

How Does Corruption Culture Affect Financial Professionals? Evidence from Financial Advisor

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Abstract

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JEL Classification: D14; D18; G24; D73; Z1

Keywords: Financial Advisors; Corruption Culture; Financial Misconduct; Career Outcomes; Household Finance

* We would like to thank Evgeny Lyandres, Vladimir Mukharlyamov, and Stephan Siegel, for their helpful comments. We also thank audience members at the 2023 Queensland Corporate Finance Conference, Curtin University, and The University of Western Australia. We thank Yuhong Tu for providing research assistance. All errors are our own. E-mail: xuxin67@mail.sysu.edu.cn (X. Xu); zhe.an@monash.edu (Z. An); chen.chen2@monash.edu (C. Chen).

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Abstract

Employing a survivorship-bias-free panel of approximately 1.5 million financial advisors (FAs) from 2010 to 2019, we show that FAs with a higher corruption value attached to their ancestry countries are more likely to commit misconduct. This relation is alleviated for female FAs and FAs who possess more non-compulsory qualifications. Following misconduct, firms tend to terminate their employment contracts. However, they are likely to rejoin another advisory firm, irrespective of their misconduct records. To explain these labor market consequences, we show that firms are less tolerant of misconduct because these FAs tend to commit repeat offenses; however, they do not necessarily commit more severe misconduct. In the job market, these FAs tend to join larger firms regardless of their misconduct records. Lastly, we show that the value of corruption culture arises when these FAs generate more revenue with a limited asset pool and when they are retained by the firm experiencing a downsize. Various additional tests confirm our findings. Our findings indicate that the corruption culture of individual financial professionals plays a vital role in shaping their behavior and career paths.

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1. Introduction

Prior literature has shown the role of corruption culture on different economic outcomes. At the macro level, corruption has been found to be associated with weaker governments (Shleifer and Vishny, 1993), slower economic growth (Mauro, 1995), less sustainable development (Aidt, 2009), and less inward foreign direct investment (Wei and Shleifer, 2000). At the firm level, corruption culture is usually proxied by the corruption exposure of key corporate persons (e.g., CEOs, executives, owners, etc.). It has been shown that firms with a higher corruption culture tend to evade tax (DeBacker, Heim, and Tran, 2015), outperform their counterparts (Mironov, 2015), and engage in corporate misconduct (Liu, 2016). Whereas the role of corruption culture at the country and firm levels are well documented, little is known about how it can affect financial professionals at the individual level. Studying the corruption culture of each individual would help us to understand the heterogeneity of employee behavior within the organization. This paper tends to fill this void by focusing on how the corrupt cultural imprints of financial advisors (FAs) affect their behavior and career paths.

We focus on the FAs to study this vital research question for two reasons. First, as a key segment of the United States (U.S.) finance and insurance sector (i.e., North American Industry Classification System [NAICS] 52), the FA industry represents roughly 10% of its total employment (Coen, 2015). The FA job market is expected to be in high demand in the next decade as a large portion of the U.S. population is approaching retirement. Therefore, the FA industry is an appropriate representative of the U.S. financial professional population. Second, each FA's career outcomes, such as working quality, career paths, and individual characteristics, are available on a large scale as per the registration requirement in the FA industry. It provides us with sufficient resources to examine the role of corruption culture at the individual level.

Following prior literature in economics and finance (e.g., Fernández, 2011; Liu, 2016), we gauge FAs' corruption attitude by using the corruption culture index of their ancestry countries, which are identified based on their surnames. This epidemiological approach is based on the idea that when individuals emigrate from their native country to a new country, their cultural beliefs and values travel with them. The immigrants not only bring their beliefs and values to the new country, but they also pass down these beliefs to their descendants (Guiso, Sapienza, and Zingales, 2006). Thus, the relevant cultural dimensions in the ancestry countries can be used as proxies of cultural imprints for immigrants and their descendants. This approach makes it possible to infer individual-level corruption culture at a large scale.

We first create a survivorship-bias-free panel of roughly 1.5 million. Using the individual-level corruption measure, we find that FAs with a more corrupt cultural background tend to engage in professional misconduct. Our results are robust to controlling for various individual characteristics at the FA level, such as prior misconduct record, working experience, gender, and professional qualifications. We also control for firm×county×year fixed effects to exploit the misconduct heterogeneity for FAs registered in the same firm, working in the same county, and in the same year. Our findings are also economically meaningful. Specifically, moving from the 25th to the 75th percentile of the distribution of the FA-level corruption index is associated with a 4.6% increase in the likelihood of misconduct related to the sample mean. Further analysis reveals that the impact of FAs' corruption attitude on misconduct tendency is alleviated for female FAs and FAs with more non-compulsory qualifications.

One natural question following our main findings is whether FAs with a more corrupt cultural background face a dimmer career prospectus than others, given they are more likely to commit misconduct. To shed light on this conjecture, we investigate these FAs' career paths following misconduct. Our analysis reveals that FAs with a higher corruption value attached to their ancestry countries are more likely to leave advisory firms following misconduct. However, the misconduct history does not limit their opportunities to rejoin another advisory firm. Unconditional on misconduct, these FAs are likely to find new jobs. These findings suggest that the labor market seems to value the corruption culture and not punish FAs with a corrupt cultural background too much if they have committed misconduct.

After documenting these interesting facts regarding FAs' career consequences, we next probe the reason why FAs with a more corrupt cultural background get penalized by their incumbent employers. We find evidence that these FAs are more likely to commit repeat offenses than their counterparts with a lower corruption value. However, we do not find evidence that they commit more severe misconduct.

We next explore why the job market values the corruption culture and does not discount FAs' job prospects following misconduct. We first find that FAs with a higher corruption value tend to join larger firms (i.e., firms with more FAs, accounts, and higher asset value). These findings may indicate that these FAs may be more productive than others. To further shed light on this conjecture, we examine whether these FAs manage fewer assets but generate more revenue. Our empirical analysis finds supporting evidence for this conjecture. Further analysis reveals that these FAs are likely retained by the firm experiencing a downsize. However, we

do not find evidence that firms value these FAs because they offer customers more flexible fee options.

Lastly, we examine the robustness of our baseline findings. First, we mitigate the measurement error concern by constructing the cultural variable using alternative approaches, including excluding female FAs, FAs with Asian and Latin American cultural origins, and non-country cultural origins. The results are similar to those of baseline regression. Second, our results remain robust when we use alternative corruption indices widely used in the literature. Third, our results remain robust in the subsamples of brokers, investment advisors, and dually registered brokers and investment advisors. Fourth, we mitigate the omitted-variable concern by controlling for (1) other cultural dimensions, (2) client-facing indicator, high-rating indicator, and self-reported AUM, and (3) additional individual FA characteristics, such as demographics, interests, and lifestyle attributes. The results are qualitatively similar, even though the sample shrinks significantly.

This paper contributes to the literature in the following three ways. First and foremost, this paper contributes to the broader literature in economics and finance, which studies the outcome of corruption culture. In addition to the existing findings on how the corruption culture affects various outcomes at the country and firm levels (e.g., Shleifer and Vishny, 1993; Mauro, 1995; Aidt, 2009; Wei and Shleifer, 2000; DeBacker, Heim, and Tran, 2015; Mironov, 2015; Liu, 2016), we are the first study to show that corruption culture affects individual financial professionals in terms of their working quality and career paths. These findings provide first-hand insights into our understanding of how corruption culture affects individual-level outcomes within the same firm.

Second, our finding enriches the understanding of the behavior of FAs, which is the focus of the burgeoning literature on FA misconduct. Several papers in this literature show that FA misconduct/complaint varies with personal and work-related circumstances. In particular, Dimmock, Gerken, and Graham (2018) show that FAs are likely to commit misconduct if their coworkers have a misconduct history. Law and Mills (2019) find that FAs with criminal records are more likely to receive customer complaints. Charoenwong, Kwan, and Umar (2019) show that customer complaints to midsize FAs increased after the Dodd-Frank Act shifted their regulatory jurisdiction from the SEC to state regulators. Kowaleski, Sutherland, and Vetter (2020) find that FAs who pass exams with more ethics coverage are less likely to commit misconduct. Clifford and Gerken (2021) document that transferring ownership of client relationships from the firm to FA could reduce customer complaints. Dimmock, Gerken, and

Van Alfen (2021) argue that personal real estate shocks affect FA misconduct and document a negative relation between FA housing returns and misconduct propensity. Law and Zuo (2021) find that FAs who start their career during recession years tend to commit professional misconduct. Law and Zuo (2022) show that customer complaints against minority FAs are more prevalent when public concern about immigration is high. Clifford, Ellis, and Gerken (2022) show that FAs' childhood exposure to misbehavior influences their financial misconduct in adulthood. Gerken and Shahraki (2022) find that being certified as a top FA reduces the likelihood of engaging in misconduct. Our paper contributes to this line of literature by documenting the corruption culture inferred based on FAs' cultural origins also matters in their propensity to commit misconduct and their future career paths following the misconduct.

Third, our paper also deepens the understanding of the labor market of FAs. Specifically,

Egan, Matvos, and Seru (2019) find that although firms are less tolerant of misconduct, the labor market partially undoes firm-level discipline by offering jobs to FAs who commit misconduct. Gurun, Stoffman, and Yonker (2021) show that firms are less willing to discipline FAs for misconduct with more client assets, demonstrating the importance of client relationships in the FA industry. Egan, Matvos, and Seru (2012) document a "gender punishment gap," where female FAs are punished more harshly than male FAs following misconduct. Consistent with the literature, which shows that misconduct affects the labor market for FAs following misconduct, we find that FAs with corruption cultural backgrounds are still highly sought after even though they are more likely to engage in misconduct. One of the reasons could be that some advisory firms value that FAs with corruption culture can generate more revenue with a limited asset pool.

The rest of the paper is organized as follows. Section 2 describes the data sources, how to measure cultural origin and corruption culture, and the summary statistics. Section 3 presents the empirical results, and Section 4 shows the results of additional tests. Lastly, Section 5 concludes the paper.

