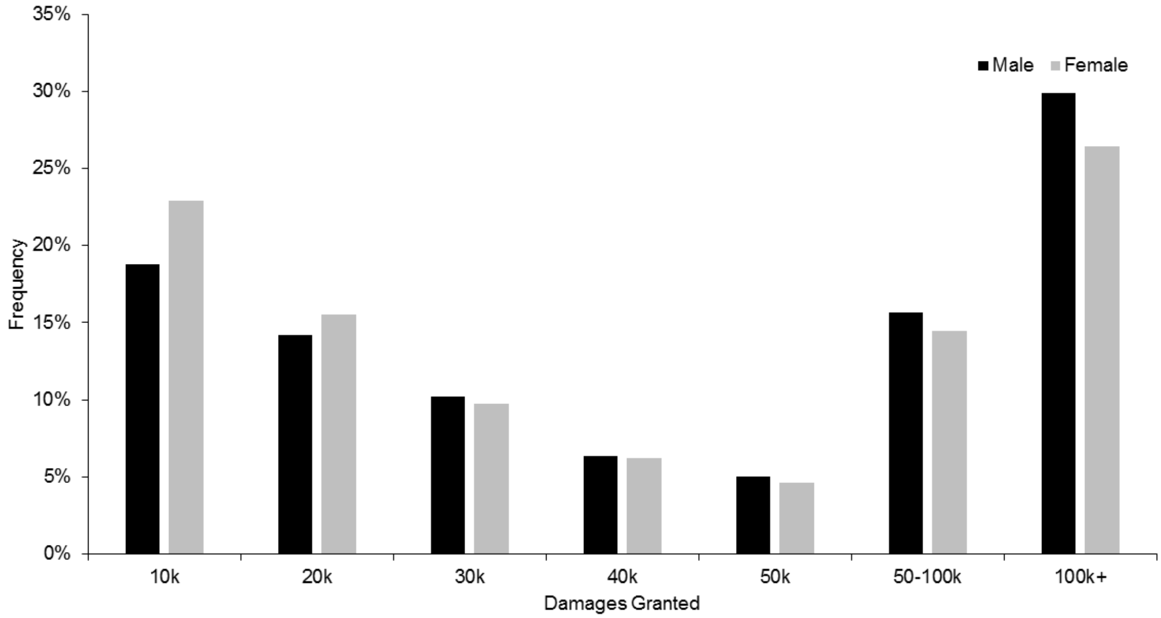


(b) Distribution of Misconduct - Repeat Offenders



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, while 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.

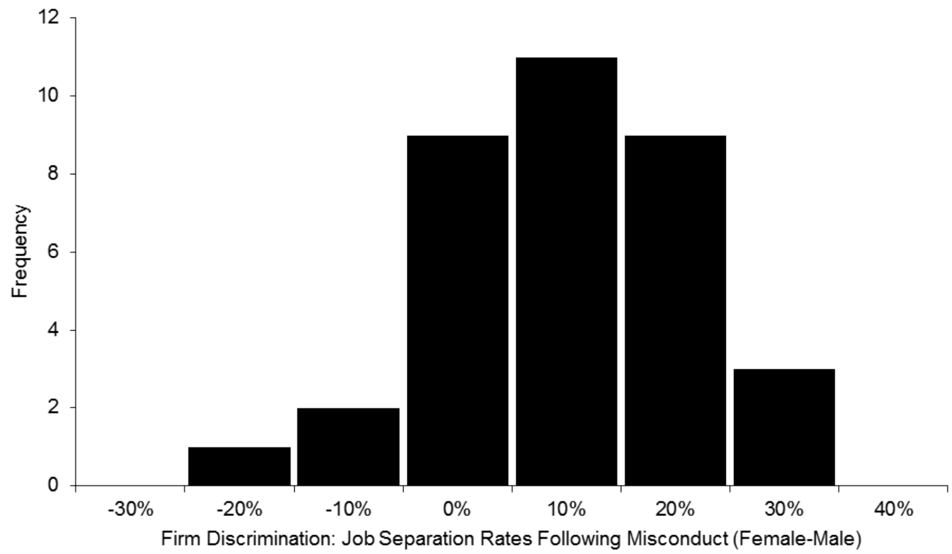
Figure 7: Distribution of Settlments/Damages



