universität innsbruck

Research Platform
Empirical and Experimental Economics

eeecon
[triple:e:con]

Gender Gaps and Racial Disparities in Labour Market Penalties for Financial Misconduct

Jun Honda

Working Papers in Economics and Statistics

2020-17

University of Innsbruck
https://www.uibk.ac.at/eeecon/

University of Innsbruck
Working Papers in Economics and Statistics

The series is jointly edited and published by

- Department of Banking and Finance
- Department of Economics
- Department of Public Finance
- Department of Statistics

Contact address of the editor:
research platform "Empirical and Experimental Economics"
University of Innsbruck
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: + 43 512 507 71022
Fax: + 43 512 507 2970
E-mail: eeecon@uibk.ac.at

The most recent version of all working papers can be downloaded at
https://www.uibk.ac.at/eeecon/wopec/

For a list of recent papers see the backpages of this paper.

Gender Gaps and Racial Disparities in Labour Market Penalties for Financial Misconduct*

Jun Honda†

June 1, 2020

Abstract

We consider the labour market for financial advisers in the US using a matched employer-employee data set over the period 2008–2018, in order to examine gender gaps and racial disparities in labour market penalties for financial misconduct. We first show that the measurement of labour market penalties for financial misconduct plays a central role and the interdependence across misconduct-categories (e.g. customer disputes, regulatory actions, terminations) is gender- and race-specific. Accounting for this, we find that there are little gender gaps in job separation following misconduct and in the incidence of employer-initiated terminations conditional on misconduct-related events. In contrast, we find that racial minorities are at least 20% more likely to leave a firm following customer disputes or regulatory actions compared to their majority counterparts, and also that the racial minorities are 25% more likely to receive terminations. This remains true even after controlling for their education.

Key Words: Financial Advisers, Misconduct, Gender Gap, Racial Inequality, Discrimination.
JEL Classification: G24, J44, J71, L22.

*I thank Lothar Gampel for legal assistance regarding the data usage and Anna Ulrichshofer for research assistance. I also thank Mark Egan for helful comments and sharing information on data construction. I acknowledge financial support by SFB63.

†Department of Economics, University of Innsbruck, Austria. Email: jun.honda@uibk.ac.at

1 Introduction

In the US, the majority of financial advisers are male with more than 70% and white with 88%. The racial minority is only 12% and consists of asians, blacks, and hispanics.[1] Like in other industries, the market is highly concentrated in major cities (e.g. California and New York), and the fraction of female advisers is larger in states with a smaller population relative to males whereas the fractions of the non-white minority is disproportionally large in states with a large population (see Figure F.1). Even when considering financial advisers, females and the minority group of blacks and hispanics are more likely to be under financial distress and file for personal bankruptcy (see Figure F.4). This implies that advisers are exposed to different circumstances across genders and races beyond firms and regions (counties and states).

It may be no surprise that even after controlling these differences across genders and races, we still find gender gaps and racial disparities in the labour market for financial advisers.[2] But noteworthy is the magnitude. Recently, Egan, Matvos and Seru (2018) found that females are 20% more likely to leave a firm following financial misconduct than their male counterparts after controlling for firm-year-county fixed effects with other observables, and also that there are similar gaps in the labour market penalties against the non-white racial minority. We first revisit their findings to highlight why they found significant penalty gaps across genders as well as races, and then provide further understanding of those gaps among financial advisers. We also pay attention to *disclosed* terminations at the individual level, which enables us to investigate differential treatment by controlling for employer-specific fixed effects at the branch level and also for their prior compliance records and education. This provides suggestive evidence for

[1] In this paper, we follow the recent literature (Egan, Matvos and Seru, 2019; Dimmock, Gerken and Graham, 2018a) and use the term, financial adviser, to refer to representatives registered with the Financial Industry Regulatory Authority (FINRA), which acts as a self-regulatory organization. In the main analysis, we divide all advisers into two groups: the white majority and non-white minority. The qualitative features of our main findings hold true even when splitting the minority group into three categories: (i) Asian; (ii) Black; (iii) Hispanic. Also, we consider more detailed categories (e.g. European white, East asian, Muslim). See the subsequent section for data on race/ethnicity in more detail. Since there is no precise, commonly-used definition of race and ethnicity in the literature, for simplicity we only use the term "race", without differentiating it from ethnicity, except when referring to data and papers. Note that the aforementioned percentages are only approximations. For the details, see Section 2.

[2] The Civil Rights Act of 1964 and subsequent related legislations have reduced part of gender and racial discrimination in the US, particularly for explicit forms of discrimination (e.g. newspaper help-wanted advertisements), while others have remained in more subtle ways (e.g. Darity and Mason, 1998; Heckman, 1998). See the related literature below.

race-based employment discrimination against the non-white minority.

Our work relies on the FINRA's BrokerCheck database, which enables us to construct a matched employer-employee data set for the universe of financial advisers. This data set is unique as it provides their compliance records, which are mainly related to their financial advisory services since entry in the industry and include customer complaints and disputes, criminal records, regulatory actions, and employer terminations. Since these compliance records are disclosed by regulation, they may lose their clients when being confronted with a disclosure event and have to confront the associated labour market penalties through job separation and a difficulty in finding a new job due to a reputation loss. In particular for the labour market penalties, we can take a look at the employment history to see if there are possible gender gaps and racial disparities, after controlling for firm-branch-specific unobserved characteristics (e.g. business models, regional demographics, regulatory environments, sales cultures) over time. When evaluating the labour market penatlies, it is important to examine if disclosure events are mutually dependent (e.g. customer disputes lead to employer-initiated terminations) and different disclosure events can lead to significantly different consequences, depending on gender and race.

We first find that our data is consistent with the findings of Egan et al. (2018) and indeed there exists a significant gender gap in the labour market penalties, if we use their measurement of financial misconduct. They define "Misconduct" by a dummy variable for whether an advisers encounters one of the major disclosure events that are related to "Misconduct". But once accounting for the distribution of those disclosure events within "Misconduct", we find no significant gender penalty gaps in our data.

To see this, we split "Misconduct" into two different categories of disclosure events, terminations and other misconduct-related disclosures (including customer disputes and regulatory actions), which we call A and B respectively from here on. By construction, the former always leads to job separation while the latter does not. If the fraction of A (terminations) over $C = A \cup B$ ("Misconduct") is larger for females, the incidence of "Misconduct" leads to a higher job separation rate for females relative to their male counterparts. This is considered to be the main driving force behind gender penalty gaps. But there may be another driving force through gender-specific (auto-)correlations between A and B, by which females disproportionately more often receive A following B relative to their male counterparts.

Consider two extreme cases: If A and B are perfectly correlated for females but not for males, this would mean that females are unfairly treated relative to males. By contrast, if A and B are independent for both females and males, it is unlikely to support the arugment. In reality, neither of these extreme cases should be true, because it is reasonable to expect that A and B are positively correlated to some extent. Our data indeed supports this and we find that there are moderate positive correlations between A and B, although we do not find any female-specific positive correlations and one of them even is negatively correlated. More precisely, we find that females are equally likely to receive A conditional on encoutering B, while they are less likely to encounter B conditional on receiving A, which suggests that terminations do not differ across genders following the other "Misconduct" and a gender penalty gap is not caused by gender-specific correlations between disclosure events. Thus, after accounting for the distribution effect, we do not find any significant gender gaps in the labour market penalties associated with misconduct-related disclosure events.

Despite finding no gender penalty gaps in our data, it is important to emphasize that females are less likely to encounter misconduct-related disclosure events relative to their male counterparts, after controlling for firm-branch-year fixed effects as well as other observables. This is in stark contrast with racial disparities between the (non-white) minority and (white) majority, as pointed out by Egan et al. (2018). The minority of advisers are significantly more likely to encounter misconduct-related disclosure events relative to the majority, which range from customer disputes to terminations (employment separation after allegations). One possible explanation might be, that they engage in misconduct more frequently than the majority, therefore receiving terminations more often. To explore if that is the case, we account for prior and concurrent compliance records as well as for education (e.g. university, law schools, MBA). Even after controlling for these, we find that the minority of advisers are 25% more likely to receive terminations compared to the majortiy, and also find that this gap in the termination rate exists for both male and female advisers, with a slightly larger gap for males.

We further explore how this gap extends to different races. We split the non-white minority (dummy variable) into smaller groups (asian, black, and hispanic) and still find significant gaps relative to the majority, where the gap is largest for hispanic over all races. It is worth mentioning that this finding is possible because we can directly observe terminations through disclosure at the individual level, which is unlikely to be available in other industries and enables us to shed light on differential treatment.

We also assess other possible racial disparities in the labour market penalties following misconduct-related disclosure events. Like gender gaps, we find that the distribution effect exists, which yields a gap between the (non-white) minority and majority group in the labour market penalties (job separation) following "Misconduct". Things are slightly different from the case of gender gap. Although a large part of the gap stems from the distribution effect, part of it cannot be explained by the distribution effect alone. We find that the minorities, especially hispanics, are at least 20% more likely to leave a firm following customer disputes or regulatory actions. This may add to our previous finding that there is differential treatment in employment.

1.1 Related Literature

Gender Gap. Gender gap has declined over decades in terms of, among many others, education, labour market participation, and wages (e.g. Blau and Kahn, 2000, 2017). But there is consensus that gender gap still persists and there are wage penalties for career interruptions (Bertrand et al., 2010; Goldin, 2014). When paying attention to the financial advisor industry, Egan, Matvos and Seru (2018) found that there is a "gender punishment gap" against female financial advisers, and also that this punishment gap is not driven by gender differences in multiple dimensions, including productivity (assets under management and quality rating at the individual level), but rather it can be explained by in-group favouritism.[3] In contrast, we control for the composition effect of disclosure events as well as for education at the individual level instead of productivity, and find that there is little gender punishment gap. Note that their data is slightly different from ours as the time period of data collection differs, but the qualitative features should remain the same.

Employment Discrimination. Employment discrimination has long been studied with a variety of approaches, including audit studies, pseudo-experiments, and correspondence studies, to examine differential treatment, with a focus on hiring.[4] There are exceptions as in court cases, which provide direct evidence on discriminatory treatment, but they are limited in the scale of data at the individual level.[5]

[3] Egan, Matvos and Seru (2018) obtained data on productivity at the individual level from Meridian IQ (acquired by Discovery Data in the year 2016), which is not publicly available.

[4] See a set of excellent surveys in the literature (e.g. Darity and Mason, 1998; Altonji and Blank, 1999; Lang and Lehmann, 2012; Bertrand and Duflo, 2017; Neumark, 2018; Lang and Spitzer, 2020).

[5] The US Equal Employment Opportunity Commission (EEOC) provides data related to private sector charges of employment discrimination and resolutions by the types of discrimination (e.g. National Origin, Race/Color, Sex) at the aggregate (national or state) level (Enforcement and Litigations Statistics: `https://www.eeoc.gov/statistics/enforcement-and-litigation-statistics`). Every year EEOC receives over 70,000 private sector charges of discrimination. In the end of year 2019, 15.6% of them are resolved with an outcome favourable to charging party and/or with meritorious alle-

Our approach differs from these in the sense that we use *disclosed* terminations in matched employer-employee data to investigate differential treatment, after controlling for firm-branch-year specific characteristics with other observables. This unique feature of data can make it possible to examine race-based discrimination at work in the US financial services industry. There is a limitation, though, that we cannot obtain information on demographics (date and location of birth, detailed education history), performance, or wages/annual earnings for advisers, by which it may be hard to argue whether racial disparities in terminations can stem from taste-based, statistical (with "correct" beliefs), or psychology-oriented (implicit) discrimination. Nonetheless, as in Egan et al. (2018), our finding does not support the idea of Bayesian profit maximizing firms (or employers) based on statistical discrimination: When limiting the sample to observations where advisers have (i) no prior and concurrent compliance records, (ii) short/long industry experience and tenure profiles, or (iii) high education (e.g. university, law schools, MBA), the minority group of advisers are still more likely to receive terminations relative to the majority.