2. Data, Variables, and Summary Statistics

2.1 Financial Advisor Data

In this paper, we refer to FAs as both brokers and investment advisors. Brokers, known as registered representatives (RR), work in broker-dealer firms and are regulated by Financial Industry Regulatory Authority (FINRA), an independent organization authorized by Congress that writes and enforces the rules governing the broker-dealer industry. FINRA defines a broker

as “*an individual who acts as an intermediary between a buyer and seller of securities and who executes such transactions.*” The BrokerCheck database of FINRA maintains broker data (<https://brokercheck.finra.org>). Investment advisors, known as investment advisor representatives (IAR), work in registered investment advisor (RIA) firms and are regulated by the SEC or state securities authorities. As defined in the U.S. Investment Advisers Act of 1940, an investment advisor is “*a person for compensation; is engaged in the business of; providing advice to others or issuing reports or analyses regarding securities.*” Investment advisor data is maintained by the Investment Adviser Public Disclosures (IAPD) database, sponsored by the SEC (<https://adviserinfo.sec.gov>). The main difference between the two is that investment advisors are held to a fiduciary standard, and brokers are held to a lower suitability standard. A FA can solely register as a broker (with FINRA) or investment advisor (with the SEC) or dually register as both broker and investment advisor. The BrokerCheck (IAPD) database includes solely registered brokers (investment advisors) and dually registered brokers and investment advisors. Both databases are based on the same data from the Central Registration Depository (CRD), maintained by FINRA since the 1970s. These two datasets use the same CRD number as FA identifiers.

In this paper, we collect a survivorship-bias-free panel of approximately 1.5 million FAs. In February 2022, we collected broker data from the BrokerCheck database, which maintains broker records for at least 10 years, even if a broker has left the industry. To obtain the universe of broker data, we queried all seven-digit CRD numbers between 1 and 9,999,999 to collect detailed reports of all brokers. As the CRD number is unique for an individual FA, this approach ensures we obtain a survivorship-bias-free dataset that includes all currently and previously registered brokers. We follow the same process and collect investment advisor data from the IAPD database. It allows us to supplement the broker data with those FAs solely registered as investment advisors. Overall, we collected detailed reports of 1,529,115 FAs, including 1,449,280 brokers from the BrokerCheck database (i.e., 930,285 solely registered brokers and 518,995 dually registered brokers and investment advisors) and 79,835 solely registered investment advisors from the IAPD database.

For each FA, we obtain information on their name, registration history, licenses, passed industry exams, employment history in the financial services industry, disclosures (i.e., customer complaints and arbitrations, regulatory actions, employment terminations, bankruptcy filings, and criminal or civil judicial proceedings), and other business activities (i.e., engage as a proprietor, partner, officer, director, employee, trustee, agent, or otherwise).

FAs' gender information is inferred based on their first names. Specifically, we use data from GenderChecker (<https://genderchecker.com>), a database of 102,240 authenticated gender-tagged first names. The data in GenderChecker is primarily compiled from the 2001 and 2011 United Kingdom census data with a conservative approach. The name is assigned as unisex when the name appears as both male and female in any instance. We use this data to match a non-unisex gender to 80% of FAs. For FAs with missing gender information, we supplement the data using a publicly available Application Programming Interface (API), genderize.io (<https://genderize.io>), which uses a large set of information on matched first names and gender from major online social networks. Finally, we match a gender to 99.3% of FAs in our sample.

2.2 Measuring Cultural Origin

In this paper, we use FAs' surnames to infer their cultural origins. This epidemiological approach is originally from the literature on name-based ethnicity classification to overcome data scarcity issues (Mateos, 2007; Fernández, 2011) and has been widely used in accounting, finance, and economic research (e.g., Guiso, Sapienza, and Zingales, 2004; Liu, 2016; Merkley, Michaely, and Pacelli, 2020; Pan, Siegel, and Wang, 2017; 2020). The key idea behind this approach is that immigrants' cultural values and beliefs travel with them from their home countries to their destinations. Furthermore, these immigrants pass on their cultural values and beliefs to later generations. The descendants generally have the same surname as their ancestors. Thus, we could use the cultural origins of FAs' ancestors to proxy the culture of FAs with the same surname. Specifically, we collect the name and ethnicity/nationality of passengers who arrived at the port of New York from foreign ports between 1820 and 1957. These U.S. historical passenger records are available on *Ancestry.com*, which is the largest genealogy company in the world and maintains approximately 30 billion historical records as of 2022 (<https://www.ancestry.com>). Figure A shows an example image of a passenger record from *Ancestry.com*.

After obtaining a list of FAs' full names, we first remove the name suffix (e.g., Jr, 2nd, III, Ms., Ph.D., etc.). We carefully extract their surnames, including those compound surnames (e.g., La Porta, de Boer, etc.). We identify 270,567 unique surnames based on the full names of 1.5 million sampled FAs. Our sample is much larger than those in prior literature studies on CEOs or financial analysts. For each surname, we search through *Ancestry.com* and obtain a list of the ethnicity/nationality of passengers with the same surname. In total, we extract approximately 32 million non-missing passenger records. We manually check and correct

apparent typos. Then, we standardize and regroup the ethnicity/nationality data when appropriate and calculate the frequency distribution of each cultural origin.¹ Online Appendix Table A1 lists the 115 cultural origins and reports the frequency distribution of each origin. Most of these cultural origins are countries. When necessary, we use geographic region (i.e., Arab World, Africa, Asia, Latin America, Central America, Pacific Islander, and West Indies), former country (i.e., Czechoslovakia, Scandinavia, Yugoslavia), and ethnic group (i.e., Hispanic, Jewish, Muslim) as cultural origins.² English, German, and Italian are the top three common cultural origins, where 21.4%, 12.9%, and 11.7% of passengers arriving at the port of New York are from these cultural backgrounds. Approximately 13% (2.6%) of passengers are U.S. citizens (have unclear ethnicity/nationality). We exclude these two cultural origins from our study. In our sample, 73.7% (49.3%) of surnames have a dominant (super dominant) cultural origin with more than 50% (75%) frequency weight. For instance, out of the 20,323 (5584) passenger records for the surname Connor (Lewis), 60% (77.3%) have an Ireland (British) origin, 38.3% (10.3%) have a British (Ireland) origin, and the rest are from other countries. On average, the largest cultural origin of sampled surnames represents 72.3% of all passenger records. In sum, these historical passenger records allow us to obtain a list of associated cultural origins and their corresponding weights for each surname.

2.3 Measuring Corruption Culture

We use the Corruption Perception Index (CPI) published by a non-profit and non-governmental organization Transparency International as our primary measure of corruption culture.³ CPI is an index that ranks and scores countries and territories “*by their perceived levels of public sector corruption, as determined by expert assessments and opinion surveys.*” It has been widely used by prior studies on corruption culture (e.g., DeBacker, Heim, and Tran, 2015; Liu, 2016). Transparency International made a significant change to the calculation methodology

¹ For example, we group England, Scotland, Wales, and North Ireland into the U.K. For some countries, we group their alternative names into one. For example, Prussian and Hessian are grouped into Germany, while Dutch and Holland are grouped into the Netherlands. For individuals with dual nationality (e.g., Dutch and Italy), we use the former as people tend to list their primary nationality in front. If the former is the U.S., we use the latter. For individuals from Korea, we assume they are all from South Korea as North Korean refugees were not allowed to enter the U.S. until the passage of the North Korean Human Rights Act in 2004.

² For non-country cultural origins, we calculate their culture index as the average culture index of constituent countries.

³ Founded in 1993, Transparency International (<https://www.transparency.org>) has published CPI annually since 1995 based on surveys of journalists, analysts, and consultants.

of the CPI starting in 2012; thus, we use the average CPI of each country before 2012.⁴ The CPI ranges from 1 to 10, where a lower value indicates a higher level of perceived corruption culture. For example, the CPI was the highest in New Zealand (9.5) and the lowest in Somalia (1) in 2011. The U.S. had a CPI of 7.1, which ranks 24 worldwide. To ease the interpretation, we subtract the CPI from 10 and rescaled it between zero and one to obtain our corruption index (denoted CPI_Scaled). Thus, a higher value of our corruption index represents a higher level of corruption culture.

To measure each FA’s corruption culture, we construct a weighted corruption index based on the weights of the cultural origins associated with the surname of the FA. Specifically, we calculate the corruption index ($FA\ corruption$) of FA i with surname k as:

$$FA\ corruption_{i,k} = \sum w_{k,c} CPI_Scaled_c, \quad (1)$$

where $w_{k,c}$ is the weight of country c for surname k , and CPI_Scaled_c is our rescaled CPI of country c .⁵

2.4 Summary Statistics

As shown in Appendix A, our initial sample includes 1,529,115 FAs extracted from BrokerCheck and IAPD. After excluding FAs with missing cultural origin information on *Ancestry.com*, we have 1,428,602 FAs left in the sample. Then, we exclude FAs with missing misconduct, experience, gender, and qualification information necessary for the baseline regression. As FINRA may remove the records of FAs who have not registered within the past 10 years, we start our sample from 2010. We exclude the recent two-year data in 2020 and 2021 as many complaints or arbitrations filed in these two years were unresolved when we collected the data.⁶ Finally, 1,043,102 FAs are left in our sample, with 169,158 unique surnames. These FAs correspond to approximately 6.3 million FA-year observations over the sample period between 2010 and 2019.

FINRA requires all registered FAs to “*disclose customer complaints and arbitrations, regulatory actions, employment terminations, bankruptcy filings, and criminal or judicial*

⁴ CPI covers 41 countries and territories in its first publication in 1995. The coverage increases to 85 in 1998, 91 in 2001, and around 180 since 2007. The results are qualitatively similar when we use CPI from different years before 2012 or the earliest year with available data.

⁵ We exclude U.S. and unclear cultural origins and rescale the weights of all other cultural origins.

⁶ We find the information availability of some FA variables is quite poor in 2009. The number of FA misconduct in 2020 was roughly half of 2019 when we collected the data. Nevertheless, the results are similar if we start our sample from 2009 or 2011 or end our sample in 2021.

proceedings.” Out of the 23 disclosure categories classified by FINRA, we consider six categories as misconduct disclosures, including *Customer Dispute-Settled*, *Regulatory-Final*, *Employment Separation After Allegations*, *Customer Dispute-Award/Judgment*, *Criminal-Final Disposition*, and *Civil-Final* (Egan, Matvos, and Seru, 2019).⁷ This misconduct definition consists of customer disputes, internal investigations, regulatory, civil, and criminal events resolved against the FA. Other categories include disclosures not necessarily indicative of misconduct (e.g., *Financial-Final* may be associated with FA’s personal bankruptcy), disputes resolved in favor of the FA, and misconducts with pending or withdrawal status.