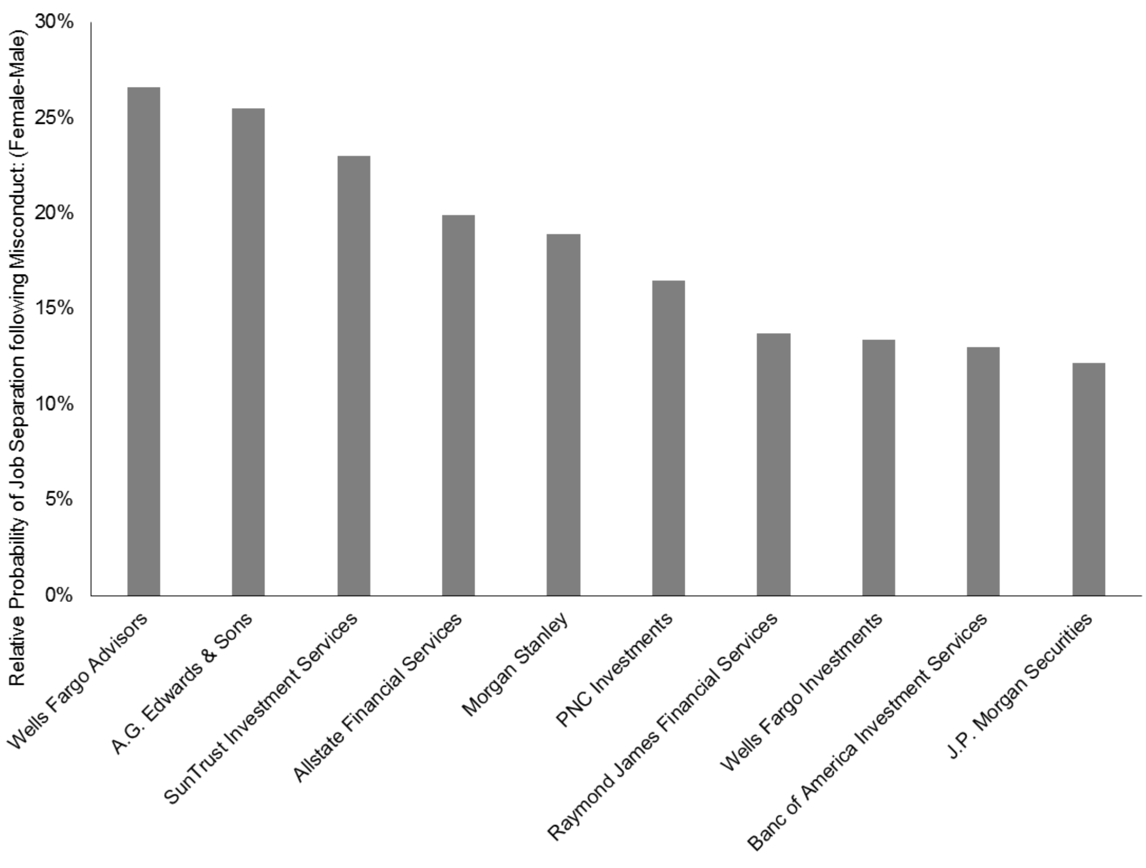
Note: Figure 7 displays the distribution of settlements/damages for male and female advisers that were granted over the period 2005-2015. In the BrokerCheck database, we observe the settlements/damages details for 45.80% of misconduct related disclosures and 0.55% of the other types of disclosures. Observations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

Figure 8: Firm Heterogeniety in Firm Discipline

(a) Distribution of Firm Discipline



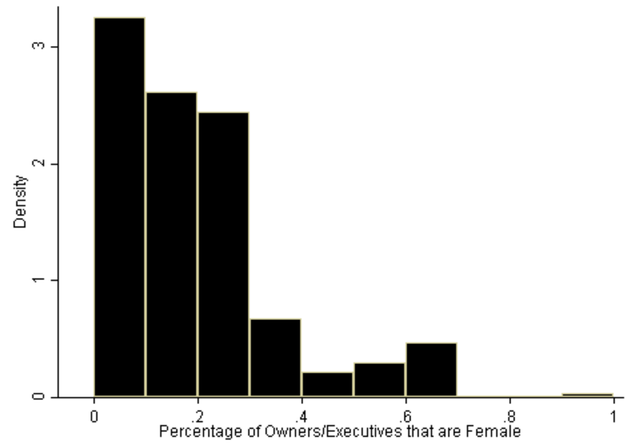
(b) Top Firms



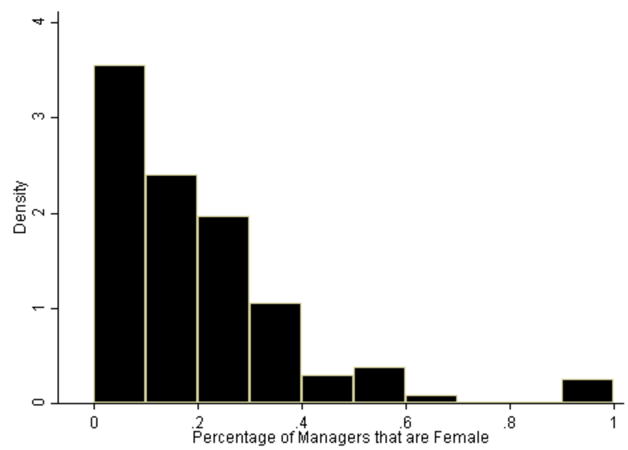
Note: Figures 8a and 8b display the distribution of discipline across firms. Specifically, the figures plot the distribution of the coefficient β_{j3} from eq. (6), which captures the probability female advisers experience an employment separation following misconduct relative to male advisers (i.e., the difference in differences for female and male advisers with and without misconduct). Figure 8b displays the firms with the ten highest coeffcient estimates. We restrict our analysis to those 44 firms where we observe at least twenty female advisers receive a misconduct disclosure.