Financial Misconduct. There has been a growing body of the literature using the FINRA's BrokerCheck database to examine financial misconduct and the associated labour market.[6] We follow Egan et al. (2018) to investigate gender gap and racial disparities in the labour market penalties. As in the research to explore the labour market consequences for earning management by top executives (Agrawal et al., 1999; Beneish, 1999; Desai et al., 2006; Feroz et al., 1991; Karpoff et al., 2008), our contribution is to complement the literature with additional evidence regarding gender gap and racial disparities in the labour market penalties for financial misconduct at the individual level.

gations, which include negotiated settlements, withdrawals with benefits, and successful conciliations. See, among others, the recent work by Boulware and Kuttner (2019) who studied the relationship between the number of discrimination charges and the unemployment rate.

[6]Since the publication by the FINRA's economists (Qureshi and Sokobin, 2015), the FINRA BrokerCheck database has been widely used in the literature. See, for instance, Charoenwong, Kwan and Umar (2019); Clifford and Gerken (2017); Cook, Kowaleski, Minnis, Sutherland and Zehms (2020); Dimmock, Gerken and Graham (2018a); Dimmock and Gerken (2018); Dimmock, Gerken and Van Alfen (2018b); Egan, Matvos and Seru (2019); Gurun, Stoffman and Yonker (2019); Honigsberg and Jacob (2019); Law and Mills (2019).

2 Data

We mainly construct a matched employer-employee data set for the universe of financial adivsers in the US with using the FINRA BrokerCheck database through Central Registration Depository (CRD). Below we will explain this data set with additional data in details.[7]

2.1 Adviser-Level Data

We follow Egan et al. (2018) to consruct adviser-year panel data based on Form U4 (in the FINRA BrokerCheck database), which provides detailed information on employment history, licenses (industry exams), and compliance records regarding disclosure events (e.g. customer disputes, disciplinary actions by employers and regulators: see Section 3.1 below for details).[8]

Concerning employment history, there are two types of information: (i) "Registration History" and (ii) "Employment History". The former provides the list of registered securities firms with their unique identifiers (CRD numbers), firm names, addresses (of branch offices), and the time periods (on a monthly basis) that they have worked for.[9] The latter provides the adviser's employment history for the last 10 years, *both in and outside* the securities industry, including full- and part-time work, self-employment, military service, unemployment, and full-time education.[10] In our panel data, we use part (i) alone as in Egan et al. (2018).[11]

There is a limitation in the FINRA BrokerCheck database due to survivorship-bias

[7] To use the FINRA BrokerCheck database, we follow the FINRA BrokerCheck® Terms of Use, Section 6 (`https://brokercheck.finra.org/`) for academic purposes. For the data usage in our paper, we follow the Austrian federal copyright law (`https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=10001848`). The right of "free use of works" (Freie Werknutzungen) applies to this research, which is stated in Section 42 (2) which allows us to produce individual copies for research (non-commercial), and Section 40h. allows us to produce individual copies of "database work" (e.g. data/statistical analysis).

[8] Form U4 (`https://www.finra.org/sites/default/files/form-u4.pdf`) is "the Uniform Application for Securities Industry Registration or Transfer" and used to become registered in the appropriate jurisdictions and/or SROs.

[9] If an adviser works for multiple firms in a given year, we select the firm with longer tenure. This does not change our main arguments and findings.

[10] The majority of financial advisers provide information on employment history for more than 10 years if it is applicable, due to severe consequences for failing to disclose information, which is a violation of Section 3(a)(39)(F) of the Securities Exchange Act of 1934 and can result in statutory disqualification.

[11] I thank Mark Egan for sharing information on data collection.

(Gurun, Stoffman and Yonker, 2019), which depends on when data is collected (August 2018 in our case).[12] In fact, Egan, Matvos and Seru (2018, 2019) and Gurun, Stoffman and Yonker (2019) restrict their sample with a ten-year interval to mitigate survivorship-bias due to the information constraint imposed on the FINRA BrokerCheck database. For this reason, we limit the sample to adviser-year observations over the period 2008–2018. With this, the total number of observations amounts to around 7.9 million and contains 1.2 million advisers, of which roughly half have left the industry (de-registered with FINRA) over the course of the period.

To replicate their findings (Egan et al., 2018), in particular for gender punishment gap, we control for firm-year-county-license fixed effects. In doing so, we assign to each adviser (i) a unique firm identifier (CRD number) in a given year with its branch location at the county level (if the adviser works for a firm),[13] and (ii) dummy variables of licenses with their acquired dates (years).[14]

2.1.1 Education

As described above, the employment history in the FINRA BrokerCheck database contains information on education and military services for a subset (approximately 14%) of financial advisers.[15] For example, education (in most cases) ranges from junior high school to higher education at universities, graduate schools (e.g. MBA), and law schools, which contain top universities and institutions. Since education matters for disclosure events, in the robustness of our main finding for racial disparities, we limit the sample

[12] There is a difference in publicly available information on financial advisers, depending on their registration status: (i) a broker who is currently registered with FINRA or a national securities exchange, or who has been registered within the last 10 years; (ii) a broker whose registration with FINRA or a national securities exchange terminated more than 10 years ago. Since we collected data in August 2018, the number of financial advisers who left the securities industry with de-registrations prior to the year 2008 can be substantially smaller than that after 2008 due in large part to omitted observations. See a brief overview of the information contained in the FINRA BrokerCheck database (`https://www.finra.org/investors/learn-to-invest/choosing-investment-professional/about-brokercheck`).

[13] We match a county-FIPS (Federal Information Processing Standard) code with each branch office's address.

[14] There are over 60 different exams observed in our sample. We limit attention to the set of major exams (Series 6, 7, 24, 63, 65/66) as license fixed effects, together with using the total number of other exams as a control variable. The definitions of currently available licenses (industry exams) are given on the FINRA website (`https://www.finra.org/registration-exams-ce/qualification-exams`). See also Egan et al. (2018, Appendix A2) for the list of licenses (industry exams).

[15] Because of the information restriction (up to 10 years) on employment history, advisers who report their education tend to be younger than those who do not. As such, the fraction of adviser-year *observations* with information on education amounts to roughly 8%.

to those who report their education that contains a college degree or above, and divide them into two groups, (i) college and (ii) university and higher degrees, as sample size is relatively small in our analysis (see summary statistics).

2.1.2 Gender and Race

The FINRA BrokerCheck database does not provide information on gender and race of financial advisers.[16] To supplement this, we use the R package, *gender* (Mullen, 2018) to identify gender for the vast majority (95%) of advisers, whereas we use the Python package, *ethnicolr* (Laohaprapanon and Sood, 2019) to identify race for the vast majority (99%) of advisers.

For gender identification, we match the first names of advisers with historical datasets (from the U.S. Social Security Administration), which are comprised of pairs of (time-dependent) names and associated gender, in order to predict whether they are male or female based on the matched frequency. We impose 80% accuracy to identify the gender for approximately 95% of all advisers, of which females account for around 30%.[17]

To determine race, we match both the first and last names of advisers with Florida voting registration data, one of three datasets provided by (Laohaprapanon and Sood, 2019), in order to predict their race, among four categories (asian, black, hispanic, white).[18] We set 50% accuracy to identify the race for approximately 99% of all advisers, of which non-white account for around 12%.[19] Instead, we can use Census data to consider the same four categories, or Wikipedia data (Ambekar et al., 2009), which provides a broader range of ethnicities and has been used in the literature (e.g. Dimmock et al., 2018a; Egan et al., 2018; Parsons et al., 2018). Note that our main findings remain unchanged when using Census or Wikipedia data, as long as the accuracy rate remains the same at 50%. In the online Appendix, we use Wikipedia data to highlight racial

[16] See footnote 1 in the introduction for the term "race".

[17] Note that this remains almost the same even when using a higher accuracy, e.g., 90% instead of 80%.

[18] To demonstrate *ethnicolr*, Laohaprapanon and Sood (2019) provide three datasets: (i) Census data; (ii) Florida voting registration data; (iii) Wikipedia data collected by Ambekar et al. (2009). Depending on imposed accuracy across datasets, there are differences in the distribution of identified races but our main findings hold in a wide range of accuracy across datasets.

[19] If we impose, for example, 80% accuracy, the rate of identified race declines to a certain level, which can significantly differ across datasets: (i) 72% in Census data; (ii) 44% in Wikipedia data; (iii) 81% in Florida voting registration data. Given that the vast majority of races are identified under 50% accuracy, this implies that there are pros and cons in setting accuracy. In this paper, we choose 50% accuracy to maintain sample size for highlighting the findings with less noisy estimation.

disparities beyond the four categories in more details.

To show our main findings, we do not split the minority group into smaller groups, with focusing on the (white) majority and (non-white) minority group of advisers, and then compare the former with the latter who work for the same firm, at the same location, at the same time, and have the same set of licenses. Note that the qualitative feature of our main findings remains the same even when splitting the minority group to smaller groups, where we can show a wide range of racial disparities.

2.2 Summary Statistics for Observable Characteristics

We briefly look at summary statistics for advisers across genders and races. Table 1 illustrates differences in observable characteristics, which include experience, tenure, job transitions, and licenses. Columns (1) and (4) in the table describe gender differences and indicate that males are more likely to (i) have longer experience and tenure profiles, (ii) swtich to a new firm (in the industry) with migrating to a different region (states/commuting zones/counties) when leaving a firm,[20] (iii) hold major licenses (Series 63, 7, 6, 65/66, 24) and have a larger number of licenses, than their female counterparts. Note that advisers are more likely to acquire a particular license to serve as investment adviser (Series 65/66) or manager (Series 24) as they have longer (industry) experience and tenure. Along with this, columns (2) and (3) display differences between the majority and minority group for males, whereas columns (5) and (6) those for females. Interestingly, they are similar to the gender differences described above.

Note that there are two possible cases where advisers cannot switch to a new firm after leaving a firm: (i) Career interruptions; (ii) Exit from the industry. We find that females are less likely to exit from the industry at early career stages as measured by experience than their male counterparts while being more likely to do so as they have longer experience (e.g. Bertrand et al., 2010). We also find that the minority of advisers are more likely to exit from the industry once leaving a firm relative to the majority.

2.3 Baseline Specification in the Linear Probability Model

Our main analysis is simply based on the comparison of two groups (male/female or majority/minority) of advisers who work for the same firm, at the same branch office (location), at the same time, and have the same set of licenses, in order to average out

[20]To capture migration across commuting zones conditional on job-to-job transitions, we use the 2000 ERS Commuting Zones (CZs) provided by the United States Department of Agriculture.

firm-location-time-license specific characteristics. Below we first introduce the notation used in estimation and subsequently the baseline model.

We denote (i) an adviser by $i = 1, \dots, I$; (ii) a firm by $j = 1, \dots, J$; (iii) a location (county FIPS) by $h = 1, \dots, H$; (iv) dummy variable $d_{i,l}$ for whether adviser i holds license $l (= 1, \dots, 5)$ in the set of five major licenses (Series 63, 6, 7, 65/66, 24) and the set of these dummies $d_i = (d_{i,1}, \dots, d_{i,5})$; (vi) time (year) by t over the period 2008–2018.[21] To simplify the notation below, we denote by $g(i, t)$ a *group* of variables for adviser i at time t that comprise either (i) firm-county (j, h) or (ii) firm-county-license (j, h, d_i).

We consider a linear probability model where the dependent variable Y_{it} with $g(i, t) = (j, h, d_i)$ is a dummy for adviser i who has worked for firm j located in county h with the set of licenses at time t; the key independent variable of interest is a dummy variable, Group_i, that indicates whether adviser i belongs to a specific group;

Our baseline model is given as follows:

$$Y_{it} \;=\; \beta_1 \,\text{Group}_i \;+\; \boldsymbol{\beta}\, \boldsymbol{X_{it}} \;+\; \alpha_{g(i,t)} \;+\; \varepsilon_{it}, \tag{1}$$

where the dependent variable, Y_{it}, is a dummy variable and $\boldsymbol{X_{it}}$ is the vector of control variables, $\alpha_{g(i,t)}$ the fixed effects regarding $g(i, t)$ (e.g., firm $\times$ county $\times$ license $\times$ time fixed effects when $g(i, t) = (j, h, d_i)$), and ε_{it} an error term. With the baseline specifications, $\boldsymbol{X_{it}}$ includes (i) industry experience (in years) and its squared term, (ii) tenure (in years) at firm j in a given year t, and (iii) the dummy variables of major licenses, which are omitted in the presence of license fixed effects, (iv) the number of other non-major licenses. Since our panel data contains a small number of time periods (over 2008-2018) while it includes over 20,000 firms, we use standard errors clustered by firms (e.g. Abadie, Athey, Imbens and Wooldridge, 2017).