Table 1 reports the average characteristics of FAs in our sample. On average, the probability that a FA engages in misconduct in a year is 0.5%. The likelihood that a FA has at least one misconduct record is 6.2%, suggesting that one in 16 FAs have a past misconduct record. Regarding the severity of the misconduct, the mean (median) of misconduct settlement/damage is approximately \$287,877 (\$45,000). As a comparison, the mean (median) of American family net worth was \$748,800 (\$121,700) in 2019, indicating that FA misconduct causes sizeable damage to American households. Regarding the corruption culture measure, the results show that our sampled FAs have an average *FA corruption* value of 0.313 with a standard deviation of 0.166.

With regard to other FA characteristics, female FAs contribute roughly a quarter of FA-year observations. An average FA in our sample has 12.6 years of experience since the FA passed the first qualification exam and possesses 2.8 qualifications. Among these qualifications, Series 65 and 66 examinations (i.e., *Uniform Investment Adviser Law Exam and Uniform Combined State Law Exam*) entitle individuals to operate as investment advisors but are not required in all states. The principles of state security regulations are covered in the Series 63 exam (i.e., *Uniform Securities Agent State Law Exam*), which most states require registered representatives to pass. The Series 7 exam (i.e., *General Securities Representative Exam*) entitles individuals to trade all types of securities products except commodities and futures. The Series 6 exam (i.e., *Investment Company and Variable Contracts Products Representative Exam*) entitles individuals to sell open-end mutual funds, variable annuities, and insurance. The Series 24 exam (i.e., *General Securities Principal Exam*) qualifies individuals to supervise and manage branch activities at general securities firms. The summary statistics of these

⁷ We provide the complete disclosure definitions in Online Appendix B.

qualification variables resemble those of Egan, Matvos, and Seru (2019), although the sample period differs.

[Insert Table 1]

We also report the variable mean of the subsamples of FAs with top and bottom quarter corruption values (*Top 1/4 FAs* and *Bottom 1/4 FAs*) and the *p-value* of the difference. The differences across the variables in the two subsamples are all statistically significant. Specifically, it shows that compared to the *Bottom 1/4 FAs*, the *Top 1/4 FAs* have a higher misconduct rate (i.e., 0.6% versus 0.5%). They are less likely to have a misconduct record (i.e., 5.5% versus 6.2%) and work for fewer years (i.e., 11.3 versus 12.9).

3 Empirical Results

3.1 Corruption Culture and Financial Advisor Misconduct

After obtaining roughly 6.3 million FA-year observations, we examine the following linear probability model to examine the relation between FA’s corruption culture and the probability of committing misconduct:

$$FA\ misconduct_{i,t} = \alpha + \beta FA\ corruption_i + \lambda X_{i,t} + \mu_{j,l,t} + \varepsilon_{i,t}, \quad (2)$$

where $FA\ misconduct_{i,t}$ indicates whether FA i has at least one misconduct disclosure in year t . Our independent variable of interest, $FA\ corruption_i$, is FA i ’ corruption value based on the CPI of FA i ’ cultural origins inferred from his/her surname.⁸ $X_{i,t}$ is a vector of FA-level controls, including *Prior misconduct* (i.e., indicating whether the FA has a prior misconduct record), *Experience* (i.e., the number of years since the FA passed the first qualification exam), and *Female* (i.e., indicating whether the gender of FA is female). We control for dummy variables indicating whether the FA passed a particular qualifying exam (i.e., Series 65/66, 63, 7, 6, and 24) and the number of other qualifications the FA possesses, which are usually non-compulsory. The variable definitions are described in Appendix B. We also include firm×county×year fixed effects, $\mu_{j,l,t}$, in the model to exploit misconduct variations for FAs registered in the same firm, working in the same county, and in the same year.⁹ This specification controls for the effects

⁸ In a robustness test, we collect FA’s ethnicity information that is inferred based on their first and last names using the API *name-prism.com* (Ye, Han, Hu, Coskun, Liu, Qin, and Skiena, 2017). Based on this information, we classify a FA into one of the following ethnic groups: *Asian and Pacific Islander*, *Black*, *Hispanic*, and *White*. We include all four ethnicity dummies in the model. None are statistically significant, while the coefficient of *FA corruption* remains positive and statistically significant at the 1% level. The results suggest that *FA corruption* captures important information on top of FA’s ethnicity.

⁹ The firm fixed effects are based on the firm(s) that the FA registered. If a FA registers with more than one firm in a year, we use the one with the largest number of employees. The county is based on the working address of

of firm characteristics (e.g., internal governance, misconduct tolerance), location effects (e.g., regulatory, demographics, and labor market conditions), and time effects (e.g., financial crisis). In addition, we cluster the standard errors at the firm level to account for any correlation of standard errors across firms.

To estimate whether FA's corruption culture is associated with the probability of committing misconduct, we start with a model without control variables and fixed effects. Column 1 of Table 2 shows the coefficient of *FA corruption* is positive and statistically significant at the 1% level. We then include FA-level controls in Column 2 and firm×county×year fixed effects in Column 3. The coefficients of *FA corruption* remain positive and statistically significant. The results are also economically meaningful. For example, Column 3 shows that the coefficient (*t-statistic*) of *FA corruption* is 0.0014 (6.096). It indicates that moving from the 25th (i.e., 0.208) to the 75th (i.e., 0.373) percentile of the distribution of *FA corruption* is associated with a 4.6% increase in the likelihood of misconduct, related to the sample mean of *FA misconduct* (i.e., 0.005). These results suggest that FAs with a higher corruption value attached to their ancestry countries are more likely to engage in misconduct than other FAs registered in the same firm, working in the same county, and in the same year.

[Insert Table 2]

The results of control variables are in line with prior studies (Egan, Matvos, and Seru, 2019; 2022). Specifically, we show that FAs with prior misconduct records are more likely to engage in misconduct, indicating recidivism is prevalent in the industry. FA's industry experiences are positively associated with the propensity of misconduct, while female FAs are less likely to involve in misconduct activities. The results of qualification variables are also in line with prior studies. For example, FAs who pass major qualification exams, Series 65, 66, or 63, are more likely to engage in misconduct. We also find a negative association between the number of other qualifications the FA possesses and the propensity of misconduct, suggesting that the cost of misconduct is high for FAs who hold more qualifications.

Next, we conduct a few cross-sectional tests to explore the variations of the above findings, conditional on a few most common FA characteristics accessible via FINRA. Specifically, we include the interaction term of *FA corruption* and the interested FA

the FA, which could be different from the address of the registered firm. In a robustness check, we control for firm×county×year×license fixed effects to examine misconduct variations for FAs who hold the same licenses, register in the same firm, work in the same county, and in the same year. The results are qualitatively unchanged.

characteristic and explore whether it can alleviate/strengthen the positive association between *FA corruption* and *FA misconduct*. First, we examine the role of FA's experience. One may expect that when the FA accumulates more experience in the industry, they become more familiar with the industry rules and loopholes; thus, they may be less likely to be caught for misconduct. In another view, FA's attitude on money and corruption may change to more modest, along with increased industry experience, leading to a lower misconduct propensity. However, as shown in Column 1 of Table 3, we do not find significant results for *FA corruption* × *Experience*, suggesting that the relation between FA's corruption value and misconduct propensity is unconditioned on industry experiences. Second, we focus on the role of gender. Egan, Matvos, and Seru (2022) find that female FAs are about half as likely to engage in misconduct compared to male FAs. We expect the role of corruption culture in misconduct propensity may be reduced for female FAs, who are less likely to engage in wrongdoings. Consistent with our conjecture, Column 2 shows that *FA corruption* × *Female* loads a negative and significant coefficient. Third, we include *FA corruption* × *Number of other qualifications* in the model and find a negative and significant coefficient. The results suggest that when the FA possesses more qualifications (other than those more comment ones that could be required as compulsory by the state), the positive association between *FA corruption* and *FA misconduct* is alleviated since the cost of misconduct is high for these FAs. In sum, we show that for female FAs and FAs with more non-compulsory qualifications, the sensitivity of *FA misconduct* to *FA corruption* is lower.

[Insert Table 3]

3.2 Labor Market Consequences of Misconduct: The Role of Corruption Culture

Egan, Matvos, and Seru (2019) find that the labor market consequences of misconduct are costly for the FA. At the firm level, misconducted FAs are more likely to be published through employment separation than those with clear records. Meanwhile, the industry only offers worse job opportunities, suggesting it is costly for FAs to engage in misconduct. In this section, we examine whether FA's corruption culture plays a role in conjunction with the labor market consequences of misconduct.

We start with a table showing the average annual job turnovers among FAs with top and bottom quarter corruption values (*Top 1/4 FAs* and *Bottom 1/4 FAs*). We have a few findings in Table 4. First, FAs are more likely to separate from the firm following misconduct, and the punishment for the *Top 1/4 FAs* is more severe. Specifically, 55.9% of the *Top 1/4 FAs* leave

the firm following misconduct, which is 5.5% higher than the *Bottom 1/4 FAs* (i.e., 50.4%). As a comparison, the job turnover rate gap between the *Top 1/4 FAs* and *Bottom 1/4 FAs* without misconduct is much smaller (i.e., 24.7% - 23% = 1.7%). Second, conditional on leaving the firm following misconduct, the likelihood that the *Top 1/4 FAs* join another firm is 22.9% which is the same as the *Bottom 1/4 FAs*, suggesting that the job market seems does not punish FAs with a higher corruption value following misconduct. For those FAs without misconduct, the likelihood that the *Top 1/4 FAs* join another firm is slightly higher than the *Bottom 1/4 FAs* (i.e., 26.6% - 25.3% = 1.3%), suggesting that on average, the *Top 1/4 FAs* may face better reemployment prospects in the job market conditional on no prior misconduct.

[Insert Table 4]

The above statistics provide preliminary insight into the role of FA's corruption culture in labor market consequences following misconduct. However, such a finding could be because FAs with more corrupted cultural origins tend to be employed by firms that punish wrongdoing more harshly or work in places where regulators are more sensitive to misconduct. To alleviate this concern, we compare the employment separation of FAs with higher or lower corruption values in a multivariant setting by employing the following linear probability model:

$$Separation_{i,t+1} = \alpha + \beta_1 FA\ corruption_i + \beta_2 FA\ misconduct_{i,t} + \beta_3 FA\ corruption_i \times FA\ misconduct_{i,t} + \lambda X_{i,t} + \mu_{j,l,t} + \varepsilon_{i,t+1}, \quad (3)$$

where $Separation_{i,t+1}$ indicates whether FA i left the firm in year $t+1$. The independent variable of interest is $FA\ corruption \times FA\ misconduct$. Its coefficient, β_3 , measures whether FAs with a higher corruption value are more likely to experience an employment separation following misconduct. We include the same set of FA controls as in Equation (2) (i.e., $X_{i,t}$), measuring FA's prior misconduct record, experience, gender, and qualifications. In addition, we include firm \times county \times year fixed effects, $\mu_{j,l,t}$, in the model to control for the unobserved firm, location, and time effects.