Figure 9: Female Representation at Financial Advisory Firms

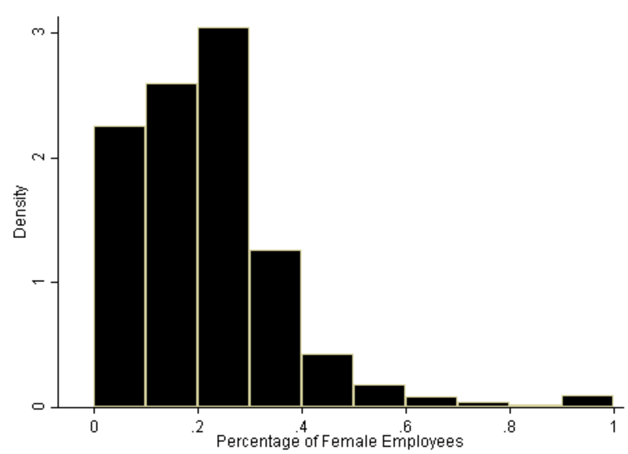
(a) Firm Executives/Ownership



(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 firm by county by year level. Figure 9c displays the percentage of advisers (weighted by experience) that are female 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.

Table 1: 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
Disclsoures:				
Disclosure (in a year)	4,932,478	0.0183	1,615,496	0.0108
Misconduct (in a year)	4,932,478	0.0072	1,615,496	0.0029
Disclosure (ever)	4,932,478	0.1489	1,615,496	0.0761
Misconduct (ever)	4,932,478	0.0908	1,615,496	0.0300
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	54.70	169,641	53.20
Productivity ($100k)	560,519	532.46	90,572	502.97
High Quality Indicator	2,272,975	0.45	559,589	0.32

Note: Table 1 displays the summary statistics corresponding to our panel of male and female financial advisers. Observations are adviser by year over the period 2005-2015. We report the standard deviation and median for the non-dummy variables.

Table 2: 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 2 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 firm in a given year. Observations are adviser by year over the period 2005-2015.

Table 3: 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 3 displays the incidence of disclosures/misconduct among male and female financial advisers. Observations are year by financial adviser over the period 2005-2015. We classify the six categories listed at the top of the table as being 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 disclsoure in that particular year and/or previously.

Table 4: Misconduct Complaints, Products, and Settlements/Damages

(a) Reasons for Complaint

Reasons for Complaint	Gender	
	Male	Female
Unsuitable	22.80%	18.30%
Misrepresentation	18.34%	14.64%
Unauthorized Activity	14.90%	14.07%
Omission of Key Facts	11.58%	8.13%
Fee/Commission Related	8.09%	5.98%
Fraud	7.80%	5.23%
Fiduciary Duty	7.05%	4.94%
Negligence	6.39%	4.56%
Risky Investments	3.92%	2.95%
Churning/ Excessive Trading	2.92%	1.01%
Other	41.73%	50.86%

(b) Products

Product	Gender	
	Male	Female
Insurance	13.23%	14.39%
Annuity	8.74%	9.73%
Stocks	6.06%	3.88%
Mutual Funds	4.73%	4.97%
Bonds	2.07%	1.61%
Options	1.27%	0.82%
Other/Not Listed	69.88%	70.25%

(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

Table 4a 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 4b displays the most frequently reported financial products in the allegations. Over half of the allegations do not list a specific financial product. Table 4c 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 5: Misconduct Among Male and Female Advisers

	(1)	(2)	(3)
Female	-0.429***	-0.331***	-0.336***
	(0.0250)	(0.0229)	(0.0300)
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

Note: Table 5 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Consequences of Misconduct

(a) Industry and Firm Discipline

	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***
	(1.473)	(1.401)	(1.524)
Misconduct × Female	8.316***	8.179***	10.19***
	(2.049)	(1.960)	(1.908)
Female	0.139	-0.878**	-0.750***
	(0.292)	(0.348)	(0.155)
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	-7.657***	-11.70***	-8.917***
	(2.129)	(1.355)	(1.026)
Misconduct × Female	-7.223***	-5.359***	-3.464***
	(1.795)	(1.296)	(1.178)
Female	-6.220***	-1.333**	-2.912***
	(0.647)	(0.617)	(0.258)
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 6a 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 the whether or not the adviser received a misconduct disclosure in the previous year.
Tables 6b and 6c display the regression results corresponding to linear probability models (eq. 2 and 3). The dependent variable in Table 6b 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 6c is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 6c, we restrict the sample to those advisers who left their firm in a given year. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24 and investment adviser exam), 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Labor Market Consequences of Misconduct