3 Problems of Measuring Labour Market Penalties for Financial Misconduct

We will investigate a gender gap in labour market penalties. We briefly describe a subset of misconduct-related disclosure events that are relavant for labour market penalties.

[21] Note that our panel data is unbalanced and all advisers have potentially different industry experience (in years) and tenures across firms.

3.1 Definition of Financial Misconduct

According to the FINRA Form U4, there are 6 broad categories of disclosure events, and of these there are 23 sub-categories.[22] They are related to a wide range of (investment-related) activities and can lead to drastically different consequences at the labour market. For instance, customer complaints and disputes may be inevitable due to clients' financial literacy and considered to be less severe than employer or regulator disciplinary actions. In fact, employer discplinary actions lead to job separation (terminations) in almost every case.[23]

To illustrate a measurement problem, we focus on the two frequently occuring disclosure events (I) Customer Dispute - Settled; (II) Employement Separation After Allegations. With these, we define "Misconduct" by set A consisting of events (I) and (II):

$$A = \{(\mathrm{I}), (\mathrm{II})\}. \tag{2}$$

Egan et al. (2018, 2019) define "Misconduct" by aggregating six different (misconduct-related) disclosure events, besides (I) and (II), including (III) Regulatory - Final; (IV) Criminal - Final Disposition; (V) Customer Dispute - Award/Judgment; (VI) Civil - Final. Our subsequent argument holds true when considering their definition "Misconduct" instead of set A defined by (2).

3.2 Summary Statistics for Disclosure Events

Table 2 shows differences in compliance records across all disclosure events. Columns (1) and (4) displays gender differences in the annual incidence of disclosure events (at percentage points),[24] and also the other remaining columns the (within-gender) differences between the (white) majority and (non-white) minority group. From columns (1) and (4), we can see that males are *more* likely to encounter disclosure events in

[22] The broad six categories are: (i) Criminal Disclosure; (ii) Regulatory Action Disclosure; (iii) Civil Judicial Disclosure; (iv) Customer Compliant/Arbitration/Civil Litigation Disclosure; (v) Termination Disclosure; (vi) Financial Disclosure. See the appendix for the definition of these disclosure events.

[23] Note that there may be a time lag before leaving a firm because some disclosure events require a longer time after allegations are intiated until the associated decision is made. Nonetheless, most cases give rise to job separation within a year following employer discplinary actions by construction.

[24] The annual incidence of disclosure events (e.g. (I) Customer Dispute - Settled) is written as a dummy variable for whether an adviser has encountered a disclosure event in that category at least once within a given year.

a wide range of categories besides "Misconduct" related disclosure events, while the ratio of (II) "Employment Separation After Separation" over all "Misconduct"-related disclosure events is significantly higher for females than for males. Also, females are more likely to receive disclosure events related to financial matters ((VII): "Financial - Final"). The table further provides the fraction of specific outcomes conditional on the incidence of certain disclosure events ((II), (IV), (VII), (VIII): "Judgment/Lien").[25] From this, we can see that females are more likely to (i) receive terminations by being discharged in (II), (ii) have bankruptcy in (VII), (iii) receive a tax lien when having (VIII).

Now, we look at differences between the majority and minority group through columns (2) and (3) for males and columns (5) and (6) for females. Unlike gender gaps, the majority of advisers are *less* likely to receive certain disclosure events ((II) and financial matters), there are no significant differences in the incidence of other disclosure events, and the incidence of "Misconduct" and all disclosure events is smaller for the majority than for the minority. It is noteworthy that, similar to gender gap, the ratio of (II) over all "Misconduct"-related disclosure events is significantly higher for the minority than for the majority. In addition, the formers are more likely to be exposed to financial matters (both for (VII) and (VIII) with a higher fraction of tax lien).

Overall, summary statistics indicates that our sample is consistent with the one used by Egan et al. (2018) and sufficient to replicate their findings. Note that our sample over the period 2008–2018 differs from theirs (over the period 2005–2015) due to a difference in time periods of data collection, and that certain aspects (the incidence of financial matters) are different between the two partly due to after financial crisis.

[25] See Section A for those definitions.

4 Gender Gap

We now examine a gender gap in the labour market penalty for "Misconduct". Summary statistics (Table 2) show that the fraction of A over all misconduct-related disclosure events ($C = A \cup B$) is way higher for females than males (see Section **??** for the definition of A and B). This may suggest that after encountering misconduct-related events, females are unfairly treated by employers relative to their male counterparts. Below we will explore this possible gender penalty gap, with accounting for possible gender-specific positive correlations between events A and B.

Below we will first revisit the recent finding by Egan et al. (2018), showing the gender punishment gap that females are 20% more likely to leave a firm following "Misconduct" relative to their male counterparts, and subsequently attempt to elaborate their finding with a focus on the interdependence between misconduct-related disclosure events.

4.1 Revisiting the Gender Punishment Gap

To examine a gender penalty gap, we consider the baseline model (1) with three differences: (i) we replace the dependent variable Y_{it} as a dummy "$\text{Job Separation}_{i,t+1}$" for whether adviser i leaves firm j by the end of year $t+1$, conditional on that s/he worked for firm j in year t; (ii) we also replace the indepdent variable "Group_i" as a dummy variable "Female" for whether adviser i is female; (iii) we add a dummy variable "Misconduct_{it}" for whether adviser i has encountered a disclosure eventin set A C (defined by (2)) at least once in a given year t, and its interaction term with "Female", as follows.

$$\begin{aligned} \text{Job Separation}_{i,t+1} \;=\; & \beta_1 \text{ Female}_i \;+\; \beta_2 \text{ Misconduct}_{it} \;+\; \beta_3 \text{ Female}_i \times \text{ Misconduct}_{it} \\ & + \boldsymbol{\beta}\, \boldsymbol{X_{it}} \;+\; \alpha_{g(i,t)} \;+\; \varepsilon_{it}. \end{aligned} \tag{3}$$

Column (1) in Table 3 provides the parameter estimates, and shows that the coefficient of "$\text{Female} \times \text{Misconduct}$" is positive with roughly the same size as in Egan et al. (2018) and statistically significant at any reasonable level, which replicates their finding and indicates that females are roughly 20% more likely to leave a firm following "Misconduct" relative to their male counterparts, which would indicate that "Misconduct" leads to a gender punishment gap.

4.2 Interdependence across Misconduct-Related Events

To further explore the gender punishment gap with accounting for possible gender-specific positive correlations between misconduct-related disclosure events, we replace the independent variable "Misconduct" in the model (3) with A (resp. B) to reconsider the gender gap. Columns (2) and (3) in Table 3 provide the parameter estimates and show that the coefficient of "Female × Misconduct" is sufficiently small relative to the one in column (1) and indistinguishable from zero, implying that there is no significant gender gap once splitting C into A and B. We illustrate all of these through Figure F.2. Note that controlling for A (terminations) mechanically controls for punishment, which is the outcome variable of interest and relates to the critique by Neal and Johnson (1996). Here our intention is to show that the presumed gender punishment gap shown in column (1) actually does not exist.

From this, we can hypothesize that the gender penalty gap is virtually absent if A and B occur, independent of each other.[26] We can also argue that A is not always caused by B and vice versa, as otherwise there should be a significant gender penalty gap after A occurs with B due to column (1), which contradicts columns (2) and (3). From this, there should be moderate positive correlations between A and B, which is indeed supported by our data and shown below. With this, a possible driving force of the gender punishment gap for "Misconduct" shown in column (1) is, that females are more likely to receive A following B (or vice versa) relative to their male counterparts, in other words, there exists a *female-specific* positive correlation between A and B.

To examine this hypothesis, we consider the baseline model (1) with the following differences: (i) we replace the dependent variable Y_{it} as a dummy for whether adviser i encounters a disclosure event in set A at least once in year t; (ii) as in the model (3), we consider a dummy variable "Female" instead of "Group_i"; (iii) we add a dummy B for whether adviser i encounters a disclosure event in set B at least once in year t as well as those interaction terms with "Female".

$$\begin{aligned} A_{it} \;=\; & \beta_1 \text{ Female}_i \;+\; \beta_2 \, B_{it} \;+\; \beta_3 \text{ Female}_i \times \; B_{it} \\ & + \boldsymbol{\beta} \, \boldsymbol{X_{it}} \;+\; \alpha_{g(i,t)} \;+\; \varepsilon_{it}. \end{aligned} \tag{4}$$

Table 4 provides the parameter estimates. The coefficient of "Female" is negative and significant at any reasonable level, and column (4) indicates that females are roughly

[26]Note that A and B may not be mutually exclusive and both events can occur in the same year.

40% less likely to receive A. As expected, the coefficient of B is positive and significant, indicating that A is 30% more likely to occur when encountering a misconduct-related disclosure event in B. This implies that there is a moderate positive correlation between A and B, indepndent of gender. In contrast, the coefficient of "Female $\times$ B" is small and indistinguishable from zero, which is contrary to the hypothesis that there is a *female-specific* positive correlation between A and B.

We can augment our argument with controlling for prior compliance records on A and B. Consider dummy variables A^{Prior} and B^{Prior} for whether adviser i has encounterd a disclosure event in A and B, respectively, at least once prior to the year t, and also their interaction terms with "Female". We add these to the model given by (4) to re-evaluate the hypothesis that there is a female-specific positive correlation between A and B.

Columns (5)–(6) in Table 4 provide the parameter estimates. The coefficients of A^{Prior} and B^{Prior} are both positive and significant at any reasonable level, which indicates that advisers with prior records on A (resp. B) are roughly twice (resp. three-times) more likely to receive A compared to the ones without. This implies that there is a significant recidivism and advisers with prior recrods are likely to be repeat offenders. When looking at female-specific correlations, the coefficients of "Female $\times$ A^{Prior}" and "Female $\times$ B^{Prior}" are both small and indistinguishable from zero, which implies that there are no female-specific positive correlations between A and prior records.

Putting all together, females are equally likely to receive A conditional on encoutering B. Thus, we do not find any gender-specific positive correlations across misconduct-related events, which does not support the hypothesis that after encountering misconduct-related events, females are unfairly treated by employers relative to their males counterparts.

The same argument holds true when considering the incidence of B with switching A and B in the model given by (4). A difference is that the coefficients of "Female $\times$ A" and "Female $\times$ B^{Prior}" are both negative and significant at any reasonable level, which indicates that females are less likely to encounter B conditional on receiving A and prior records on B, respectively. This implies that there are female-specific negative correlations across misconduct-related events, and suggests that recidivism explains part of the reason why the fraction of terminations over all misconduct-related events is higher for females than males.

5 Racial Disparities

We now turn to racial disparities among financial advisers, with accounting for differences between the (white) majority and (non-white) minority group, as seen in summary statistics (Table 1 and 2).[27] As in the preceding gender gap analysis, we will investigate a punishment gap following "Misconduct" between the two groups, and will subsequently explore its possible driving forces.

5.1 Punishment Gap

We consider racial inequality in the labour market penalty (through job separation) for "Misconduct". Since summary statistics tell us that there is a substantial difference between the majority and minority group in the distribution of misconduct-related disclosure events $C = A \cup B$ (see the definition (2) in Section **??**) and the fraction of A over $C = A \cup B$ is larger for the minority than for the majority, we anticipate from the gender gap analysis that without accounting for the difference in distribution, there are significant punishment gaps between the majority and minority groups when evaluating "Misconduct", while those gaps are absent when assessing "Misconduct" separately from A (terminations).

To see this, we reconsider the model given by (3) where we replace the independent variable "Female" with "Minority", a dummy variable for whether an adviser belongs to the minority group. Column (1) in Table 5 provides the parameter estimates and shows that there is a significant punishment gap against the minority group of advisers who are roughly 30% more likely to leave a firm following "Misconduct" relative to the majority group.[28] Note that we do not split the sample into males and females to evaluate the gap while instead we introduce a dummy variable "Female". Our subsequent findings are qualitatively the same as evaluating for males and females, separately.