The results are presented in Panel A of Table 5. We start with a model without the interaction term. Column 1 shows a positive and significant relation between $Separation$ in year $t+1$ and $FA\ misconduct$ in year t , suggesting that FAs are more likely to leave the firm following misconduct. The coefficient of $FA\ corruption$ is insignificant, indicating that FA's corruption culture alone is not contributing to employment separation. Then, we add the interaction term to the model. Column 2 shows that the coefficient of $FA\ corruption \times FA\ misconduct$ is positive and statistically significant at the 1% level, indicating that following misconduct, FAs with a

higher corruption value are punished more harshly through employment separation. A coefficient of 0.1405 suggests that moving from the 25th (i.e., 0.208) to the 75th (i.e., 0.373) percentile of the distribution of *FA corruption* is associated with an 8.7% increase in the likelihood of employment separation following misconduct, related to the sample mean of *Separation* (i.e., 0.24). These results suggest that firms are less tolerant of misconduct among FAs with a higher corruption value, and the punishment is severe.

[Insert Table 5]

Next, we examine whether FAs with a higher corruption value are less likely to be reemployed in the industry, especially following misconduct. Specifically, we employ the following linear probability model:

$$Reemployment_{i,t+1} = \alpha + \beta_1 FA\ corruption_i + \beta_2 FA\ misconduct_{i,t} + \beta_3 FA\ corruption_i \times FA\ misconduct_{i,t} + \lambda X_{i,t} + \mu_{j,l,t} + \varepsilon_{i,t+1}, \quad (4)$$

where $Reemployment_{i,t+1}$ indicates whether FA i join a new firm within one year following misconduct.¹⁰ We restrict the sample to FAs with job turnover in a given year and include the same controls as in Equation (2). We have firm×county×year fixed effects, $\mu_{j,l,t}$, in the model to ensure we compare the extent of reemployment of FAs registered in the same firm, working in the same county, and in the same year. A negative and significant coefficient of the interaction term, β_3 , would suggest FAs with a higher corruption value are less likely to be reemployment following misconduct.

Panel B reports the estimation results. Like in Panel A, we start with a model without the interaction term in Column 1 and add *FA corruption*×*FA misconduct* in Column 2. In both Columns 1 and 2, we find a negative and significant relation between *Reemployment* in year $t+1$ and *FA misconduct* in year t , suggesting that FAs are less likely to find a new job following misconduct. Interestingly, *FA corruption* is positively associated with the likelihood of reemployment, indicating that FAs with a higher corruption value are somewhat attractive in the job market. In addition, Column 2 shows that the coefficient of *FA corruption*×*FA misconduct* is insignificant, suggesting that following misconduct, FAs with a higher corruption value are not punished more heavily by the FA job market.¹¹ Elaborating on it in an

¹⁰ As a robustness check, we also define *Separation* and *Reemployment* using a two-year window. The results are similar to those of using a one-year window.

¹¹ In this test, we compare the re-employability of FAs with a higher corruption value with those with a lower corruption value. One concern is that the employment separation could be endogenous as better job opportunities could attract FAs with specific characteristics to switch jobs, while some FAs changing jobs may indicate poor

alternative way, the fact that the job market values the corruption culture of FAs is unconditional on their misconduct history.

3.3 Explaining the Labor Market Consequences: The Role of Corruption Culture

3.3.1 Recidivism

FAs are likely to experience employment separation following misconduct; either the firm fires the FA or the FA voluntarily leaves the firm. In both cases, the punishment is quite heavy for the FA as finding a new job is costly. Likewise, it is not costless for the firm because hiring a suitable replacement FA is also expensive. The biggest concern of the firm keeping the employment is that the concern of FA may re-offend in the future. In the previous section, we find that FAs with a higher corruption value are more likely to experience employment separation following misconduct. A possible explanation is that the probability of recidivism is higher for these FAs; thus, they are punished more harshly following misconduct. We employ the following linear probability model to examine the above conjecture:

$$FA\ misconduct_{i,t} = \alpha + \beta_1 FA\ corruption_i + \beta_2 Prior\ misconduct_{i,t} + \beta_3 FA\ corruption_i \times Prior\ misconduct_{i,t} + \lambda X_{i,t} + \mu_{j,l,t} + \varepsilon_{i,t}, (5)$$

The control variables and fixed effects of this model are identical to Equation (2). The independent variable of interest is *FA corruption* × *Prior misconduct*. Its coefficient, β_3 , measures whether FAs with a higher corruption value are more likely to commit repeat offenses.

We report the results in Table 6. As shown in Column 1, the coefficient of the interaction term is positive and significant, indicating that FAs with a higher corruption value tend to be repeat offenders. A coefficient of 0.0138 suggests that the FA with a 75th (i.e., 0.373) percentile value of *FA corruption* is 45.5% more likely to re-offense than that with a 25th (i.e., 0.208) percentile value of *FA corruption*, related to the sample mean of *FA misconduct* (i.e., 0.005). These results indicate that FAs with a higher corruption value are likely to re-offense, thus explaining why firms punish these FAs more heavily following misconduct.

[Insert Table 6]

Our results show that FAs with a higher corruption value seem not to learn the lesson but tend to re-offense. If these FAs are punished harshly by job separation, do they still manage to

quality. As a robustness check, we conduct an additional test to account for endogenous separation. Specifically, we focus on dissolved firms being closed down by regulators, acquisitions, and so on. Therefore, all FAs in the firm are forced to look for new jobs regardless of their past misconduct history, quality, and corruption attitude. The results are similar to those of the full sample.

be repeat offenders? To find out the answer to this query, we create a dummy variable, *Prior discipline*, equals one if the FA previously experienced an employment separation following misconduct and replace *Prior misconduct* with *Prior discipline* in Equation (5). We restrict the sample to those FAs with prior misconduct records. Thus, we compare the recidivism rate between those misconducted FAs who leave the firm and those who stay. As shown in Column 2, the coefficient of *FA corruption* × *Prior discipline* is insignificant, suggesting that FA's corruption value is irrelevant to the recidivism rate when the punishment is heavy. FAs with a higher corruption value seem to learn the lesson when they have experienced a job separation following the misconduct. These findings align with the earlier results that FAs with a higher corruption value are punished harshly following misconduct by the firm. Still, they are not severely punished by the job market, potentially because they seem to learn the lesson through painful job separation.

There is a potential selection issue when we examine FA's recidivism. Specifically, we can only observe the repeat offenses for those FAs who find new jobs in another FA firm. It could be the case that the FAs with a higher recidivism rate but a lower corruption value leave the industry. As a robustness check, we employ a semiparametric control function and find consistent results that FAs with a higher corruption value tend to be re-offenders. We describe the approach in Online Appendix C and report the results in Online Appendix Table A2.

3.3.2 Misconduct Severity

If FAs with a higher corruption value tend to engage in more severe misconduct that causes more monetary damage to the firms, it is reasonable that the firm punishes them more harshly following misconduct. In this section, we examine whether the corruption culture matters for more severe misconduct. First, we construct two alternative misconduct measures (i.e., *Severe FA misconduct 1* and *Severe FA misconduct 2*) based on more definitive misbehaviors of FAs. Specifically, we define *Severe FA misconduct 1* as those noncriminal disclosures (i.e., regulatory, civil, and customer disputes) involving unauthorized activity, fraud and forgery, churning, selling unregistered securities, misrepresentation, and omission of material facts. For criminal disclosures, we include those involving investment-related activities and fraud and forgery when constructing *Severe FA misconduct 1*. Based on *Severe FA misconduct 1*, we define *Severe FA misconduct 2* more restrictively by excluding noncriminal disclosures involving misrepresentation and omission of material facts. Recall that the mean (median) settlement/damage amount is approximately \$287,877 (\$45,000) for our primary misconduct measure, \$ 476,873 (\$75,000) for *Severe FA misconduct 1*, and \$ 528,899 (\$80,000) for *Severe*

FA misconduct 2. Second, we create a variable to measure the severity of misconduct based on the settlement amount granted following a misconduct incident. Specifically, we calculate $\ln(\text{Settlement})$ as the natural logarithm of the total paid out by the firm on behalf of a FA as a result of a misconduct settlement. Due to the data limitation, the sample size is significantly reduced when we include $\ln(\text{Settlement})$ in the model.

The results are shown in Table 7. Although the coefficients of *FA corruption* are positive, we do not find any significant association between *FA corruption* and *Severe FA misconduct 1* or *Severe FA misconduct 2* in Columns 1 and 2. Similarly, we do not find any significant relation between *FA corruption* and $\ln(\text{Settlement})$ in Column 3. These results suggest that the corruption culture attached to FAs may not necessarily be related to the severity of the misconduct, indicating that the firm punishing FAs with a higher corruption value more heavily is less likely due to these FAs committing more severe misconduct.

[Insert Table 7]

3.3.3 New Firm Characteristics

Thus far, we have shown that due to the concern of recidivism, the firm punishes FA with a higher corruption value more harshly following misconduct. Turning to the recruitment market, Table 5 shows that, somewhat unexpectedly, these FAs face better reemployment prospects regardless of their past misconduct history. Our earlier results show that this is possibly due to the fact that these FAs learn the lesson through painful job separation. In this section, we are interested in whether the industry offers FAs with a higher corruption value with worse job opportunities, conditional/unconditional on misconduct. We employ SEC-registered RIA firms, as Form ADV filings provide more granular firm information and annual frequency data in this sample. Specifically, we use the following OLS model:

$$\begin{aligned} \text{New firm characteristic}_{i,j^*,t+1} = & \alpha + \beta_1 \text{FA corruption}_i + \beta_2 \text{FA misconduct}_{i,t} + \\ & \beta_3 \text{FA corruption}_i \times \text{FA misconduct}_{i,t} + \lambda \mathbf{X}_{i,t} + \mu_{j^*,l,t} + \varepsilon_{i,j^*,t+1}, \end{aligned} \quad (6)$$

where $\text{New firm characteristic}_{i,j^*,t+1}$ is the characteristics of new firm j^* in year $t+1$ that FA i joined after leaving the original firm j . Specifically, to measure the prevalence of misconduct within the firm, we calculate *Firm misconduct* as the proportion of FAs with at least one misconduct disclosure working in the firm in a year. We measure the size of a firm through its employment, account, and assets. *Number of advisors*, *Number of accounts*, and *Assets (\$Billion)* represent the number of advisors, the number of accounts, and the asset value of the firm, respectively. We include *FA corruption*, *FA misconduct*, and their interaction term in the

model to assess the role of corruption culture in the characteristics of the new firm. We also have original firm×county×year fixed effects, $\mu_{j*,l,t}$. We restrict the sample to firms with both FAs who change jobs following or not following misconduct in a given year.