(a) Unemployment Duration

	(1)	(2)
Misconduct (Male)	0.843***	0.845***
	(0.00754)	(0.00757)
Misconduct (Female)	0.743***	0.754***
	(0.0192)	(0.0195)
Female	0.961***	0.961***
	(0.00294)	(0.00294)
Adviser Controls	X	X
Year F.E.		X
Observations	1,109,210	1,109,210

(b) New Firm Characteristics and Misconduct

	Firm Size	Misc. Rate (pp)
Misconduct	-1,300***	0.0420***
	(162.0)	(0.00312)
Misconduct $\times$Female	-798.5***	-0.0137***
	(222.6)	(0.00387)
Year$\times$Firm$\times$County F.E.	X	X
Observations	519,758	519,758
R-squared	0.588	0.546

Note: Table 7a 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 7b displays the characteristics of new firms joined by advisers who switched firms as a function of whether or not the adviser was reprimanded for misconduct in the year prior to the job transition (eq. 15). Observations are adviser by job transition for which the adviser found a job within a year. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Distribution of Misconduct Claims

(a) Financial Adviser Misconduct

Misconduct	Conditional Probability	
	Male	Female
Customer Dispute - Settled	55%	44%
Employment Separation	28%	41%
Regulatory - Final	17%	13%
Criminal - Final Disposition	4%	4%
Customer Dispute - Award	3%	2%
Civil - Final	0%	0%
Any Misconduct Disclosure	100%	100%

(b) Reasons for Complaint

Reasons for Employment Separation	Gender	
	Male	Female
Unauthorized Activity	12.95%	13.67%
Omission of Key Facts	9.36%	4.62%
Fee/Commission Related	3.13%	2.39%
Unsuitable	2.67%	1.34%
Misrepresentation	1.86%	1.34%
Fraud	1.78%	1.89%
Other	70.88%	76.42%

(c) Firm Initiated Misconduct

	(1)	(2)	(3)
Female	13.72***	7.166***	3.348***
	(2.462)	(1.257)	(0.923)
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 8a displays the conditional probability an adviser has a particular type of misconduct disclosure in a given year, conditional on the adviser engaging in misconduct in the given year. Observations are at the adviser-by-year level over the period 2005-2015.
Table 8b 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 8c 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Firm Characteristics and Discrimination

(a) Executive Gender Composition and Firm Discipline

	(1)	(2)	(3)
Misconduct	53.51***	54.08***	51.39***
	(4.861)	(4.429)	(5.292)
Misconduct × Female	14.69***	14.06***	16.41***
	(3.025)	(2.966)	(3.517)
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 Discipline

	(1)	(2)	(3)
Misconduct	25.24***	26.78***	19.98***
	(1.259)	(1.183)	(1.299)
Misconduct × Female	11.23***	10.86***	13.55***
	(2.675)	(2.542)	(2.350)
Misconduct × (Pct Female Mgmt)	10.09***	9.826***	11.15***
	(2.643)	(2.508)	(2.451)
Misconduct × Female × (Pct Female Mgmt)	-13.49***	-12.58***	-18.15***
	(4.652)	(4.462)	(3.736)
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 Discipline

	(1)	(2)	(3)
Misconduct	24.27***	25.62***	16.62***
	(1.112)	(1.067)	(1.290)
Misconduct × Female	10.44***	10.57***	11.79***
	(3.226)	(3.067)	(3.111)
Misconduct × (Pct Female)	19.80**	19.87***	30.00***
	(8.275)	(7.616)	(8.805)
Misconduct × Female × (Pct Female)	-15.93*	-16.86**	-16.17**
	(8.162)	(7.611)	(6.786)
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 9: Firm Characteristics and Discrimination

(d) Firm Hiring

	(1)	(2)	(3)
Pct Female Exec	0.00820**	0.00820**	0.00931**
	(0.00369)	(0.00369)	(0.00377)
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 9a 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 exam), and number of other qualifications. Observations in Table 9a are at the adviser level in 2015. Observations in Tables 9b and 9c are at the adviser-by-year level over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.
Table 9d 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. 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 parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Adviser Misconduct

	(1)	(2)	(3)
Prior Misconduct	2.421***	2.315***	1.924***
	(0.102)	(0.0995)	(0.0767)
Prior Misconduct × Female	-0.686***	-0.696***	-0.573***
	(0.0987)	(0.0985)	(0.0897)
Female	-0.268***	-0.222***	-0.245***
	(0.0173)	(0.0180)	(0.0256)
Adviser Controls		X	X
Year×Firm×County F.E.			X
Observations	6,547,974	6,547,974	6,221,173
R-squared	0.007	0.007	0.101

Note: Table 10 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. 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 11: Settlements/Damages Granted by Gender

	(1)	(2)	(3)
Female	-0.200***	-0.109**	-0.141***
	(0.0518)	(0.0480)	(0.0383)
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 11 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 exam), 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 12: Consequences of Unauthorized Activity