Next, we consider the labour market penalty following the disclosure events in A and B respectively, instead of the aggregate measure "Misconduct", in order to see if there is still a punishment gap. As expected, column (2) in the table shows no significant gap in job separation following A (terminations) by construction. Also, column (3) indicates that a large part of the gap stems from the distribution effect as seen in the gender gap analysis (see Table 3). However, a sizable part of the gap still remains at

[27]See Section 2.1.2 for the definition of race in this paper.

[28]Note that we can also see from the table that in the absence of disclosure events, the minority group of advisers are roughly 5% more likely to leave a firm relative to the majority counterparts.

column (3), which accounts for roughly 25% increase in the job separation relative to the majority.

To explore a possible driving force of the remaining gap in column (3) between the two groups, we consider a subset of B and pay attention to two major disclosure events (I) and (III) (see Section 3.1 for the definition of (I) and (III)). Columns (4) and (5) in Table 5 indicate that customer disputes (resp. regulator actions) can lead to roughly 20% (resp. 30%) higher job separation for the minority relative to the majority counterparts.

To better understand this, we now split the minority group into three different categories of races (Asian, Black, and Hispanic) and re-do the same analysis.[29] Table 6 provides the parameter estimates, and indicates that especially regulatory actions lead to a significantly higher job separation rate for the non-white minority group than for the white majority.

Education. It may be plausible that the minority group of advisers have a lower level of education on average relative to the majority and are more likely to engage in "Misconduct", and therefore a gap in the termination rate between the minority and majority group is likely to be overestimated due to omitted variable bias. To mitigate this, we pay attention to a subset of advisers who provide information on their education in the employment history (see Section 2.1.1 for categorical variables of education). With this, we reconsider a possible gap in the termination rate.

To control for education, we limit the sample to advisers who report information on education and have education level of college and above (e.g. university and graduate school), and redo the same analysis. Table 7 provides the parameter estimates and indicates from columns (3) and (6) (evaluated with fixed effects) that the minority advisers are roughly 15% more likely to leave a firm following "Misconduct" than the majority, and are furthermore around 50% more likely so following B. Note that the former is significant at any conventional level while the latter is so only at the 5% level.

Our findings also hold true when limitting the sample to advisers whose education level is university and above with excluding college. But there is a limitation that we cannot control for pre-market factors, unlike Neal and Johnson (1996).

Other Concurrrent Disclosure Events and Prior Records. As in the gender gap analysis, one might argue that each misconduct-related disclosure event can simul-

[29]See Section 2.1.2 for the definition of race.

taneously occur with other events in the same year, and also advisers with prior records tend to be repeat offenders. By the same argument in Section 4.2, we control for those and find that our finding remains the same even when accounting for such positive correlations across diclosure events.

5.2 Unequal Terminations

Summary statistics indicate that terminations (disclosure events in set A) occur way more frequently for the minority group than the majority. We will investigate whether it is indeed true after controlling for fixed effects with observable characteristics. In doing so, we reconsider the model given by (4) where we replace "Female" with "Minority" and add dummy variables A^{prior} and B^{prior} to control for prior records, as in Section 4.2. Note that as in the previous section 5.1, we do not split the sample into males and females to evaluate the gap while instead we introduce a dummy variable "Female".

Table 8 provides the parameter estimates across columns (1)–(3). The coefficient of "Minority" is positive and significant at any conventional level, which indicates that the minority is roughly 25% more likely to receive A (terminations) relative to the majority counterparts. This suggests that employers force their minority employees to resign more frequently than the majority employees who work for the same firm at the same branch office in the same year with the same set of licenses.

Following the definition (see the appendix), a termination can occur 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. Taking this into account, it is of importance to examine whether all the difference in the incidence of terminations can be attributed to the minority's higher propensity for misconduct-related activities relative to the majority, while having no indication of differential treatment at work.

When looking at the coefficient of "Minority $\times$ B" is positive and significant at any reasonable level, which indicates that the minorities are roughly 35% more likely to receive A (terminations) than their majority counterparts, when confronting a misconduct-related disclosure event in set B in the same year. This may suggest that when a misconduct-related event is revealed, employers tend to treat the minority more severely relative to the majority.

The coefficient of "Female" is negative and significant at any conventional level, implying that the gaps between the majority and minority become larger for females than males. For instance, the minority female advisers are roughly 40% more likely to receive terminations relative to their majority counterparts, and especially when having B, they are around 50% more likely to receive terminations. This may suggest that the racial inequality in employer treatment is larger for females than males.

Below we also examine other possibilities for why there is a significant difference in the incidence of terminations between the two groups. See the Online Appendix for details.

Education. When we limit the sample to advisers who report information on education and have university education, we still find that the minorities are at least 25% more likely to receive terminations than their majority counterparts.

Settlement Gap. Also, there may be a concern that cost associated with disclosure events is higher for the minority group than the majority. For this, we find that there is no significant difference in the associated cost between the two groups.

Conditional on No Prior Compliance Records. We also find that the termination rate is higher for the minority relative to the majority, conditional on that they have no prior compliance records before receiving a termination. The same is true even if we limit the sample to "loyal" advisers who have never switched firms in the industry prior to terminations.

Different Experience and Tenure Profiles. Our main finding remains true over a wide range of career stages as measured by experience since entry into the industry. For example, when considering different career stages across five-year windows of experience, the termination rate is higher for the minority than the majority even after 15-year industry experience and the difference between the two group gets larger after 5-year experience than before.

6 Concluding Remarks

We considered the US financial advisor industry to investigate gender gap and racial inequality in the labour market. In particular, we paid attention to those gaps in employer treatment concerning misconduct-related disclosure events. We mainly found that there are racial disparities in the labour market penalties, through job separation and terminations, against the minorities, including asians, blacks, and hispanics. This is based on disclosed compliance records for the vast majority of financial advisers in the US, and suggests differential treatment at work in this industry.

Below we mention a couple of other related works.

Employer Learning and Terminations of Lemons. Gibbons and Katz (1991) and Farber and Gibbons (1996) provide evidence that employers learn characteristics (e.g. productivity and skills) of their employees over time. Although there is a difficulty in differentiating (unobservable) involuntary layoffs from self-selection of job separation, we utilize a unique feature of our panel data through which we can *directly* observe forced layoffs at the individual level in matched employer-employee data. This unique feature enables us to provide suggestive evidence that employer learning is *asymmetric*, meaning that information on employees differs between their employer and other prospective employers in the market. We show this as a right-skewed distribution of termination rates over *tenure*, where an employer detects "lemons" especially at early stages after hiring, even when they have long enough industry experience.

Dynamics of Gender Gap for Financial Advisers. Bertrand et al. (2010) examine dynamics of gender gap in finance industry, and provide evidence that career interruption is one of the main causes for the gender pay gap. This fits well with financial advisers in our sample: At the beginning of career, females work for firms of larger size and are less likely to exit from the industry than their male counterparts, while the exit rate for females relative to males gradually increases over industry experience. They continue to work for a firm of larger size than males but are less likely to get promoted as measured by specific license (Series 24) to serve as manager at a given firm, especially when they have long industry experience over 10 years, and also they are less likely to move to a different state or commuting zone when switching firms relative to their male counterparts. These facts may capture a part of glass ceiling that preveils in this industry.

Financial Distress for Financial Advisers. In the US, an individual files for bankruptcy under one of two procedures, Chapter 7 or 13, in most cases. When qualified for the former, most unsecured assets are discharged and future earnings are entirely exempt, although debtors have to repay debt using their non-exempt assets. When filing under the latter instead, their assets are entirely exempt while they are obliged to use their future earnings to repay debt. Note that the exemption levels vary across states.

One would assume that financial advisers would likely have more sophisticated financial literacy than the average US citizen, which leads to a lower annual incidence of bankruptcy on average, and also that they take advantage of that knowledge to file for bankruptcy through Chapter 7 (instead of Chapter 13) to discharge their debt and have a "fresh start", with a higher rate, when they expect that benefits from filing for bankruptcy are higher than cost (e.g. Gropp et al., 1997; Domowitz and Sartain, 1999; Fay et al., 2002).

In fact, following the aggregate statistics provided by the American Bankruptcy Institute,[30] the annual bankruptcy filing rate for the average citizen has been higher than for the average financial adviser, while the variation in filing rate after the financial crisis was larger for the latter than the former (see Figure F.3). Also, the percentage of Chapter 7 filing over the period 2008–2018 is between 65–70% for the average citizen, while that in our sample is about 75% for both the majority and minority group, irrespective of gender (see Table 9 for summary statistics).[31]

Using our panel data over the period 2008–2018, we consider the effect of the financial crisis on the (personal) bankruptcy filing rate for financial advisers and find that there are gender gaps and racial disparities in the incidence of financial disclosure events assocciated with the financial crisis, which caused a sharp increase in the bankruptcy filing rate after the year 2008 and hit female advisers harder than males, even significantly more so for the minority than the majority group. After reaching the peak in 2010, the bankruptcy rate steadily declined over time until it went back to the original level before the crisis (see Figure F.4 for an illustration). Indeed, after controlling for firm-year-county-license fixed effects as in the main analysis, we find that there

[30]See the quarterly statistics for the non-business bankruptcy filing: https://abi-org.s3.amazonaws.com/Newsroom/Bankruptcy_Statistics.

[31]From summary statistics in Table 9, we can see that some cases under Chapter 13 yield the disposition, "Discharge", which may appear inconsistent with the feature of Chapter 13. This is because these cases are dissolved after a certain time period (within 5 years), resulting in "Discharged". This differs from the case of Chapter 7, where "Discharged" is often implemented after filing.

was a significant negative impact on their financial matters with heterogenous effects across genders and races, and females (resp. hispanics) were hit harder than their male (resp. whites) counterparts, with 20% (resp. 70%) higher bankruptcy filing rate over 2009–2011, the first 3-year window after the financial crisis.[32] This is of importance because confronting a financial issue would likely cause another problem related to personal finance, which further leads to significantly higher incidence of misconduct-related events.

More precisely, we find that prior records on financial matters, which include disclosure events "Financial - Final" and "Judgment/Lien",[33] are highly indicative of future incidence of those events (Qureshi and Sokobin, 2015; Egan et al., 2019), which further causes misconduct-related disclosure events (e.g. customer disputes (settled), terminations, regulatory actions). Of importance is the magnitude of correlations between the future incidence of misconduct-related disclosures and prior records on financial matters. For instance, the incidence of terminations (resp. regulatory actions) with prior recrods on financial matters is four-times (resp. six-times) as large as the one without.

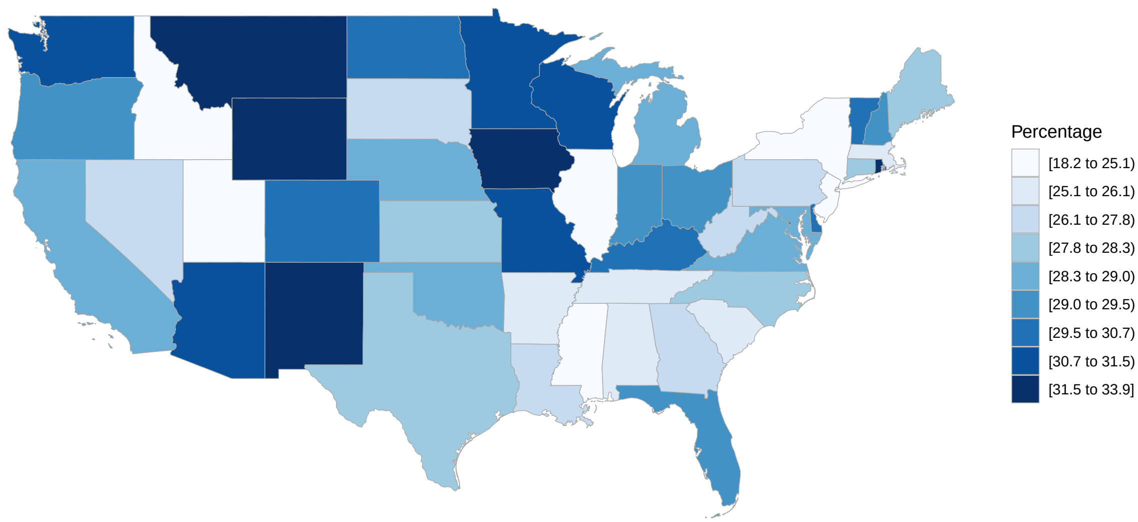
There is a recent study related to financial distress for financial advisers. Using the FINRA BrokerCheck database, Dimmock et al. (2018b) considered region-specific real estate shocks that were supposed to influence a subset of financial advisers based on their home addresses, and found that advisers are more likely to engage in misconduct under financial distress than not.