The results are presented in Table 8. We show that the coefficients of *FA misconduct* are positive in Column 1 and negative in Columns 2-4. It suggests that FAs with misconduct records tend to find new jobs in firms with a higher misconduct rate that are more tolerant of misconduct and that are smaller in terms of the number of employees, the number of accounts, and asset value. Interestingly, we find that FAs with a higher corruption value tend to join larger firms based on the positive coefficients of *Firm corruption* in Columns 2-4, suggesting larger firms are less likely to judge potential employees based on their corruption value inferred from their surnames. Lastly, we do not find any significant results for *FA corruption*×*FA misconduct*, suggesting that the job market punishes wrongdoing FAs regardless of their corruption value. Elaborating on it in an alternative way, FAs with a higher corruption value tend to join larger firms irrespective of their misconduct records. These findings indicate that these FAs may have specific values; thus, large firms hire them.

[Insert Table 8]

3.3.4 The Value of Corruption Culture in the Job Market

Next, we explore the source of the value of corruption culture that makes FAs attractive in the job market. First, we examine whether FA's corruption culture can directly relate to their AUM and production/revenue. Specifically, we obtain information on FA's self-reported AUM and production/revenue from the Discovery Data and examine their relations with *FA corruption*. We create three dependent variables, including $\ln(AUM)$, $\ln(Production)$, and $Production/AUM$. $\ln(AUM)$ and $\ln(Production)$ are the natural logarithms of FA's self-reported AUM and production/revenue in millions. $Production/AUM$ is the ratio of production/revenue over AUM.

Column 1 of Panel A of Table 9 shows *FA corruption* loads a negative and significant coefficient when the dependent variable is $\ln(AUM)$. In Column 2, we find a positive and significant relation between *FA corruption* and $\ln(Production)$, although the number of observations is significantly reduced due to data constraints. These results suggest that FAs with a higher corruption value have smaller AUM (potentially due to the perceived cultural bias from large clients) but can generate higher revenue. The results in Column 3 show that *FA*

corruption is positively correlated with *Production/AUM*, further supporting the notion that these FAs are more effective in generating revenue with a limited asset pool.

[Insert Table 9]

When the firm is hit with a negative shock and has to downsize, it is optimal to dismiss the least productive employees. If FAs with a more corrupt cultural background are more effective than others, we should observe that firms are more likely to lay off FAs with a lower corruption value. To test this conjecture, we examine whether FAs with a higher corruption value are more likely to experience job separation when the firm undergoes a downsize.

In Columns 1-3 of Panel B, we examine employment separation at firms that reduce the size by at least 15%, 20%, and 25%, respectively. We observe a negative coefficient of *FA corruption* × *Downsize*, and the *t*-statistics are getting more significant along with the magnitude of downsizing from *-1.420* to *-2.192*. These results suggest that when the firm experiences a downsize, FAs with a lower corruption value are more likely to be laid off, and this effect is more pronounced for larger downsizes. Overall, it suggests that FAs with a more corrupt cultural background are likely more productive than others; thus, they can still keep their job when the firm is hit by a crisis.

Most FAs charge their service based on fees and/or commissions. Fee-based FAs charge fixed, hourly, AUM-based fees, or their combinations. Commission-based FAs receive compensation based on product sales. As FAs with a more corrupt cultural background pay greater attention to monetary gain, they may offer more charging options to meet the needs of different customers. Thus, firms may value their flexibility and offer them positions in the job market. To test this conjecture, we manually collect information on how FAs charge their service from the websites of four major FA associations in the U.S.: National Association of Personal Financial Advisors (NAPFA) (<https://www.napfa.org>), Garrett Planning Network (<https://www.garrettplanningnetwork.com>), and XY Planning Network (<https://www.xyplanningnetwork.com>), and Financial Planning Association (FPA) (<https://www.financialplanningassociation.org>). The former three associations accept only fee-based FAs as their members, disclosing whether the FA charge fixed, hourly, and/or AUM-based fees on their websites. The FPA does not have such a requirement and reveals whether a FA is fee-based and/or commission-based.

Based on the above information, we create a dummy variable, *Fee and Commission*, indicating whether the FA charges both fees and commissions. Based on the subsample of fee-

based FAs, we create *No. of Fee Options*, calculated as the number of fee options the FA offers customers, ranging from one to three. In our sample, 38.3% of FAs charge both fees and commissions. On average, fee-based FAs offer two fee options to customers. As shown in Panel C, we regress *FA corruption* on *Fee and Commission* in Column 1 and *No. of Fee Options* in Column 2. Although the coefficients of *FA corruption* are positive, the results are statistically insignificant. These results suggest that firms value FAs' corruption culture in the job market is less likely because they offer customers more flexible fee options.

Overall, our results provide insights into why FAs with a higher corruption value are somewhat attractive in the job market. First, although the firm punishes misconduct more harshly for these FAs through employment separation, they seem to learn the lesson and not have a higher recidivism rate in the new job compared to those FAs without job separation. Second, the value of these FAs arises when they generate more revenue with a smaller AUM and when they are retained by the firm hit by a crisis to downsize.

4 Additional Tests

4.1 Measurement Error

In this paper, we infer 1.5 million FAs' cultural origins based on their surnames. Although this epidemiological approach makes it possible to obtain the cultural origins of such a large FA sample, it may induce measurement error because we can only approximate FAs' true origins based on the frequency distribution of cultural origins extracted from the passenger records. In this section, we conduct a few tests to validate the accuracy of our cultural measure and alleviate the measurement error concern.

First, most U.S. women adopt their husband's surnames when married. Thus, female FAs in our sample may carry their husband's surnames that do not reflect their true cultural origins if the couple is from different countries. Unfortunately, we do not have information on female FAs' premarital surnames. As a robustness check, we exclude female FAs from our sample. As shown in Column 1 of Panel A of Table 10, the magnitude and statistical significance of the coefficient of *FA corruption* are similar to those of baseline regression when we employ *FA misconduct* as the dependent variable. The results in Panels B and C are also similar to those of baseline regression when we use *Separation* or *Reemployment* as the dependent variable.

[Insert Table 10]

Second, we conduct a test to alleviate the data quality concern of FAs with Asian and Latin American cultural origins. We use the passenger records of the port of New York between 1820 and 1957. During this period, most passengers that entered the port of New York were from Europe, raising a data quality concern for the sample of FAs with Asian and Latin American cultural origins, which consists of 3.1% of all cultural origins. Therefore, we exclude these FAs and examine the subsample of FAs with non-Asian and non-Latin American cultural origins. As shown in Column 2 of Panel A, although the magnitude of the coefficient of *FA corruption* is smaller than that of baseline regression when we employ *FA misconduct* as the dependent variable, our main finding remains. The results in Panels B and C also remain consistent when we use *Separation* or *Reemployment* as the dependent variable.

Third, due to the nature of raw data on *Ancestry.com*, there are some non-country cultural origins in our sample (e.g., geographic region, former country, and ethnic group), which consists of 6.4% of all cultural origins. When computing our cultural variables, we consider these non-country cultural origins and calculate their culture index as the average culture index of constituent countries. In a robustness test, we remove these non-country cultural origins. As shown in Table 10, the results are qualitatively similar.

Fourth, the epidemiological approach assumes that cultural values and beliefs can be imported from foreign countries and passed to later generations. To ensure this assumption is reasonable, using the data from the U.S. General Social Survey between 1972 and 2021, we directly test the relation between the corruption value of the country of ancestry and the corruption attitudes of respondents in the survey (Gu, Liu, and Simunic, 2020).¹² We identify individuals' country of ancestry based on the responses to the survey question "*From what countries or part of the world did your ancestors come?*" Based on this information, we construct the ancestry corruption value for each respondent in the survey (*Corruption survey*).

Individuals with a lower sense of right vs. wrong and who emphasize the value of money tend to engage in and tolerate more corrupt behavior. To capture the corruption attitudes, we use the responses to six survey questions regarding the sense of ethical values and the view on the importance of money:

¹² General Social Survey collects data from American individuals on various demographic, behavioral, and attitudinal questions. The data is available on its website: <https://gss.norc.org/>

(1) *Govcheat*: Do you feel it is wrong or not wrong if a person gives the government incorrect information about himself to get government benefits that he is not entitled to? (1, not wrong - 4, seriously wrong)

(2) *Taxcheat*: Do you feel it is wrong or not wrong if a taxpayer does not report all of his income in order to pay less income taxes? (1, not wrong - 4, seriously wrong)

(3) *Anomia3*: To make money, there are no right and wrong ways anymore, only easy and hard ways. (1, agree - 2, disagree)

(4) *Anomia1*: Next to health, money is the most important thing in life. (1, agree - 2, disagree)

(5) *Wklearn*: A job is just a way of earning money - no more. (1, strongly agree - 5, strongly disagree)

(6) *Hiinc*: How important you personally consider high income is in a job? (1, strongly agree - 5, strongly disagree)

We regress each of the above six survey variables on *Corruption survey* at the individual level, controlling for other personal characteristics, including gender (*Female*), age (*Age*), the number of years of formal education (*Education*), family income (*Income*), marital status (*Married*), race (*White*; *Black*), and employment status (*Employed*). As a higher value of these six survey variables indicates a lower level of corruption attitudes, we expect they are negatively associated with *Corruption survey*. To ensure our results are not driven by first-generation immigrants who may spend their childhood in foreign countries, we exclude foreign-born respondents.¹³ The results of individual-level regressions are shown in Online Appendix Table A3. The results are in line with our expectation, in which the coefficients of *Corruption survey* are negative and significant across all regressions. It indicates that the respondents with ancestors from higher-corruption countries view monetary gains as more important and have a higher tolerance for questionable activities. Overall, our results suggest that the corrupt attitude of descendants is highly related to the corruption value of the country of ancestry, supporting the validation of the epidemiological approach.

¹³ The results are qualitatively similar when we exclude second-generation immigrants.