(a) Employment Separation

	(1)	(2)	(3)
Unauthorized Activity	35.60***	36.81***	27.84***
	(1.567)	(1.479)	(1.855)
Unauthorized Activity × Female	10.35***	10.27***	14.46***
	(3.205)	(3.047)	(3.213)
Female	0.0572	-0.939***	-0.790***
	(0.289)	(0.347)	(0.156)
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***
	(2.474)	(1.644)	(1.191)
Unauthorized Activity × Female	-13.44***	-11.57***	-7.227**
	(2.480)	(2.542)	(3.526)
Female	-6.210***	-1.289**	-2.875***
	(0.646)	(0.614)	(0.255)
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 12a and 12b display the regression results corresponding to linear probability models (eq. 2 and 3). The dependent variable in Table 12a 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 12b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 12b, 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 disclsoure in a given year where 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 exam), 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 parenthesis and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 13: Alternative Misconduct Classification

(a) Severe Misconduct

Disclosure Classification	Frequency: Current Male	Current Female	Current and Past Male	Current and Past 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 Discipline

Dependent Variable	Severe Misconduct	Job Separation	New Employment
Female	-0.138***	-0.780***	-2.889***
	(0.0135)	(0.156)	(0.256)
Severe Misconduct		17.40***	-8.891***
		(1.112)	(1.033)
Severe Misconduct × Female		6.762***	-3.687
		(1.936)	(2.274)
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 finanlized criminal cases involving investment-related activites, fraud, and/or forgery. Table 13a reports the incidence of severe misconduct among male and female advisers.
Table 13b 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 those advisers who left their firm 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 exam), and number of other qualifications. Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 14: Productivity Differences

Dependent Variable	Misconduct	Job Separation
Female	-0.333***	-0.647***
	(0.0569)	(0.110)
Misconduct		8.914***
		(0.882)
Misconduct × Female		4.362***
		(1.573)
High Rating	0.0107	-4.097***
	(0.0597)	(0.634)
ln(AUM)	0.0348**	-0.433***
	(0.0156)	(0.0736)
ln(Production)	0.184***	-0.250***
	(0.0227)	(0.0716)
Adviser Controls	X	X
Year×Firm×County F.E.	X	X
Observations	487,159	442,159
R-squared	0.181	0.627

Note: Table 14 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). Coefficients are in percentage points. We observe the adviser's quality rating (as per Meridian IQ), self-reported AUM, and self-reported revenue (production) generated by the adviser as of 2016. Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 15: Career Interruptions

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.335***	-0.811***	-2.889***
	(0.0298)	(0.155)	(0.259)
Misconduct		22.41***	-9.112***
		(1.511)	(1.017)
Misconduct × Female		10.09***	-3.331***
		(1.890)	(1.177)
Career Interruption	-0.117***	5.194***	-3.789***
	(0.0182)	(0.243)	(0.208)
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 15 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 those advisers who left their firm 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 exam), and number of other qualifications. Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 16: Adviser 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

Table 16: Adviser Experience

(c) Advisers with 5 or Fewer Years Experience (within the Firm)

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.338***	-0.888***	-2.275***
	(0.0287)	(0.179)	(0.243)
Misconduct		24.26***	-10.86***
		(1.945)	(1.098)
Misconduct × Female		12.46***	-3.382**
		(1.941)	(1.317)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	3,890,742	3,619,403	753,714
R-squared	0.108	0.322	0.358

(d) Advisers with 15 or More Years Experience (within the Firm)

Dependent Variable	Misconduct	Job Separation	New Employment
Female	-0.369***	0.244*	-5.478***
	(0.0471)	(0.147)	(0.962)
Misconduct		16.36***	0.159
		(2.375)	(2.546)
Misconduct × Female		1.503	4.940
		(3.491)	(4.807)
Adviser Controls	X	X	X
Year×Firm×County F.E.	X	X	X
Observations	514,935	449,430	37,316
R-squared	0.177	0.482	0.620

Note: Tables 16a-d 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 firm 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. In panel (c), we restrict our analysis to those advisers with five or fewer years of experience within their current firm. In panel (d), we restrict our analysis to those advisers with fifteen or more years of experience within their current firm. Coefficients are in 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 over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 17: Displaced Advisers

	(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 17 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 10% or more between time t and $t+1$. In columns (1)-(3), we define a *Downsize* as a firm that reduced the number of advisers it employs by 10% or more. In columns (4) and (5), we redefine *Downsize* as a firm that reduced the number of advisers it employs 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 exam), and number of other qualifications. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 18: Adviser Ethnicity

(a) Employment Separation

	(1)	(2)	(3)
Misconduct	27.11***	28.54***	21.73***
	(1.369)	(1.307)	(1.395)
Misc. × African	8.984***	8.920***	7.596***
	(2.000)	(1.912)	(2.177)
Misc. × Hispanic	6.017**	5.553**	6.470**
	(2.502)	(2.414)	(2.748)
African	2.407***	1.512***	0.457***
	(0.317)	(0.280)	(0.147)
Hispanic	2.786***	1.603***	0.408**
	(0.617)	(0.536)	(0.195)
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