[32]We also find significant heterogeneity in the bankruptcy filing rate across firms and regions (states and counties).

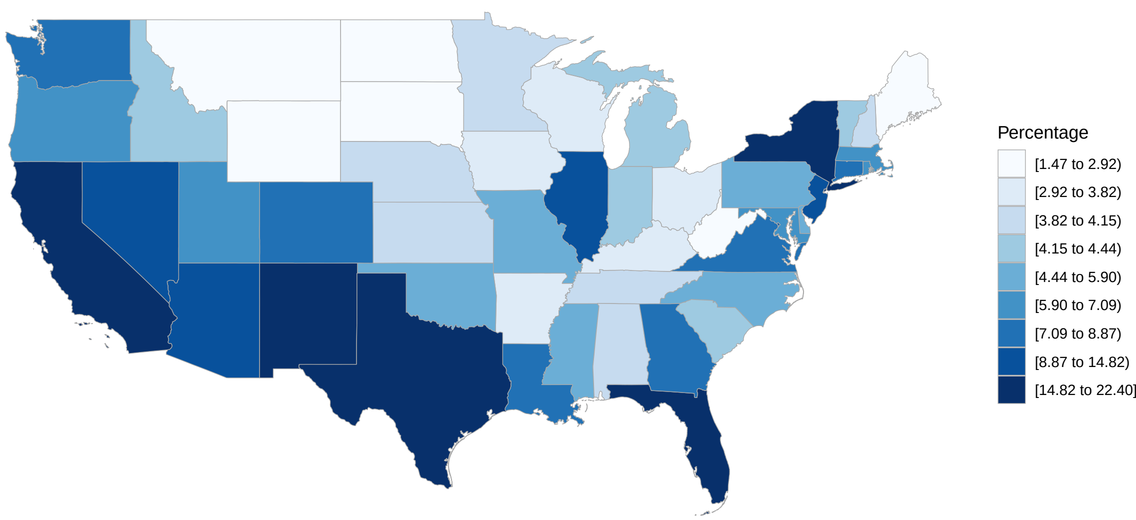
[33]See the appendix for the definition of disclosure events.

Figure F.1: Population of Financial Advisers Across States

(a) Female Percentage

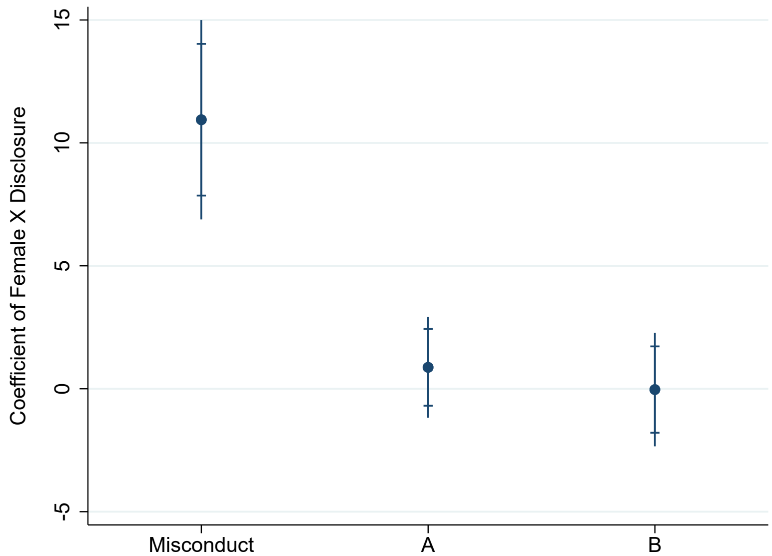


(b) (Non-White) Minority Percentage



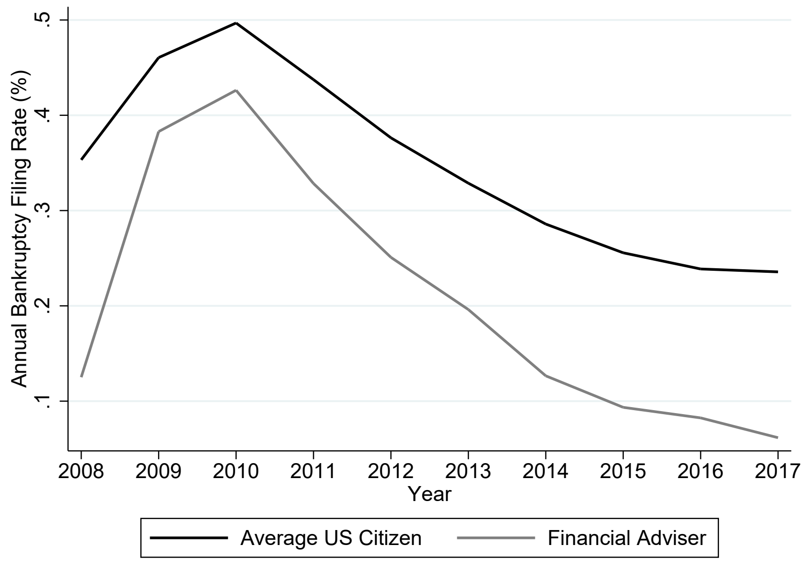
Note: Observations are based on the adviser-year panel data over the period 2008-2018. Panel (a) in the figure displays the (average) percentage of female advisers across states over the period, whereas panel (b) the percentage of the non-white minority. See Section 2 for detailed data.

Figure F.2: Gender Punishment Gap



Note: The figure displays a gender gap in the job separation rate following misconduct-related dislosure events across different categories, and illustrates the coefficients of the interaction term "Female × Disclosure" across columns (2), (4), and (6) in Table 3. See Section 4 for details.

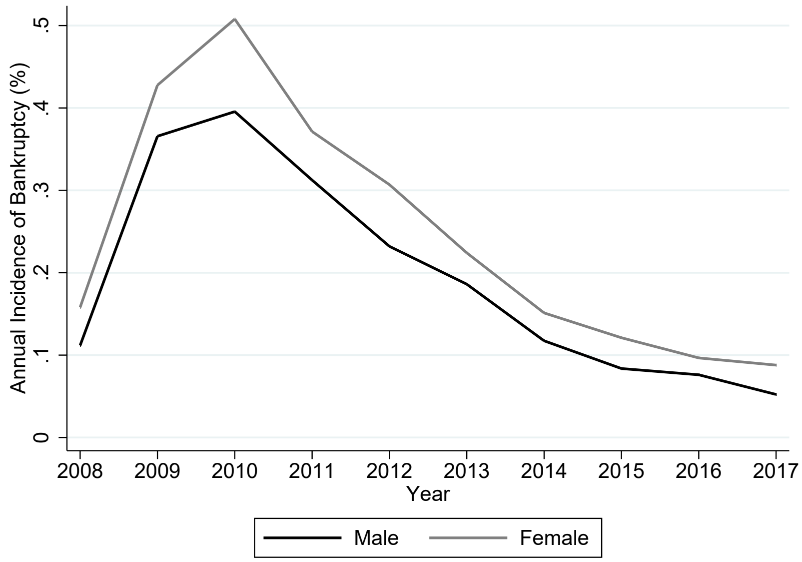
Figure F.3: Bankruptcy Filing Rates for the Average US Citizen and Financial Advisers



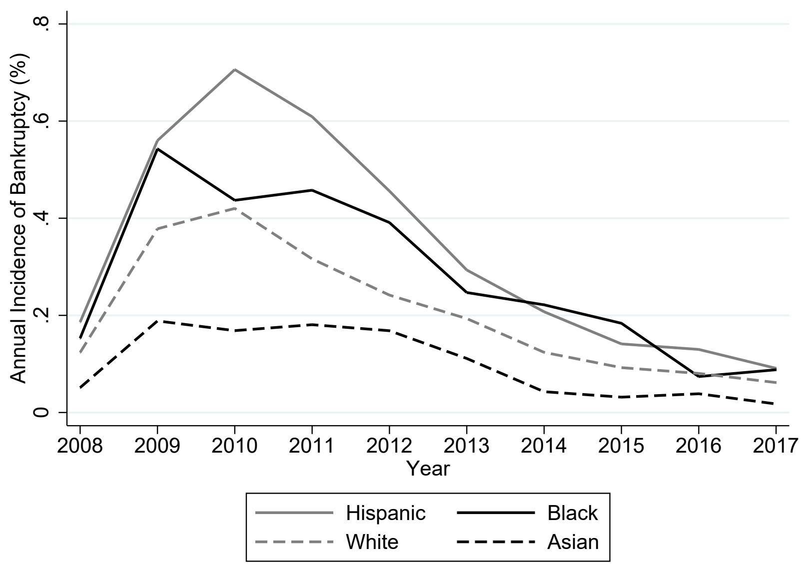
Note: The figure displays the annual (non-business) bankruptcy filing rates for the average US citizen and financial advisers over the period 2008-2017. To construct the annual filing rate for the average US citizen, we use (i) quarterly statistics for the non-business bankruptcy filing (including Chapter 7, 11, 13) provided by the American Bankruptcy Institute, and (ii) the annual population estimates over the period 2008–2018 provided by U.S. Census Bureau. To construct the filing rate for financial advisers, we use our panel data with bankruptcy disclosure events over the period. See the appendix for the definition of bankruptcy. Since information on the disclosure event "Financial - Final" (including bankruptcy) is limited to 10 years before the date of data collection and we collected our data in August 2018, the annual bankruptcy filing rate in 2008 for financial advisers is supposed to be smaller than the actual value, so that comparisons in the year 2008 should be made with care.

Figure F.4: Bankruptcy Filing Rate for Financial Advisers Across Genders and Races

(a) Gender



(b) Race



Note: Observations are based on the adviser-year panel data over the period 2008-2017. Advisers are divided into males and females in Panel (a), and into four categories of race (asian, black, hispanic, white) in Panel (b) (see Section 2.1.2 for the definition of race). We consider the annual incidence of "Bankruptcy", which is a subcategory of the disclosure event "Financial - Final", over the period (see Table 2 summary statistics for the annual incidence of disclosure events). The figure displays that within-group annual incidence. Since information on the disclosure event "Financial - Final" (including bankruptcy) is limited to 10 years before the date of data collection and we collected our data in August 2018, the annual bankruptcy filing rate in 2008 for financial advisers is supposed to be smaller than the actual value, so that comparisons in the year 2008 should be made with care.