The results of the above tests suggest that measurement error is less likely to drive our results. Although we could not completely avoid measurement error, our approach attempts to manage it at the lowest level, and our findings are factual inferences from the data.

4.2 Alternative Corruption Index

In the baseline regression, we use the CPI of Transparency International as our primary corruption measure. To ensure our results are robust, we employ a set of alternative country-level corruption variables. First, we collect the corruption index from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998) (*Corruption_L*), which measures the likelihood of a country's government officials demanding special payments and the prevalence of illegal payments throughout lower levels of government. Second, we obtain the Corporate Illegal Corruption Component (*CICC*) index from Kaufmann (2004), which captures the extent of firms in a country that report a satisfactory situation regarding illegal corruption activities. Third, we collect the Control of Corruption Indicator from Kaufmann, Kraay, and Mastruzzi (2009) (*Corruption_K*), which measures the perceptions of the extent to which public power is exercised for private gain. When necessary, we multiply the variable with -1; thus, a higher value of these variables represents a higher level of corruption. Same as CPI, we rescale these variables between zero and one.

As shown in Table 11, the relation between *FA corruption* and *FA misconduct* remains in Panel A when we use the corruption index from alternative sources. The results in Panels B and C are generally consistent when we employ *Separation* or *Reemployment* as the dependent variable, except the interaction term is shy of significant in Column 2 of Panel B. These results suggest our findings are robust to alternative sources of the corruption index.

[Insert Table 11]

4.3 Brokers Versus Investment Advisors

As discussed earlier, a FA could register as a broker or investment advisor or dually register as both. Brokers and investment advisors provide services to different clientele and are subject to different legal and regulatory requirements. The main difference between the two is that investment advisors are held to a fiduciary standard, and brokers are held to a lower suitability standard. Recall that among our 1.5 million initial FA sample, we have roughly 1.4 million brokers and 0.6 million investment advisors. About 0.5 million, or 34% of FAs dually register as brokers and investment advisors. As a robustness check, we test whether our finding is sensitive to the broker and investment advisor subsamples.

Table 12 shows the results of the subsample of brokers, investment advisors, and dually registered brokers and investment advisors. The results are similar to those of the full sample, suggesting that our results are robust when employing alternative FA subsamples.

[Insert Table 12]

4.4 Additional Controls

In the baseline regression, we control for high-dimensional fixed effects at the firm×county×year level to explore the within-firm variations in FA misconduct. Although we control for FA’s historical misconduct record, experience, gender, and qualification information in the model, other unobservable FA characteristics may drive our results. To mitigate the omitted-variable concern, we examine the relation between *FA corruption* and the likelihood of misconduct controlling for FAs’ cultural characteristics based on other cultural dimensions. Specifically, we employ three cultural dimensions that have been studied extensively in prior literature: trust, hierarchy, and individualism (Ahern, Daminelli, and Fracassi, 2015; Guiso, Sapienza, and Zingales, 2006; Pevzner, Xie, and Xin, 2015). Trust refers to the dependence on another to fulfill an implicit or explicit obligation. In a hierarchical culture, members are delineated into multiple vertical power ranks, and subordinates tend to follow instructions from their superiors. Individualistic culture focuses on individual accomplishment, self-orientation, and autonomy. Individuals in individualistic cultures view themselves as having independent identities.

We construct our cultural dimensions based on the responses to the World Values Survey (WVS) (<https://www.worldvaluessurvey.org/wvs.jsp>), comprising nationally representative surveys conducted in almost 100 countries and territories that samples from nearly 90% of the world population. The surveys were carried out in seven waves in 1981-1984, 1990-1994, 1995-1998, 1999-2004, 2005-2009, 2010-2014, and 2017-2022. We use the average value of the culture index of these seven waves and rescaled them between zero and one for ease of interpretation. Using the same approach to constructing *FA corruption*, we calculate *Trust*, *Hierarchy*, and *Individualism* at the FA level.

As shown in Panel A of Table 13, we include *Trust*, *Hierarchy*, and *Individualism* in Columns 1-3 and all variables in Column 4. The results show that the positive relation between *FA corruption* and the likelihood of misconduct remains controlling for these additional

cultural variables.¹⁴ The results are also consistent with the baseline regression when we employ *Separation* or *Reemployment* as the dependent variable in Panels B and C, respectively.

[Insert Table 13]

Next, we further supplement our data with additional FA-level variables obtained from the Discovery Data, which provides granular FA-level information (<https://discoverydata.com>). Specifically, we extract additional FA characteristics measuring from the Discovery Data, including *Client facing* (i.e., indicating whether the FA directly interacts or contacts the client),¹⁵ *High rating* (i.e., indicating whether the FA has a high rating in Discovery Data), and *Ln(AUM)* (i.e., the natural logarithm of FA's self-reported AUM in millions). Egan, Matvos, and Seru (2019; 2022) and Law and Zuo (2021) use the same data from Meridian-IQ, which was acquired by Discovery Data in 2016. However, Discovery Data only provide information for a subsample of currently active FAs. Thus, we employ these variables in a separate test.

Among 1,043,102 FAs in our baseline sample, 660,691 or 63.3% are currently active FAs. For *Client facing* and *High rating*, we can match 77.6% and 44.8% of the currently active FAs in our baseline sample to the Discovery Data. The availability of *AUM* is relatively poor (i.e., 21.5%). Client-facing (High-rating) FAs contribute 55.4% (54.7%) of observations in our sample. An average active FA in this subsample self-reports \$108.5 million AUM. In addition, there are more female FAs and fewer client-facing and high-rating FAs in the sample of the *Top 1/4 FAs* than in the *Bottom 1/4 FAs*. Lastly, we find that the *Top 1/4 FAs* have less AUM (i.e., 103.846 versus 107.321) than the *Bottom 1/4 FAs*.

As shown in Panel A of Table 13, we include *Client facing*, *High rating*, and *Ln(AUM)* in Columns 5-7 and all variables in Column 8. Consistent with prior studies, we show FAs who directly interact or contact the client, have a high-quality rating, and manage a larger pool of AUM, are more likely to engage in misconduct, as they have more opportunities to commit misconduct. In Columns 5-7, the positive association between *FA corruption* and *FA misconduct* continues to hold, and the coefficients range from 0.0007 to 0.0012. Lastly, we

¹⁴ Column 1 (2) of Panel A of Table 13 shows that FAs with a higher trust (hierarchy) culture tend to involve in misconduct activities. We also conduct other tests for *Trust* and *Hierarchy*; however, the results are not robust as for *FA corruption*.

¹⁵ *Client facing* is determined based on the job title categories in Discovery Data. Using an alternative approach, we define client-facing FAs as those who register in more than three states (*Registration 3+*). Qureshi and Sokobin (2015) note that “based on its experience, FINRA staff believes that brokers with more than three state registrations generally deal with public investors.” We find the association between *FA corruption* and the likelihood of misconduct when we define client-facing in an alternative way.

have all three variables in Column 8. The results are unchanged, except the *t-statistic* of *FA corruption* is lower than the baseline regression. These results suggest that the effect of *FA corruption* on *FA misconduct* is incremental to these additional control variables. We also conduct tests on employment separation and reemployment with these additional controls. Panels B and C show that though the number of observations significantly shrinks, the results remain consistent.

Next, we conduct further tests to alleviate the omitted-variable concern using data from a newly available sub-dataset of Discovery Data, which contains granular information on FAs' demographics, interests, and lifestyle attributes. Specifically, we first supplement our baseline regression with a few demographic variables, including *Age*, *No. of children*, *Marital status* (i.e., indicating whether the FA is married), *No. of firms associated* (i.e., the number of firms the FA is associated with), and *Education* (i.e., equals three, two, one, and zero if the highest degree of the FA is Doctor, Master, Bachelor, and others, respectively). However, including these additional attributes in our model significantly reduces the sample size, as not all currently active FAs disclose the information. As shown in Columns 1-5 of Panel A of Table 14, FAs who are older, married, and have a better education background are less likely to involve in misconduct activities. FAs associated with more firms are more likely to engage in misconduct. The positive relation between *FA corruption* and *FA misconduct* remains; however, the statistical significance is reduced compared to the baseline regression due to the smaller sample. Overall, these results suggest that the effect of *FA corruption* on *FA misconduct* is incremental to these additional control variables.

[Insert Table 14]

In addition, we employ a few interests and lifestyle variables, indicating whether the FA voluntarily discloses that they have any hobbies and interests (*General interests*, *Music interests*, *Reading interests*, and *Sports interests*), conscientious, general, political, or religious contributions (*Contributions*), and investments (*Investments*), as well as the inferred wealth segment of the FA (*Wealth*, equals four, three, two, and one, if the inferred wealth segment of the FA is between \$2-5million, \$500,000-2million, \$100,000-500,000, and less than \$100,000).¹⁶ We include these variables separately in the model in Columns 6-9. We find that

¹⁶ A caveat of these tests is that these variables may capture FA's willingness to disclose personal information rather than the indicated meanings. Except for *Wealth*, we fill the missing values for these variables with zeros. Thus, zero could mean the FA has no interest, makes no contribution or investment, or is less willing to disclose the information. However, we do not have enough information to examine the effects separately.

FAs who disclose any form of contribution are associated with a higher propensity for misconduct, suggesting FAs are more likely to engage in misconduct when they gain a moral license from contributing to others (Merritt, Effron, and Monin, 2010; Monin and Miller, 2001). In addition, FAs with investment disclosures are less likely to engage in misconduct, indicating that FAs with their own investments also manage their client's assets more carefully. We also show that more wealthy FAs tend to engage in misconduct, probably due to their risk-taking attributes, which help accumulate wealth. More importantly, we show the positive relation between *FA corruption* and *FA misconduct* remains statistically significant in all models. Column 10 shows the results are similar when we include all variables in a single model. These results suggest that the corruption culture of FAs is distinct from their interests and lifestyle attributes and carry important incremental information that can explain their misconduct behavior. It is less likely that omitted-variable problems drive our results.

Lastly, as shown in Panels B and C of Table 14, we conduct tests on employment separation and reemployment with these additional controls. Not surprisingly, the number of observations shrinks significantly. Nevertheless, the results are qualitatively similar to those of baseline regression even with this shrinkage sample, suggesting that the omitted-variable issue is less likely a concern in our study.

The trade-off of using Discovery Data is that these measures are only available for currently active FAs, resulting in a much smaller sample. However, since our sampled FAs with misconduct records survived as of 2022, they tend to have better-unobserved characteristics available. Thus, the potential selection likely biases against us finding the results in this subsample.