(b) New Employment

	(1)	(2)	(3)
Misconduct	-7.222***	-11.69***	-8.832***
	(1.950)	(1.247)	(1.020)
Misc. × African	2.077	3.073	3.502
	(3.514)	(2.976)	(2.920)
Misc × Hispanic	-8.427***	-5.625***	-5.291***
	(2.793)	(1.984)	(1.423)
African	-2.930***	-0.755	-0.975**
	(0.746)	(0.717)	(0.384)
Hispanic	-0.621	3.108**	1.898***
	(1.217)	(1.239)	(0.281)
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

(c) Misconduct

	(1)	(2)	(3)
African	0.0878**	0.163***	0.0944***
	(0.0429)	(0.0429)	(0.0318)
Hispanic	0.164***	0.277***	0.0900***
	(0.0483)	(0.0469)	(0.0257)
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

Tables 18a, 18b, and 18c display the regression results corresponding to linear probability models (eq. 2, 3, and 1) where we examine the relationship between misconduct and ethnicity among male advisers. The dependent variable in Table 18b 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 18b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table 18b, we restrict the sample to those advisers who left their firm in a given year. The dependent variable in Table 18c is a dummy variable indicating whether or not the adviser received a misconduct disclosure in a given year. Other adviser controls include the adviser's experience, tests (series 6, 7, 63, 24 and investment adviser exam), 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table 19: Firm Discipline by Management Composition, Adviser Ethnicity

(a) Employment Separation, African Managers

	(1)	(2)	(3)
Misconduct	26.25***	27.83***	21.42***
	(1.432)	(1.341)	(1.444)
Misconduct × African	10.26***	10.07***	9.037***
	(2.286)	(2.190)	(2.330)
Misconduct × (Pct African Mgmt)	19.65***	18.50***	14.47**
	(5.553)	(5.470)	(6.274)
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, Hispanic Managers

	(1)	(2)	(3)
Misconduct	(2.350)		
Misconduct × Hispanic	7.797***	7.133**	7.797**
	(3.025)	(2.870)	(3.244)
Misconduct × (Pct Hispanic Mgmt)	9.165	8.564	9.697*
	(5.654)	(5.373)	(5.567)
Misconduct × Hispanic × (Pct Hispanic Mgmt)	-22.57**	-21.90**	-18.32*
	(9.709)	(9.195)	(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, Placebo Test

	(1)	(2)	(3)
Misconduct	26.51***	28.04***	21.65***
	(1.471)	(1.373)	(1.478)
Misconduct × Female	8.924***	8.737***	10.07***
	(2.050)	(1.937)	(1.961)
Misconduct × (Pct African Mgmt)	15.35***	14.69***	8.628
	(5.073)	(4.982)	(5.840)
Misconduct × Female × (Pct African Mgmt)	-3.605	-2.756	1.493
	(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 19: Firm Discipline by Management Composition, Adviser Ethnicity

(d) Employment Separation, Placebo Test

	(1)	(2)	(3)
Misconduct	26.56***	28.11***	21.52***
	(1.427)	(1.329)	(1.437)
Misconduct × Female	9.107***	8.932***	10.55***
	(1.995)	(1.907)	(1.900)
Misconduct × (Pct Hispanic Mgmt)	4.757	4.301	7.149*
	(4.250)	(4.086)	(4.207)
Misconduct × Female × (Pct Hispanic Mgmt)	-6.573	-6.384	-10.93
	(7.738)	(7.665)	(7.399)
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 19 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 exam), 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 parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Appendix

A1: Disclosure Definitions[26]

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.

[26] 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.

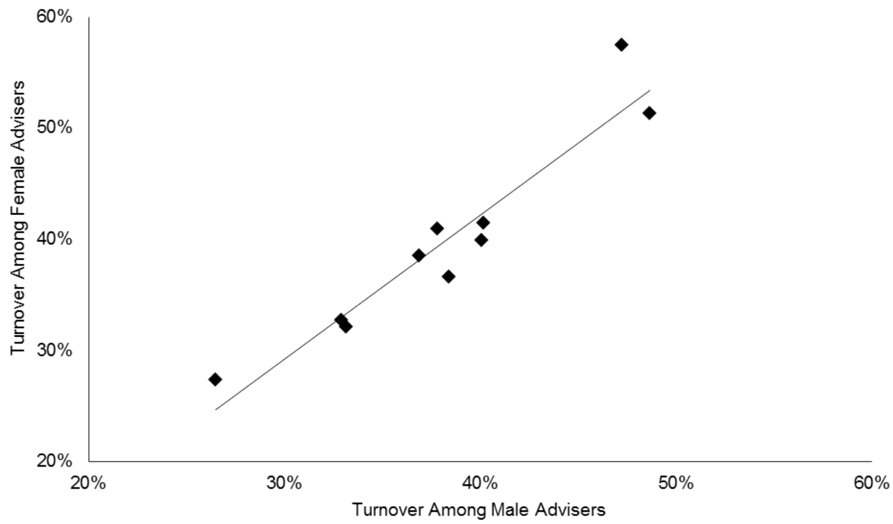
Regulatory - On Appeal: This type of disclosure event may involves (1) a formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulator such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation 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 those firms that reduce the number of financial advisers they employ by 10% or more in a given year.