Table 1: Summary Statistics for Characteristics of Advisers with Gender and Race (White Majority and Non-White Minority)

	Male			Female		
	(1) All	(2) Majority	(3) Minority	(4) All	(5) Majority	(6) Minority
Employment History and Status:						
Experience (years)	13.4	13.9	9.3	10.8	11.2	8.1
Tenure (years)	6.3	6.5	4.6	5.7	5.9	4.5
Currently Registered (in 2018)	72.0	72.5	67.7	69.6	70.0	67.7
Job Transitions (%):						
(1) Remain at a Firm	83.2	83.6	80.3	83.6	83.9	81.6
(2) Leave a Firm	16.8	16.4	19.7	16.4	16.1	18.4
Conditional on Leaving a Firm:						
(3) New Employment	50.1	50.8	44.8	43.8	44.3	40.5
Migration Across						
States	24.0	24.5	20.4	20.8	21.2	18.1
Commuting Zones	31.1	31.6	27.0	27.4	27.9	24.1
Counties	42.1	42.6	38.5	38.3	38.9	34.5
Licenses/Industry Exams						
Series 63 (General Securities Agent)	74.3	74.8	70.4	68.7	68.9	67.9
Series 7 (General Securities Representative)	69.0	69.8	61.4	62.4	63.6	55.1
Series 6 (Insurance and Annuities)	35.5	35.2	38.6	42.4	42.0	45.2
Series 65/66 (Investment Adviser)	42.1	43.4	31.0	34.8	36.0	27.1
Series 24 (Principal/Supervisory Management)	15.4	16.0	10.3	10.6	11.2	7.1
Total Number of Licenses	2.9	2.9	2.5	2.5	2.6	2.3
Observations	5,753,021	5,150,027	542,597	2,153,206	1,843,251	267,990

Note: Observations are based on the adviser-year panel data over the period 2008-2018. Advisers are divided into males and females, and further split into the white majority and non-white minority group (see Section 2.1.2 for details). Regarding "Job Transitions", the variable (1) "Remain at a Firm" is the percentage that an adviser who works for a firm in a given year (excluding the year 2018) remains at the firm in the following year; (2) "Leave a Firm" is the percentage of the opposite case of (1); (3) "New Employment" is the percentage of advisers who work for a firm in a given year (excluding the year 2018) switching to a new firm in the following year, conditional on that they leave the original firm by the end of the following year. "Migration Across States/Commuting Zones/Counties" is the percentage of advisers migrating from a given state (resp. commuting zone, county) to a different one, conditional on switching firms. To define commuting zones, we use the 2000 ERS Commuting Zones (CZs) provided by the United States Department of Agriculture. See footnote 14 for the definitions of licenses/qualifications.

Table 2: Summary Statistics for the Incidence of Disclosure Events with Gender and Race (the White Majority and Non-White Minority Group)

	Male			Female		
	(1) All	(2) Majority	(3) Minority	(4) All	(5) Majority	(6) Minority
Misconduct Related Disclosure Events (%):						
Customer Disputes - Settled	0.37	0.37	0.34	0.13	0.13	0.12
Employment Separation After Allegations	0.23	0.21	0.37	0.15	0.14	0.24
Regulatory - Final	0.12	0.12	0.12	0.04	0.04	0.04
Criminal Disposition - Final	0.03	0.03	0.04	0.01	0.01	0.01
Customer Disputes - Award/Judgment	0.02	0.02	0.02	0.01	0.01	0.00
Civil - Final	0.00	0.00	0.00	0.00	0.00	0.00
Any Misconduct Related Disclosure	0.71	0.70	0.82	0.32	0.31	0.39
Other Disclosure Events (%):						
Financial - Final	0.42	0.40	0.51	0.49	0.47	0.58
Judgment/Lien	0.33	0.33	0.39	0.20	0.18	0.28
Customer Disputes - Denied	0.33	0.34	0.27	0.14	0.14	0.14
Customer Disputes - Closed-No Action	0.07	0.07	0.07	0.02	0.02	0.03
Financial - Pending	0.04	0.04	0.05	0.06	0.05	0.07
Customer Disputes - Pending	0.06	0.06	0.11	0.02	0.02	0.03
Customer Disputes - Withdrawn	0.02	0.02	0.02	0.01	0.01	0.01
Criminal - Pending	0.01	0.01	0.01	0.00	0.00	0.01
Investigation	0.01	0.01	0.01	0.00	0.00	0.00
Regulatory - Pending	0.00	0.00	0.00	0.00	0.00	0.00
Civil - Pending	0.00	0.00	0.00	0.00	0.00	0.00
Customer Disputes - Final	0.00	0.00	0.00	0.00	0.00	0.00
Customer Disputes - Dismissed	0.00	0.00	0.00	0.00	0.00	0.00
Civil Bond	0.00	0.00	0.00	0.00	0.00	0.00
Regulatory - On Appeal	0.00	0.00	0.00	0.00	0.00	0.00
Criminal - On Appeal	0.00	0.00	0.00	0.00	0.00	0.00
Civil - On Appeal	0.00	0.00	0.00	0.00	0.00	0.00
Total (%):	1.89	1.86	2.13	1.21	1.17	1.46
Observations	5,753,021	5,150,027	542,597	2,153,206	1,843,251	267,990

Note: Observations are based on the adviser-year panel data over the period 2008-2018. Advisers are divided into males and females, and further split into the white majority and non-white minority group (see Section 2.1.2 for details). Each value (except for conditional variables) indicates the annual incidence of the disclosure event in percentage points, which is given by a dummy variable for whether an adviser has encountered a disclosure event in the respective category (see Section 3.1) at least once within a given year. For the subset of disclosure events ("Employment Separation After Allegations", "Criminal - Final", "Financial - Final", "Judgment/Lien"), we display the fraction of specified outcomes conditional on that the adviser has encountered the respective disclosure event.

Table 3: Gender Punishment Gap in Job Separation with/out Misconduct-Related Disclosure Events $C = A \cup B$

	Misconduct		A		B	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.85***	-0.26**	-0.86***	-0.24*	-0.89***	-0.30**
	(0.27)	(0.13)	(0.27)	(0.13)	(0.27)	(0.13)
Disclosure	32.16***	29.24***	78.36***	74.92***	15.42***	10.02***
	(1.65)	(2.20)	(0.73)	(1.40)	(0.85)	(0.73)
Female × Disclosure	9.68***	10.94***	0.08	0.87	-0.36	-0.03
	(1.55)	(1.57)	(0.56)	(0.80)	(0.89)	(0.90)
Adviser Controls	✓	✓	✓	✓	✓	✓
Firm × Year × County × License FE		✓		✓		✓
Observations	7,022,703	5,736,702	7,022,703	5,736,702	7,022,703	5,736,702
R^2	0.017	0.316	0.022	0.320	0.013	0.312
Mean of Dependent Variable	16.66	16.58	16.66	16.58	16.66	16.58

Note: Observations are based on the adviser-year panel data over the period 2008-2018. The dependent variable is a dummy variable equal to one if an adviser worked for a given firm in a given year (excluding the last year 2018) and left the firm by the end of next year (see Section 4 for details). "Disclosure" is a dummy variable for whether an adviser encounters at least once in a given year a disclosure event in the respective set: Columns (1)–(2): "Misconduct" ($C = A \cup B$); Columns (3)–(4): A; Columns (5)–(6): B. All of these sets are defined in Section 3. "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients are in percentage points. Standard errors are in brackets and clustered by firms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Gender Gap: Incidence of Misconduct-Related Disclosure Events in Set A and B with Concurrent and Prior Records

	Incidence of A(%)			Incidence of B(%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.11***	-0.09***	-0.08***	-0.23***	-0.20***	-0.14***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
B(%)		0.07***	0.07***			
		(0.01)	(0.01)			
Female × B(%)		0.00	0.00			
		(0.01)	(0.01)			
B^{Prior}			0.25***			1.27***
			(0.02)			(0.07)
A^{Prior}			0.43***			1.98***
			(0.06)			(0.12)
Female × B^{Prior}			-0.05*			-0.45***
			(0.03)			(0.08)
Female × A^{Prior}			-0.03			-0.20
			(0.13)			(0.27)
A(%)					0.14***	0.14***
					(0.01)	(0.01)
Female × A(%)					-0.06***	-0.06***
					(0.01)	(0.01)
Adviser Controls	✓	✓	✓	✓	✓	✓
Firm × Year × County × License FE	✓	✓	✓	✓	✓	✓
Observations	6,273,000	6,273,000	6,273,000	6,273,000	6,273,000	6,273,000
R^2	0.139	0.146	0.147	0.189	0.196	0.199
Mean of Dependent Variable	0.21	0.21	0.21	0.40	0.40	0.40

Note: Observations are based on the adviser-year panel data over the period 2008-2018. The dependent variable is a dummy equal to one if an adviser encounters a disclosure event in set A across columns (1)–(3) and in set B across columns (4)–(6). (see Section 3 for the definition of A and B and the model given by (4) in Section 4.2). A and B are dummy variables for whether the adviser encounters a disclosure event in A and B, respectively, at least once prior to that year. A^{Prior} and B^{Prior} are dummy variables for whether adviser i has encounterd a disclosure event in A and B, respectively, at least once prior to the year t. "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients (except those for A and B) are in percentage points. Standard errors are in brackets and clustered by firms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Job Separation with/out Misconduct-Related Disclosure Events for the Minority and Majority Group

	Misconduct	A	B	(I)	(III)
	(1)	(2)	(3)	(4)	(5)
Minority	0.57***	0.63***	0.66***	0.67***	0.67***
	(0.19)	(0.18)	(0.18)	(0.18)	(0.18)
Disclosure	29.14***	75.36***	9.36***	5.89***	25.21***
	(2.09)	(1.39)	(0.69)	(0.64)	(2.28)
Minority × Disclosure	13.76***	-1.52	6.41***	4.41***	12.44***
	(2.48)	(1.29)	(1.40)	(1.30)	(2.84)
Female	-0.23*	-0.25*	-0.31**	-0.33**	-0.33**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Adviser Controls	✓	✓	✓	✓	✓
Firm × Year × County × License FE	✓	✓	✓	✓	✓
Observations	5,736,702	5,736,702	5,736,702	5,736,702	5,736,702
R^2	0.316	0.320	0.312	0.312	0.312
Mean of Dependent Variable	16.58	16.58	16.58	16.58	16.58

Note: Observations are based on the adviser-year panel data over the period 2008-2018. The dependent variable is a dummy equal to one if an adviser leaves firm j in year $t+1$, conditional on that the adviser worked for the firm in year t (see Section 5.1 for details). The independent variable "Minority" is a dummy for whether an adviser is in the non-white minority group (see Section 2.1.2 for the definition of the non-white minority group); "Disclosure" is a dummy variable for whether an adviser encounters a disclosure event in the respective columns (1)–(5) at least once in year t (The definitions of "Misconduct", A, B, (I), and (III) are given in Section 3.1 and **??**). "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients are in percentage points. Standard errors are in brackets and clustered by firms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Job Separation with/out Misconduct-Related Disclosure Events for the White Majority and Non-White Minority (Asian, Black, Hispanic) Group

	Misconduct	*A*	*B*	(I)	(III)
	(1)	(2)	(3)	(4)	(5)
Asina	0.79***	0.84***	0.89***	0.90***	0.90***
	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)
Black	0.98***	1.04***	1.05***	1.07***	1.07***
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Hispanic	0.18	0.24	0.26	0.27	0.27
	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)
Disclosure	29.14***	75.35***	9.36***	5.88***	25.21***
	(2.09)	(1.39)	(0.69)	(0.64)	(2.28)
Asina × Disclosure	17.32***	0.97	5.75***	4.52**	13.98**
	(2.35)	(1.25)	(1.99)	(2.27)	(5.83)
Black × Disclosure	13.37***	-1.61	8.09***	4.12	14.67**
	(2.13)	(1.47)	(2.11)	(2.61)	(5.75)
Hispanic × Disclosure	12.17***	-2.83	6.20***	4.52***	11.12***
	(3.43)	(2.04)	(1.87)	(1.52)	(3.48)
Female	-0.24*	-0.26**	-0.32**	-0.33**	-0.33**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Adviser Controls	✓	✓	✓	✓	✓
Firm × Year × County × License FE	✓	✓	✓	✓	✓
Observations	5,736,702	5,736,702	5,736,702	5,736,702	5,736,702
R^2	0.316	0.320	0.312	0.312	0.312
Mean of Dependent Variable	16.58	16.58	16.58	16.58	16.58

Note: Observations are based on the adviser-year panel data over the period 2008-2018. The dependent variable is a dummy equal to one if an adviser leaves firm j in year $t+1$, conditional on that the adviser worked for the firm in year t (see Section 5.1 for details). The independent variables "Asian", "Black", and "Hispanic" are dummies for whether an adviser is asian, black, or hispanic, respectively, conditional on that the base group of advisers is set as white (see Section 2.1.2 for the definition of races in our data). "Disclosure" is a dummy variable for whether an adviser encounters a disclosure event in the respective columns (1)–(5) at least once in year t (The definitions of "Misconduct", A, B, (I), and (III) are given in Section 3.1 and **??**). The variable "Minority" is a dummy for whether an adviser is in the non-white minority group (see Section 2.1.2 for the definition of the non-white minority group). "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients are in percentage points. Standard errors are in brackets and clustered by firms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Job Separation with/out Misconduct-Related Disclosure Events for the Majority and Minority Group with Education Information