5 Conclusion

Employing a survivorship-bias-free panel of approximately 1.5 million FAs between 2010 and 2019, we examine the role of corruption culture in explaining the propensity of FA misconduct and their career outcomes following misconduct. We show that FAs with a more corrupt cultural background are more likely to conduct misconduct activities than other FAs registered in the same firm, working in the same county, and in the same year. This association is attenuated for female FAs and FAs who possess more non-compulsory qualifications. Furthermore, we show that following misconduct, FAs with a higher corruption value are punished more harshly by firms through employment separation. However, these FAs are somewhat attractive in the job market, irrespective of their misconduct records. Next, we

attempt to explain these labor market consequences. We find that firms are less tolerant of misconduct because FAs with a higher corruption value are likely to re-offense, but not these FAs commit more severe misconduct. In the job market, these FAs tend to join larger firms irrespective of their misconduct records. Lastly, we show that the value of corruption culture that makes FAs attractive in the job market arises when they can generate more revenue with a limited asset pool but not because they offer customers more flexible fee options. Their value is also reflected by the fact that they are retained by the firm experiencing a downsize.

We conduct a series of additional tests to ensure our results are robust. First, to mitigate the measurement error concern, we construct the cultural variable in alternative approaches by excluding female FAs, FAs with Asian and Latin American cultural origins, and non-country cultural origins. We also verify the epidemiological approach using the data from the U.S. General Social Survey. Second, we employ a few alternative corruption indices widely used in the literature to ensure our results are not sensitive to alternative sources of corruption index. Third, we conduct tests on the subsample of brokers, investment advisors, and dually registered brokers and investment advisors to ensure our results are not sensitive to alternative samples. Fourth, to mitigate the omitted-variable concern, we include a few sets of additional controls in the model, including (1) FAs' cultural characteristics based on other cultural dimensions, (2) client-facing indicator, high-rating indicator, and self-reported AUM from Discovery Data, and (3) demographics, interests, and lifestyle attributes from a newly available sub-dataset of Discovery Data. All the above results are consistent with our baseline model and suggest that our findings are robust.

Our findings suggest that individual financial professionals' behavior and career paths are largely influenced by their corruption value. Although firms are less tolerant of FAs with a higher corruption value due to their repeated offenses, the job market updos the firm discipline by rehiring them, primarily due to their superior performance. Thus, our findings might be generalized to any FA with outstanding performance. Another possible reason is that the new employers may not worry too much about misconduct history as there is no evidence that these FAs tend to commit severe fraud. However, such a mechanism could lead to the prevalence of non-severe misconduct in the market, given the low cost of committing misconduct. These non-severe misconducts are likely to happen to less-wealthy individuals who are less sophisticated and have fewer resources (e.g., legal support) for financial disputes. To improve the mechanism, the FA market, especially the job market, may need to establish an effective way to increase the price of committing non-severe misconduct.

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Figure A. Image of a Passenger Record on *Ancestry.com*

Peter Anderson

in the New York, U.S., Arriving Passenger and Crew Lists (including Castle Garden and Ellis Island), 1820-1957



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Name:	Peter Anderson
Gender:	Male
Ethnicity/ Nationality:	Swedish
Age:	60
Birth Date:	abt 1826
Place of Origin:	Sweden
Departure Port:	Liverpool, England and Queenstown, Ireland
Destination:	New York
Arrival Date:	14 May 1886
Arrival Port:	New York, New York, USA
Ship Name:	City of Chester
Search Ship Database:	Search for the City of Chester in the 'Passenger Ships and Images' database

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Table 1 Summary Statistics

This table presents the summary statistics of variables in our baseline regression. Specifically, we report the number of observations, the number of FAs, the mean, standard deviation, and 25th, 50th, and 75th percentile values of each variable. In addition, we also report the variable mean of the subsamples of FAs with top and bottom quarter corruption values and the *p-value* of the difference.

	<i>N</i>	<i>No. of FAs</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>p25</i>	<i>p50</i>	<i>p75</i>	<i>Mean (Top 1/4 FAs)</i>	<i>Mean (Bottom 1/4 FAs)</i>	<i>Top - Bottom (p-value)</i>
<i>FA misconduct</i>	6,345,308	1,043,102	0.005	0.072	0	0	0	0.006	0.005	<0.01
<i>FA corruption</i>	6,345,308	1,043,102	0.313	0.166	0.208	0.239	0.373	0.576	0.180	<0.01
<i>Prior misconduct</i>	6,345,308	1,043,102	0.062	0.240	0	0	0	0.055	0.062	<0.01
<i>Experience</i>	6,345,308	1,043,102	12.591	10.128	4	11	19	11.304	12.880	<0.01
<i>Female</i>	6,345,308	1,043,102	0.267	0.442	0	0	1	0.278	0.268	<0.01
<i>Investment Adviser (65/66)</i>	6,345,308	1,043,102	0.442	0.497	0	0	1	0.386	0.469	<0.01
<i>Securities Agent State Law (63)</i>	6,345,308	1,043,102	0.701	0.458	0	1	1	0.702	0.698	<0.01
<i>General Securities Rep. (7)</i>	6,345,308	1,043,102	0.664	0.472	0	1	1	0.654	0.659	<0.01
<i>Investment Company Product Rep. (6)</i>	6,345,308	1,043,102	0.359	0.480	0	0	1	0.359	0.369	<0.01
<i>General Securities Principal (24)</i>	6,345,308	1,043,102	0.135	0.342	0	0	0	0.125	0.134	<0.01
<i>Number of other qualifications</i>	6,345,308	1,043,102	0.456	0.832	0	0	1	0.449	0.444	<0.01

Table 2. Corruption Culture and Financial Advisor Misconduct

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. Variables definitions are described in Appendix B. *Experience (Number of other qualifications)* is measured in tens of years (tens of qualifications). Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	[1]	[2]	[3]
<i>FA corruption</i>	0.0024*** (4.165)	0.0035*** (6.119)	0.0014*** (6.096)
<i>Prior misconduct</i>		0.0232*** (16.947)	0.0186*** (20.038)
<i>Experience (tens of years)</i>		0.0003* (1.650)	0.0003** (2.165)
<i>Female</i>		-0.0019*** (-16.955)	-0.0019*** (-12.822)
<i>Exams and Qualifications (series):</i>			
<i>Investor Adviser (65/66)</i>		0.0018*** (10.635)	0.0014*** (7.966)
<i>Securities Agent State Law (63)</i>		0.0011*** (5.959)	0.0009*** (7.873)
<i>General Securities Rep. (7)</i>		0.0004 (1.279)	-0.0002 (-0.440)
<i>Investment Company Product Rep. (6)</i>		0.0008** (2.372)	0.0009** (2.529)
<i>General Securities Principal (24)</i>		0.0000 (0.205)	-0.0001 (-0.663)
<i>Number of other qualifications (tens of qualifications)</i>		-0.0051*** (-5.591)	-0.0037*** (-3.383)
<i>Firm × County × Year FE</i>			Yes
<i>N</i>	6,345,308	6,345,308	6,345,308
<i>R²</i>	0.0000	0.0069	0.0991

Table 3. Corruption Culture and Financial Advisor Misconduct: Cross-sectional Tests

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. Variables definitions are described in Appendix B. *Experience (Number of other qualifications)* is measured in tens of years (tens of qualifications). Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	[1]	[2]	[3]
<i>FA corruption</i>	0.0012** (2.544)	0.0017*** (5.360)	0.0017*** (5.305)
<i>Experience (tens of years)</i>	0.0002* (1.923)		
<i>FA corruption</i> × <i>Experience (tens of years)</i>	0.0002 (0.520)		
<i>Female</i>		-0.0017*** (-9.799)	
<i>FA corruption</i> × <i>Female</i>		-0.0009** (-2.024)	
<i>Number of other qualifications (tens of qualifications)</i>			-0.0018 (-1.459)
<i>FA corruption</i> × <i>Number of other qualifications (tens of qualifications)</i>			-0.0060* (-1.703)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	Yes
<i>N</i>	6,345,308	6,345,308	6,345,308
<i>R</i> ²	0.0991	0.0992	0.0992

Table 4. Job Turnover Following Misconduct

This table shows the average annual job turnover among FAs with top and bottom quarter corruption values (*Top 1/4 FAs* and *Bottom 1/4 FAs*). Observations are at the FA-year level. A FA is considered to “leave the industry” if he/she is not employed as a FA for more than one year. A FA is considered to “join another firm” if he/she is employed at another FA firm within one year.

<i>FA corruption:</i>	<i>No Misconduct (%)</i>		<i>Misconduct (%)</i>	
	<i>Top 1/4 FAs</i>	<i>Bottom 1/4 FAs</i>	<i>Top 1/4 FAs</i>	<i>Bottom 1/4 FAs</i>
Remain with the firm	75.3%	77.0%	44.1%	49.6%
Leave the firm	24.7%	23.0%	55.9%	50.4%
<i>Conditional on leaving the firm:</i>				
Leave the industry	73.4%	74.7%	77.1%	77.1%
Join another firm	26.6%	25.3%	22.9%	22.9%

Table 5. Employment Separation and Reemployment

This table presents the regression results of a linear probability model that estimates the relation between FA's corruption culture and labor market consequences. Observations are at the FA-year level. The dependent variable in Panel A, *Separation*, equals one if the FA left the firm the following year and zero otherwise. The dependent variable in Panel B, *Reemployment*, equals one if the FA joined a new firm within one year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. *FA misconduct* equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. In Panel B, we restrict the sample to FAs with job turnover in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Employment Separation		
<i>Dep. Var.:</i>	<i>Separation</i>	
	[1]	[2]
<i>FA corruption</i>	0.0007 (0.416)	0.0000 (0.007)
<i>FA misconduct</i>	0.2859*** (12.321)	0.2447*** (14.511)
<i>FA corruption</i> × <i>FA misconduct</i>		0.1264*** (3.207)
<i>FA controls</i>	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes
<i>N</i>	6,345,308	6,345,308
<i>R</i> ²	0.4933	0.4934
Panel B: Reemployment		
<i>Dep. Var.:</i>	<i>Reemployment</i>	
	[1]	[2]
<i>FA corruption</i>	0.0069*** (2.943)	0.0070*** (2.894)
<i>FA misconduct</i>	-0.1381*** (-13.982)	-0.1363*** (-13.364)
<i>FA corruption</i> × <i>FA misconduct</i>		-0.0054 (-0.276)
<i>FA controls</i>	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes
<i>N</i>	1,435,578	1,435,578
<i>R</i> ²	0.5316	0.5316