Figure A2: Job Turnover by Experience

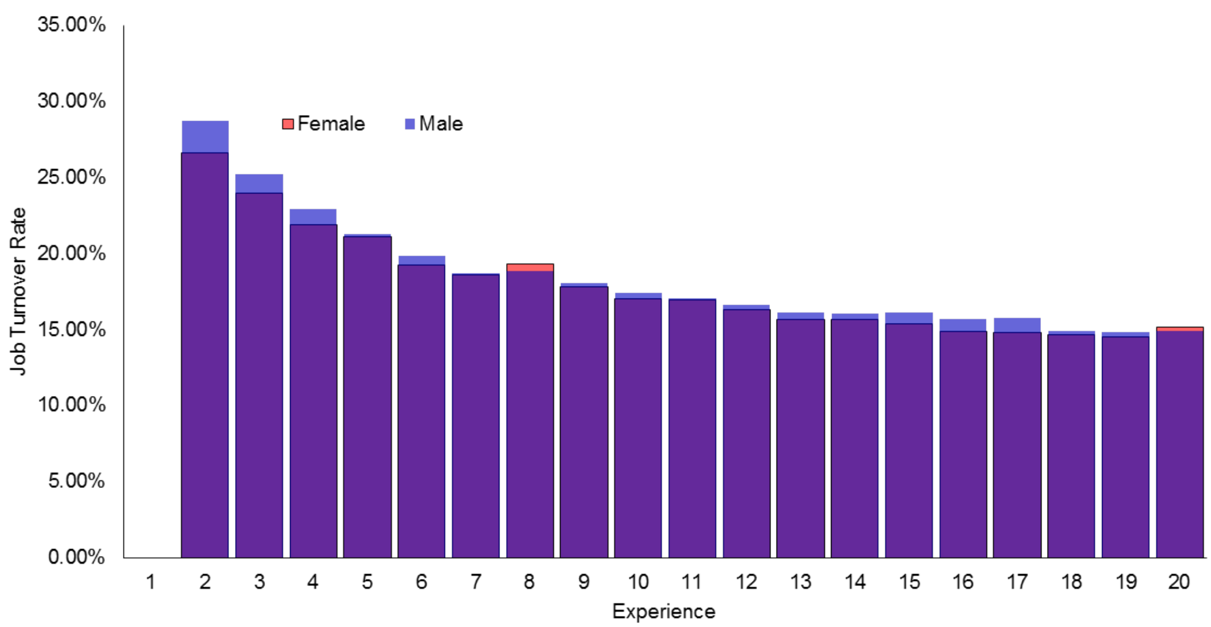


Figure A2 displays job turnover among male and female advisers conditional on the advisers' experience. Observations are at the adviser-by-year level over the period 2005-2015.

Table A1: Promotions

	(1)	(2)	(3)
Misconduct	-0.173**	-0.138**	-0.0964
	(0.0754)	(0.0650)	(0.0649)
Misconduct × Female	-0.247**	-0.181*	-0.133
	(0.106)	(0.104)	(0.113)
Female	-0.251***	-0.203***	-0.0716***
	(0.0302)	(0.0339)	(0.0237)
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 A1 displays the regression results corresponding to a linear probability model (eq. 13). 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 exam), and number of other qualifications. Standard errors are in parenthesis and are clustered by firm. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Geographic Differences

(a) Firm Level Consequences - Employment Separation

	(1)	(2)	(3)	(4)
Female	-0.545***	-0.526***	-0.492**	-0.458**
	(0.196)	(0.201)	(0.204)	(0.218)
Misconduct	27.90***	28.39***	27.96***	28.91***
	(2.282)	(2.074)	(2.314)	(2.414)
Misconduct × Female	15.66***	15.77***	15.61***	14.07***
	(2.444)	(2.470)	(2.223)	(2.125)
Gender Gap × Female	-0.0387	-0.00208	0.0651	0.136
	(0.123)	(0.128)	(0.152)	(0.171)
Gender Gap × Misconduct	-2.765**	-1.876	-2.690***	-0.922
	(1.123)	(1.243)	(1.042)	(1.249)
Gender Gap × Misconduct× Female	4.013*	4.307	3.796	1.116
	(2.278)	(2.630)	(2.427)	(2.772)
Gender Gap: Wages (Finanical Sector)	X			
Gender Gap: Wages (All)		X		
Gender Gap: Participation (Financial Sector)			X	
Gender Gap: Participation (All)				X
Adviser Controls	X	X	X	X
Year×Firm×County F.E.	X	X	X	X
Observations	2,696,417	2,698,886	2,697,749	2,697,749
R-squared	0.256	0.256	0.256	0.256