	Misconduct			A			B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Minority	2.20***	1.85***	1.54***	2.21***	1.86***	1.55***	2.30***	1.95***	1.58***
	(0.53)	(0.51)	(0.21)	(0.53)	(0.51)	(0.21)	(0.51)	(0.50)	(0.21)
Disclosure	49.64***	48.80***	51.45***	73.90***	72.81***	71.28***	16.49***	15.88***	14.80***
	(3.64)	(3.47)	(3.95)	(1.04)	(1.13)	(1.78)	(3.09)	(3.00)	(4.18)
Minority × Disclosure	11.94***	11.55***	10.46***	0.28	-0.05	0.20	13.03**	12.63**	15.32**
	(2.48)	(2.50)	(3.09)	(1.54)	(1.63)	(2.57)	(6.10)	(6.16)	(6.68)
Female	-1.26***	-1.49***	-0.18	-1.28***	-1.51***	-0.18	-1.33***	-1.56***	-0.25
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)
Adviser Controls		✓	✓		✓	✓		✓	✓
Firm × Year × County × License FE			✓			✓			✓
Observations	510,644	510,644	386,400	510,644	510,644	386,400	510,644	510,644	386,400
R^2	0.006	0.011	0.248	0.008	0.013	0.249	0.001	0.006	0.244
Mean of Dependent Variable	20.60	20.60	20.03	20.60	20.60	20.03	20.60	20.60	20.03

Note: Observations are based on the adviser-year panel data over the period 2008-2018. We limit the sample to advisers who report education in their employment history and if the level is college and above (e.g. university and graduate school). The dependent variable is a dummy equal to one if an adviser leaves firm j in year $t+1$, conditional on that the adviser worked for the firm in year t (see Section 5.1 for details). The independent variables "Asian", "Black", and "Hispanic" are dummies for whether an adviser is asian, black, or hispanic, respectively, conditional on that the base group of advisers is set as white (see Section 2.1.2 for the definition of races in our data). "Disclosure" is a dummy variable for whether an adviser encounters a disclosure event in the respective columns (1)–(5) at least once in year t (The definitions of "Misconduct", A, and B, are given in Section 3.1 and **??**). The variable "Minority" is a dummy for whether an adviser is in the non-white minority group (see Section 2.1.2 for the definition of the non-white minority group). "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients are in percentage points. Standard errors are in brackets and clustered by firms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Incidence of Misconduct-Related Disclosure Events in Set A and B for the Majority and Minority Group

	Incidence of A(%)			Incidence of B(%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Minority	0.07***	0.05***	0.05***	0.02**	0.02*	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.11***	-0.09***	-0.08***	-0.23***	-0.21***	-0.17***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
B(%)		0.07***	0.07***			
		(0.01)	(0.01)			
Minority $\times$ B(%)		0.05***	0.05***			
		(0.01)	(0.01)			
B^{Prior}			0.23***			1.19***
			(0.02)			(0.06)
A^{Prior}			0.41***			1.96***
			(0.05)			(0.13)
Minority $\times$ B^{Prior}			0.09*			0.22
			(0.05)			(0.21)
Minority $\times$ A^{Prior}			0.19			0.11
			(0.18)			(0.37)
A(%)					0.13***	0.13***
					(0.01)	(0.01)
Minority $\times$ A(%)					-0.02**	-0.02**
					(0.01)	(0.01)
Adviser Controls	✓	✓	✓	✓	✓	✓
Firm $\times$ Year $\times$ County $\times$ License FE	✓	✓	✓	✓	✓	✓
Observations	6,273,000	6,273,000	6,273,000	6,273,000	6,273,000	6,273,000
R^2	0.139	0.147	0.147	0.189	0.196	0.198
Mean of Dependent Variable	0.21	0.21	0.21	0.40	0.40	0.40

Note: Observations are based on the adviser-year panel data over the period 2008-2018. The dependent variable is a dummy equal to one if an adviser encounters a disclosure event in set A across columns (1)–(3) and in set B across columns (4)–(6) (see Section 2 for the definition of A and B and Section 5.2 for the model). The variable "Minority" is a dummy for whether an adviser is in the non-white minority group (see Section 2.1.2 for the definition of the non-white minority group). "A" and "B" are dummy variables for whether the adviser has encountered a disclosure event in A and B, respectively, at least once prior to that year. A^{Prior} and B^{Prior} are dummy variables for whether the adviser has encounterd a disclosure event in A and B, respectively, at least once prior to the year t. "Adviser Controls" include industry experience and its squared term; tenure; the number of other licenses excluding the major ones. "License FEs" include the set of major licenses (Series 63, 7, 6, 65/66, 24) but not other exams. The coefficients (except those for A and B) are in percentage points. Standard errors are in brackets and clustered by firms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Summary Statistics for the Incidence of Financial-Related Disclosure Events

	Male			Female		
	(1) All	(2) Majority	(3) Minority	(4) All	(5) Majority	(6) Minority
Financial-Related Disclosure Events (%):						
Financial - Final	0.42	0.40	0.51	0.49	0.47	0.58
Conditional on Financial - Final:						
Bankruptcy	43.39	43.56	42.46	46.77	47.06	45.43
Compromise	56.65	56.49	57.54	53.25	52.96	54.57
Conditional on Bankruptcy:						
Chapter 7	76.65	76.77	75.95	75.57	75.74	74.61
Disposition:						
Discharged	96.34	96.43	95.68	96.59	96.78	95.61
Chapter 13	19.93	19.73	21.01	21.42	21.17	22.79
Disposition:						
Discharged	87.93	88.30	85.64	87.91	88.31	85.84
Judgment/Lien	0.33	0.33	0.39	0.20	0.18	0.28
Conditional on Judgment/Lien						
Civil	64.31	65.40	56.19	48.21	50.88	37.26
Tax	35.69	34.60	43.81	51.79	49.12	62.74
Total (%):	1.89	1.86	2.13	1.21	1.17	1.46
Observations	5,753,021	5,150,027	542,597	2,153,206	1,843,251	267,990

Note: Observations are based on the adviser-year panel data over the period 2008-2018. Advisers are divided into males and females, and further split into the white majority and non-white minority group (see Section 2.1.2 for details). We limit attention to the financial-related disclosure events ("Financial - Final" and "Judgment/Lien"). See the appendix for the definition of these disclosure events. Each value (except for conditional variables) indicates the annual incidence of the disclosure event in percentage points, which is given by a dummy variable for whether an adviser has encountered a disclosure event in the respective category (see Section 3.1) at least once within a given year.

Appendix

A Definition of the Major Disclosure Events

Disclosure events details are described in Form U4.[34] Below we consider the major disclosure events excluding those on appeal and pending ones, and give their definitions used in the FINRA's BrokerCheck database.

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 broker that resulted in a monetary settlement to the customer.

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 broker that resulted in an arbitration award or civil judgment for the customer.

Customer Dispute - Closed-No Action / Withdrawn / Dismissed / Denied: 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 broker that was dismissed, withdrawn, or denied; or (2) a consumer-initiated, investment-related written complaint containing allegations that the broker 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.

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

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.

Employment Separation After Allegations: This type of disclosure event involves a situation where the broker voluntarily resigned, was discharged, or was permitted to resign after being accused

[34] The Form U4 is available via https://www.finra.org/sites/default/files/form-u4.pdf. Note that the definition of each event is given in the FINRA's BrokerCheck report for financial advisers (registered representatives) who have indeed received that disclosure in the past. See https://brokercheck.finra.org/ and also https://www.finra.org/sites/default/files/AppSupportDoc/p015111.pdf.

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.
Termination Type: Discharged, Permitted to Resign, Voluntary Resignation.

Regulatory Final: This type of disclosure event may involve (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 broker's authority to act as an attorney, accountant, or federal contractor.

Financial - Final: This type of disclosure event involves a bankruptcy, compromise with one or more creditors, or Securities Investor Protection Corporation liquidation involving the broker or an organization/brokerage firm the broker controlled that occurred within the last 10 years.
Action Type: Bankruptcy [Chapter 7, Chapter 11, Chapter 13, Other], Compromise, Declaration, Liquidation, Receivership, Other.
Disposition Type: Direct Payment Procedure, Discharged, Dismissed, Dissolved, SIPA Trustee Appointed, Satisfied/Released, Other.

Judgment / Lien: This type of disclosure event involves an unsatisfied and outstanding judgments or liens against the broker.
Type: Civil, Tax.

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

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.

B Definition of the Major Qualification Exams (Licenses)

The definitions of qualification exams (licenses) are described in the FINRA website.[35] Below we consider the major qualification exams (Series 6, 7, 24, 63, 65, 66) as in the main text and give their definitions used in the website. Series 6 and 7 are categorized as "FINRA Representative-level Exams", Series 24 as "FINRA Principal-level Exams", Series 63, 65, and 66 as "North American Securities Administrators Association (NASAA) Exams". Note that the definitions of NASAA Exams are given by the NASAA website.[36]

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

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

Series 24: The Series 24 exam – the General Securities Principal Qualification Exam (GP) – assesses the competency of an entry-level principal to perform their job as a principal dependent on their corequisite registrations. The exam measures the degree to which each candidate possesses the knowledge needed to perform the critical functions of a principal, including the rules and statutory provisions applicable to the supervisory management of a general securities broker-dealer.[37]

Series 63: The Series 63 exam – the Uniform Securities State Law Examination – is a North American Securities Administrators Association (NASAA) exam administered by FINRA.
(Definition given by NASAA:) The Uniform Securities Agent State Law Examination was developed

[35] See the website: https://www.finra.org/registration-exams-ce/qualification-exams.

[36] See the website: https://www.nasaa.org/exams/study-guides.

[37] In addition to the Series 24 exam, candidates must pass the Securities Industry Essentials (SIE) Exam (since October 1, 2018 with a complete overhaul) and a representative-level qualification exam, or the Supervisory Analysts Exam (Series 16) exam, to hold an appropriate principal registration. See the FINRA website for the definitions of related exams.

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

Series 65: The Series 65 exam – the NASAA Investment Advisers Law Examination – is a North American Securities Administrators Association (NASAA) exam administered by FINRA.
(Definition given by NASAA:) The Uniform Investment Adviser Law Examination and the available study outline were developed by NASAA. The examination, called the Series 65 exam, is designed to qualify candidates as investment adviser representatives. The exam covers topics that have been determined to be necessary to understand in order to provide investment advice to clients.

Series 66: The Series 66 exam – the NASAA Uniform Combined State Law Examination – is a North American Securities Administrators Association (NASAA) exam administered by FINRA.
(Definition given by NASAA:) The Uniform Combined State Law Examination was developed by NASAA based on industry requests. The examination (also called the "Series 66") is designed to qualify candidates as both securities agents and investment adviser representatives. The exam covers topics that have been determined to be necessary to provide investment advice and effect securities transactions for clients.[38]

[38] The FINRA Series 7 is a corequisite exam that needs to be successfully completed in addition to the Series 66 exam before a candidate can apply to register with a state.

References

Abadie, A., S. Athey, G. W. Imbens and J. Wooldridge, "When should you adjust standard errors for clustering?," Technical Report, National Bureau of Economic Research, 2017.

Agrawal, A., J. F. Jaffe and J. M. Karpoff, "Management turnover and governance changes following the revelation of fraud," *The Journal of Law and Economics* 42 (1999), 309–342.

Altonji, J. G. and R. M. Blank, "Race and gender in the labor market," *Handbook of labor economics* 3 (1999), 3143–3259.

Ambekar, A., C. Ward, J. Mohammed, S. Male and S. Skiena, "Name-ethnicity classification from open sources," in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge Discovery and Data Mining* (2009), 49–58.

Beneish, M. D., "Incentives and penalties related to earnings overstatements that violate GAAP," *The Accounting Review* 74 (1999), 425–457.

Bertrand, M. and E. Duflo, "Field Experiments on Discriminationa," in *Handbook of Economic Field Experiments*volume 1 (Elsevier, 2017), 309–393.

Bertrand, M., C. Goldin and L. F. Katz, "Dynamics of the gender gap for young professionals in the financial and corporate sectors," *American Economic Journal: Applied Economics* 2 (2010), 228–55.

Blau, F. D. and L. M. Kahn, "Gender differences in pay," *Journal of Economic perspectives* 14 (2000), 75–99.

———, "The gender wage gap: Extent, trends, and explanations," *Journal of Economic Literature* 55 (2017), 789–865.

Boulware, K. D. and K. N. Kuttner, "Labor Market Conditions and Discrimination: Is There a Link?," in *AEA Papers and Proceedings*volume 109 (2019), 166–70.

Charoenwong, B., A. Kwan and T. Umar, "Does Regulatory Jurisdiction Affect the Quality of Investment-Adviser Regulation?," *American Economic Review* 109 (2019), 3681–3712.

Clifford, C. and W. Gerken, "Investment in human capital and labor mobility: Evidence from a shock to property rights," (2017).

Cook, J., Z. T. Kowaleski, M. Minnis, A. Sutherland and K. M. Zehms, "Auditors are known by the companies they keep," *Journal of Accounting and Economics* (2020), 101314.

Darity, W. A. and P. L. Mason, "Evidence on discrimination in employment: Codes of color, codes of gender," *Journal of Economic Perspectives* 12 (1998), 63–90.

Desai, H., C. E. Hogan and M. S. Wilkins, "The reputational penalty for aggressive accounting: Earnings restatements and management turnover," *The Accounting Review* 81 (2006), 83–112.

Dimmock, S. G. and W. C. Gerken, "Assessing Risk using Self-Regulatory Organization Disclosures," , 2018.

Dimmock, S. G., W. C. Gerken and N. P. Graham, "Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors," *The Journal of Finance* 73 (2018a), 1417–1450.

Dimmock, S. G., W. C. Gerken and T. D. Van Alfen, "Real Estate Shocks and Financial Advisor Misconduct," (2018b).

Domowitz, I. and R. L. Sartain, "Determinants of the consumer bankruptcy decision," *The Journal of Finance* 54 (1999), 403–420.

Egan, M., G. Matvos and A. Seru, "When Harry Fired Sally: The Double Standard in Punishing Misconduct," (2018).

———, "The market for financial adviser misconduct," *Journal of Political Economy* 127 (2019), 233–295.

Farber, H. S. and R. Gibbons, "Learning and wage dynamics," *The Quarterly Journal of Economics* 111 (1996), 1007–1047.

Fay, S., E. Hurst and M. J. White, "The household bankruptcy decision," *American Economic Review* 92 (2002), 706–718.

Feroz, E. H., K. Park and V. S. Pastena, "The financial and market effects of the SEC's accounting and auditing enforcement releases," *Journal of accounting research* 29 (1991), 107–142.

Gibbons, R. and L. F. Katz, "Layoffs and lemons," *Journal of labor Economics* 9 (1991), 351–380.

Goldin, C., "A grand gender convergence: Its last chapter," *American Economic Review* 104 (2014), 1091–1119.

Gropp, R., J. K. Scholz and M. J. White, "Personal bankruptcy and credit supply and demand," *The Quarterly Journal of Economics* 112 (1997), 217–251.

Gurun, U. G., N. Stoffman and S. E. Yonker, "Unlocking Clients: Non-compete Agreements in the Financial Advisory Industry," (2019).

Heckman, J. J., "Detecting discrimination," *Journal of economic perspectives* 12 (1998), 101–116.

Honigsberg, C. and M. Jacob, "Deleting misconduct: The expungement of BrokerCheck records," *Available at SSRN 3284738* (2019).

Karpoff, J. M., D. S. Lee and G. S. Martin, "The consequences to managers for financial misrepresentation," *Journal of Financial Economics* 88 (2008), 193–215.

Lang, K. and J.-Y. K. Lehmann, "Racial discrimination in the labor market: Theory and empirics," *Journal of Economic Literature* 50 (2012), 959–1006.

Lang, K. and A. K.-L. Spitzer, "Race Discrimination: An Economic Perspective," *Journal of Economic Perspectives* 34 (2020), 68–89.

Laohaprapanon, S. and G. Sood, *ethnicolr: Predict Race and Ethnicity From Name* (2019), python package version 0.3.0.

Law, K. K. and L. F. Mills, "Financial gatekeepers and investor protection: Evidence from criminal background checks," *Journal of Accounting Research* 57 (2019), 491–543.

Mullen, L., *gender: Predict Gender from Names Using Historical Data* (2018), r package version 0.5.2.

Neal, D. A. and W. R. Johnson, “The role of premarket factors in black-white wage differences,” *Journal of political Economy* 104 (1996), 869–895.

Neumark, D., “Experimental research on labor market discrimination,” *Journal of Economic Literature* 56 (2018), 799–866.

Parsons, C. A., J. Sulaeman and S. Titman, “The geography of financial misconduct,” *The Journal of Finance* (2018).

Qureshi, H. and J. S. Sokobin, “Do Investors Have Valuable Information About Brokers?,” (2015).

University of Innsbruck - Working Papers in Economics and Statistics
Recent Papers can be accessed on the following webpage:

https://www.uibk.ac.at/eeecon/wopec/

2020-17 **Jun Honda:** Gender Gaps and Racial Disparities in Labour Market Penalties for Financial Misconduct

2020-16 **Jun Honda:** Career Concerns, Risk-Taking, and Upward Mobility in the Financial Services Industry: Evidence from Top Ranked Financial Advisers

2020-15 **Christina Bannier, Eberhard Feess,Natalie Packham, Markus Walzl:** Differentiation and Risk-Aversion in Imperfectly Competitive Labor Markets

2020-14 **Felix Holzmeister, Rudolf Kerschbamer:** oTree: The Equality Equivalence Test

2020-13 **Parampreet Christopher Bindra, Graeme Pearce:** The effect of priming on fraud: Evidence from a natural field experiment

2020-12 **Alessandro De Chiara, Marco A. Schwarz:** A Dynamic Theory of Regulatory Capture

2020-11 **Christoph Huber, Jürgen Huber, Michael Kirchler:** Market shocks and professionals' investment behavior - Evidence from the COVID-19 crash

2020-10 **Elisabeth Gsottbauer, Daniel Müller, Samuel Müller, Stefan T. Trautmann, Galina Zudenkova:** Social class and (un)ethical behavior: Causal versus correlational evidence

2020-09 **Parampreet Christopher Bindra, Rudolf Kerschbamer, Daniel Neururer, Matthias Sutter:** Reveal it or conceal it: On the value of second opinions in a low-entry-barriers credence goods market

2020-08 **Robert Steiger, Eva Posch, Gottfried Tappeiner, Janette Walde:** Effects of climate change on tourism demand considering individual seasonal preferences

2020-07 **Fang Liu, Alexander Rasch, Marco A. Schwarz, Christian Waibel:** The role of diagnostic ability in markets for expert services

2020-06 **Matthias Stefan, Jürgen Huber, Michael Kirchler, Matthias Sutter, Markus Walzl:** Monetary and Social Incentives in Multi-Tasking: The Ranking Substitution Effect

2020-05 **Michael Razen, Jürgen Huber, Laura Hueber, Michael Kirchler, Matthias Stefan:** Financial Literacy, Economic Preferences, and Adolescents' Field Behavior

2020-04 **Christian König-Kersting, Johannes Lohse, Anna Louisa Merkel:** Active and Passive Risk-Taking

2020-03 **Christoph Huber, Jürgen Huber:** Bad bankers no more? Truth-telling and (dis)honesty in the finance industry

2020-02 **Dietmar Fehr, Daniel Müller, Marcel Preuss:** Social Mobility Perceptions and Inequality Acceptance

2020-01 **Loukas Balafoutas, Rudolf Kerschbamer:** Credence goods in the literature: What the past fifteen years have taught us about fraud, incentives, and the role of institutions

2019-21 **Felix Holzmeister, Martin Holmen, Michael Kirchler, Matthias Stefan, Erik Wengström:** Delegated Decision-Making in Finance

2019-20 **Julia Rose, Michael Kirchler, Stefan Palan:** Status and Reputation Nudging

2019-19 **Felix Holzmeister, Matthias Stefan:** The risk elicitation puzzle revisited: Across-methods (in)consistency?

2019-18 **Katharina Momsen, Markus Ohndorf:** Information Avoidance, Selective Exposure, and Fake(?) News-A Green Market Experiment

2019-17 **Stjepan Srhoj, Bruno Skrinjaric, Sonja Radas, Janette Walde:** Closing the Finance Gap by Nudging: Impact Assessment of Public Grants for Women Entrepreneurs

2019-16 **Adam Farago, Martin Holmen, Felix Holzmeister, Michael Kirchler, Michael Razen:** Cognitive Skills and Economic Preferences in the Fund Industry

2019-15 **Christopher Kah, Daniel Neururer:** Generiert der stationäre Buchhandel positive Nachfrageeffekte und verhilft dadurch dem Kulturgut Buch bei seiner Verbreitung? - Ein natürliches Experiment

2019-14 **Stjepan Srhoj, Michael Lapinski, Janette Walde:** Size matters? Impact evaluation of business development grants on SME performance

2019-13 **Andrea M. Leiter, Engelbert Theurl:** Determinants of prepaid systems of healthcare financing - A worldwide country-level perspective

2019-12 **Michael Razen, Michael Kirchler, Utz Weitzel:** Domain-Specific Risk-Taking Among Finance Professionals

2019-11 **Jonathan Hall, Rudolf Kerschbamer, Daniel Neururer, Eric Skoog:** Uncovering sophisticated discrimination with the help of credence goods markups - evidence from a natural field experiment

2019-10 **Daniela Glätzle-Rützler, Philipp Lergetporer, Matthias Sutter:** Collective intertemporal decisions and heterogeneity in groups

2019-09 **Morten Hedegaard, Rudolf Kerschbamer, Daniel Müller, Jean-Robert Tyran:** Distributional Preferences Explain Individual Behavior Across Games and Time

2019-08 **Daniel Müller, Sander Renes:** Fairness Views and Political Preferences - Evidence from a representative sample

2019-07 **Florian Lindner, Michael Kirchler, Stephanie Rosenkranz, Utze Weitzel:** Social Status and Risk-Taking in Investment Decisions

2019-06 **Christoph Huber, Julia Rose:** Individual attitudes and market dynamics towards imprecision

2019-05 **Felix Holzmeister, Jürgen Huber, Michael Kirchler, Florian Lindner, Utz Weitzel, Stefan Zeisberger:** What Drives Risk Perception? A Global Survey with Financial Professionals and Lay People

2019-04 **David M. McEvoy, Tobias Haller, Esther Blanco:** The Role of Non-Binding Pledges in Social Dilemmas with Mitigation and Adaptation

2019-03 **Katharina Momsen, Markus Ohndorf:** When do people exploit moral wiggle room? An experimental analysis in a market setup

2019-02 **Rudolf Kerschbamer, Daniel Neururer, Matthias Sutter:** Credence goods markets and the informational value of new media: A natural field experiment

2019-01 **Martin Geiger, Eric Mayer, Johann Scharler:** Inequality and the Business Cycle: Evidence from U.S. survey data

University of Innsbruck

Working Papers in Economics and Statistics

2020-17

Jun Honda

Gender Gaps and Racial Disparities in Labour Market Penalties for Financial Misconduct

Abstract
We consider the labour market for financial advisers in the US using a matched employer-employee data set over the period 2008-2018, in order to examine gender gaps and racial disparities in labour market penalties for financial misconduct. We first show that the measurement of labour market penalties for financial misconduct plays a central role and the interdependence across misconduct-categories (e.g. customer disputes, regulatory actions, terminations) is gender- and racespecific. Accounting for this, we find that there are little gender gaps in job separation following misconduct and in the incidence of employer-initiated terminations conditional on misconduct-related events. In contrast, we find that racial minorities are at least 20 % more likely to leave a firm following customer disputes or regulatory actions compared to their majority counterparts, and also that the racial minorities are 25 % more likely to receive terminations. This remains true even after controlling for their education.

ISSN 1993-4378 (Print)
ISSN 1993-6885 (Online)