(b) Industry Level Consequences - New Employment

	(1)	(2)	(3)	(4)
Female	-4.050***	-3.505***	-4.489***	-2.976***
	(0.502)	(0.502)	(0.547)	(0.443)
Misconduct	-11.33***	-11.19***	-11.85***	-12.66***
	(1.616)	(1.696)	(1.461)	(1.957)
Misconduct × Female	-4.351*	-2.589	-4.962**	-4.942**
	(2.424)	(2.904)	(2.141)	(1.948)
Gender Gap × Female	-0.817**	0.238	-1.781***	1.318***
	(0.389)	(0.393)	(0.538)	(0.397)
Gender Gap × Misconduct	2.281	2.589**	1.299	-0.393
	(1.556)	(1.237)	(1.335)	(1.466)
Gender Gap × Misconduct× Female	-2.387	0.686	-3.307	-4.443*
	(2.363)	(3.281)	(2.345)	(2.571)
Gender Gap: Wages (Finanical Sector)	X			
Gender Gap: Wages (All Sectors)		X		
Gender Gap: Participation (Financial Sector)			X	
Gender Gap: Participation (All Sectors)				X
Adviser Controls	X	X	X	X
Year×Firm×County F.E.	X	X	X	X
Observations	404,114	404,277	404,185	404,185
R-squared	0.363	0.363	0.363	0.363

Note: Table A2 displays the regression results for two linear probability models (eq. 14). The dependent variable in Table A2a is a dummy variable indicating whether or not a financial adviser left his firm. The dependent variable in Table A2b is a dummy variable indicating whether or not a financial adviser joined a new firm within one year. In Table A2b we restrict the sample to those advisers who left their firm in a given year. Each column in Tables A2a and A2b differs in terms of how the variable Gender Gap is constructed. First, we construct the variable Gender Gap as a dummy variable equal to one if county wage gap is above the median wage gap in the sample. We define the wage gap in the financial sector and across all sectors such that $Wage\_Gap_{lt} = \frac{Median\_Male\_Wages_{lt} - Median\_Female\_Wages_{lt}}{Median\_Male\_Wages_{lt}}$. Second, we construct the variable Gender Gap as a dummy variable equal to one if county participation gap is above the median participation gap in the sample. We define the participation gap in the financial sector and across all sectors such that $Participation\_Gap_{lt} = \frac{\#Male\_Employees_{lt}}{\#Female\_Employees_{lt} + \#Male\_Employees_{lt}}$. Coefficients are in 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 over the period 2010-2015. Standard errors are in parenthesis 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 those advisers who left their firm 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, this limits our ability to identify the impact of misconduct on an adviser's reemployment prospects (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 exam), and number of other qualifications. Observations are at the adviser-by-year level over the period 2005-2015. Standard errors are in parenthesis and are clustered by firm. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

A3: Model of Firm Discipline

We consider a simple model of financial advisory firm 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 a low propensity 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 $\nu_M \sim F_M(\cdot)$.

Firm Firing Decisions Following Misconduct:

We next consider a firm's decision to fire an employee following a 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 first period, a firm observes a noisy signal d_{it} where

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

where ν_i reflects an adviser's misconduct propensity and ϵ_{it} is some idiosyncratic misconduct shock. The disclosure data is censored such that firms only observe disclosure signals d_i if they are sufficiently large such that $d > D^*$ where $D^* > \bar{v}_M$. Firms use this information to update their beliefs regarding an adviser's net productivity and propensity to engage in misconduct, $E[\nu|d_{it}, g_i]$.

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 with disclosure d_{it} is fired if

$$S_g^* > \eta_i - E[\nu|d_{it}, g_i]$$

where S_g^* is the threshold which potentially varies across gender, η_i is the adviser's productivity, and $E[\nu, d_{it}, g_i]$ is the firm's updated beliefs about the adviser's propensity to engage in misconduct. The threshold S_g reflects taste-based discrimination at the firing stage. Firms may hold male and female advisers to different standards.

Recidivism:

Recidivism is observed in the data conditional on the adviser 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 engaging in misconduct at time $t-1$ is given by

$$E[d_{it}|E[\nu|d_{it-1}, g] < \eta - S_g^*]$$

The model produces several key predictions about the nature of recidivism and the types of discrimination. If male and and female advisers are held to the same standard ($S_M^{"*} = S_F^*$) and firms have unbiased beliefs about future misconduct across genders, we would expect the rates of recidivism conditional η to be the same across male and female advisers at the margin. Alternatively, if we observe different rates of recidivism across male and female advisers, there are two potential explanations for this. First, if women are held to a higher standard ($S_F^* > S_M^*$) such that firm's engage in taste-based discrimination, we would expect the rates of recidivism conditional on η to be lower for female advisers than male advisers at the margin and vice versa. Second, if firms systematically over-estimate a female adviser's propensity to be a repeat offender, we would expect the rates of recidivism conditional on η to be lower for female advisers than male advisers at the margin and vice versa.