Table 6. Recidivism

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. *Prior misconduct* equals one if the FA has at least one prior misconduct record and zero otherwise. *Prior discipline* equals one if the FA previously experienced an employment separation following misconduct. In Column 2, We restrict the sample to those FAs with prior misconduct records. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>FA misconduct</i>	
	[1]	[2]
<i>FA corruption</i>	0.0007** (2.344)	0.0040 (1.411)
<i>Prior misconduct</i>	0.0144*** (12.100)	
<i>FA corruption</i> × <i>Prior misconduct</i>	0.0138*** (3.485)	
<i>Prior discipline</i>		0.0448*** (6.468)
<i>FA corruption</i> × <i>Prior discipline</i>		-0.0009 (-0.046)
<i>FA controls</i>	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes
<i>N</i>	6,345,308	321,541
<i>R</i> ²	0.0992	0.2401

Table 7. Misconduct Severity

This table presents the regression results of a linear probability/OLS model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. *Severe FA misconduct1* equals one if the FA has at least one severe misconduct disclosure in a year and zero otherwise. Severe misconduct disclosures include noncriminal disclosures (i.e., regulatory, civil, and customer disputes) involving unauthorized activity, fraud and forgery, churning, selling unregistered securities, misrepresentation, and omission of material facts, and criminal disclosures involving investment-related activities and fraud and forgery. *Severe FA misconduct2* is defined more restrictively by excluding noncriminal disclosures involving misrepresentation and omission of material facts. $\ln(\textit{Settlement})$ is the natural logarithm of the total paid out by the firm on behalf of a FA as a result of a misconduct settlement. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>Severe FA misconduct1</i>	<i>Severe FA misconduct2</i>	$\ln(\textit{Settlement})$
	[1]	[2]	[3]
<i>FA corruption</i>	0.0001 (1.120)	0.0001 (1.156)	0.0029 (0.028)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	
<i>Firm FE</i>			Yes
<i>County FE</i>			Yes
<i>Year FE</i>			Yes
<i>N</i>	6,345,308	6,345,308	13,301
<i>R</i> ²	0.1276	0.0967	0.2734

Table 8. New Employer Characteristics

This table presents the regression results of the OLS model that estimates the relation between FA corruption culture and new employer characteristics. Observations are at the FA-year level. *Firm misconduct* is the proportion of FAs with at least one misconduct disclosure working in a FA firm in a year. *Number of advisors*, *Number of accounts*, and *Assets (\$Billion)* represent the number of advisors, the number of accounts, and the asset size of the firm, respectively. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. *FA misconduct* equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. We restrict the sample to firms with both FAs who change jobs following or not following misconduct in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>Firm misconduct</i>	<i>Number of advisors</i>	<i>Number of accounts</i>	<i>Assets (\$Billion)</i>
	[1]	[2]	[3]	[4]
<i>FA corruption</i>	-0.0000 (-0.436)	0.0010*** (3.936)	0.0161* (1.757)	5.2186* (1.955)
<i>FA misconduct</i>	0.0081*** (5.972)	-0.0039*** (-7.811)	-0.1491*** (-6.928)	-44.0758*** (-6.304)
<i>FA corruption</i> × <i>FA misconduct</i>	-0.0044 (-1.341)	-0.0009 (-0.716)	-0.0057 (-0.127)	-7.5673 (-0.523)
<i>FA controls</i>	Yes	Yes	Yes	Yes
<i>Original firm</i> × <i>Year FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	157,578	157,578	157,578	157,578
<i>R</i> ²	0.5741	0.5174	0.4098	0.4098

Table 9. The Value of Corruption Culture in the Job Market

This table presents evidence to assess the value of corruption culture in the job market. Observations are at the FA-year level. In Panel A, $\ln(AUM)$ and $\ln(Production)$ are the natural logarithms of FA's self-reported AUM and production/revenue in millions. $Production/AUM$ is the ratio of production/revenue over AUM. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. In Panel B, *Separation* equals one if the FA left the firm the following year and zero otherwise. *Downsize* equals one if the firm is downsized by at least 15%, 20%, or 25% in Columns 1-3, respectively, and zero otherwise. In Panel C, *Fee and Commission* is a dummy variable indicating whether the FA charges based on both fees and commissions. *No. of Fee Options* is the number of fee structures the FA offers customers, ranging from one to three. We use the OLS model, linear probability model, and linear probability/OLS model in Panels A, B, and C, respectively. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: AUM and Production			
<i>Dep. Var.:</i>	$\ln(AUM)$	$\ln(Production)$	$Production/AUM$
	[1]	[2]	[3]
<i>FA corruption</i>	-0.0897*** (-3.862)	0.0275** (2.214)	1.3764* (1.840)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	Yes
<i>N</i>	1,314,738	497,157	493,041
<i>R</i> ²	0.2471	0.2202	0.2298
Panel B: Firm Downsize			
<i>Dep. Var.:</i>	<i>Separation</i>		
	[1]	[2]	[3]
<i>FA corruption</i>	0.0013 (0.735)	0.0013 (0.736)	0.0013 (0.748)
<i>FA corruption</i> × <i>Downsize</i>	-0.0082 (-1.420)	-0.0115** (-1.834)	-0.0154** (-2.192)
<i>Downsize 15%</i>	Yes		
<i>Downsize 20%</i>		Yes	
<i>Downsize 25%</i>			Yes
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	Yes
<i>N</i>	5,612,790	5,612,790	5,612,790
<i>R</i> ²	0.5029	0.5029	0.5029

Table 9. (Cont.)

Panel C: Fee Options		
<i>Dep. Var.:</i>	<i>Fee and Commission</i>	<i>No. of Fee Options</i>
	[1]	[2]
<i>FA corruption</i>	0.0382 (0.989)	0.1956 (0.849)
<i>FA controls</i>	Yes	Yes
<i>Firm FE</i>	Yes	Yes
<i>County FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>N</i>	34,763	4,622
<i>R²</i>	0.675	0.6822

Table 10. Measurement Error

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable in Panel A, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. The dependent variable in Panel B, *Separation*, equals one if the FA left the firm the following year and zero otherwise. The dependent variable in Panel C, *Reemployment*, equals one if the FA joined a new firm within one year and zero otherwise. In Panel C, we restrict the sample to FAs with job turnover in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Misconduct			
<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	<i>Exclude female FAs</i>	<i>Exclude FAs with Asian and Latin American cultural origins</i>	<i>Exclude FAs with non-country cultural origins</i>
	[1]	[2]	[3]
<i>FA corruption</i>	0.0015*** (5.306)	0.0008*** (3.521)	0.0015*** (6.630)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm × County × Year FE</i>	Yes	Yes	Yes
<i>N</i>	4,611,321	6,296,396	6,345,308
<i>R</i> ²	0.1127	0.0994	0.0991

Table 10. (Cont.)

Panel B: Employment Separation						
<i>Dep. Var.:</i>	<i>Separation</i>					
	<i>Exclude female FAs</i>		<i>Exclude FAs with Asian and Latin American cultural origins</i>		<i>Exclude FAs with non-country cultural origins</i>	
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	0.0019 (1.212)	0.0012 (0.760)	-0.0059*** (-5.101)	-0.0062*** (-5.280)	0.0003 (0.171)	-0.0002 (-0.142)
<i>FA misconduct</i>	0.2690*** (12.863)	0.2329*** (15.079)	0.2851*** (12.345)	0.2673*** (14.844)	0.2859*** (12.321)	0.2510*** (14.730)
<i>FA corruption × FA misconduct</i>		0.1111*** (2.823)		0.0586* (1.687)		0.1007*** (2.673)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	4,611,321	4,611,321	6,296,396	6,296,396	6,345,308	6,345,308
<i>R²</i>	0.5282	0.5282	0.5231	0.5231	0.5226	0.5226
Panel C: Reemployment						
<i>Dep. Var.:</i>	<i>Reemployment</i>					
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	0.0067** (2.494)	0.0066** (2.400)	0.0239*** (11.652)	0.0240*** (11.413)	0.0068*** (2.757)	0.0069*** (2.730)
<i>FA misconduct</i>	-0.1405*** (-14.525)	-0.1417*** (-12.023)	-0.1385*** (-13.800)	-0.1365*** (-14.194)	-0.1381*** (-13.981)	-0.1364*** (-12.598)
<i>FA corruption × FA misconduct</i>		0.0036 (0.175)		-0.0063 (-0.287)		-0.0048 (-0.253)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1,034,187	1,034,187	1,422,686	1,422,686	1,435,578	1,435,578
<i>R²</i>	0.5454	0.5454	0.5324	0.5324	0.5316	0.5316

Table 11. Alternative Corruption Index

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable in Panel A, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on different corruption indexes of FAs' cultural origins inferred from the surname, calculated based on the corruption indexes *Corruption_L*, *CICC*, or *Corruption_K*. The dependent variable in Panel B, *Separation*, equals one if the FA left the firm the following year and zero otherwise. The dependent variable in Panel C, *Reemployment*, equals one if the FA joined a new firm within one year and zero otherwise. In Panel C, we restrict the sample to FAs with job turnover in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Misconduct			
<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	<i>Corruption_L in La Porta, Lopez-de- Silanes, Shleifer, and Vishny (1998)</i>	<i>CICC in Kaufmann (2004)</i>	<i>Corruption_K in Kaufmann, Kraay, and Mastruzzi (2009)</i>
	[1]	[2]	[3]
<i>FA corruption</i>	0.0011*** (3.861)	0.0008*** (4.714)	0.0015*** (6.736)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes
<i>N</i>	6,264,783	6,333,487	6,336,107
<i>R</i> ²	0.0995	0.0991	0.0992

Table 11. (Cont.)

Panel B: Employment Separation						
<i>Dep. Var.:</i>	<i>Separation</i>					
	<i>Corruption_L in La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998)</i>		<i>CICC in Kaufmann (2004)</i>		<i>Corruption_K in Kaufmann, Kraay, and Mastruzzi (2009)</i>	
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	-0.0065*** (-4.234)	-0.0066*** (-4.191)	-0.0022* (-1.793)	-0.0025** (-1.994)	0.0016 (0.862)	0.0011 (0.568)
<i>FA misconduct</i>	0.2857*** (12.342)	0.2758*** (12.207)	0.2857*** (12.342)	0.2675*** (13.972)	0.2857*** (12.325)	0.2587*** (14.074)
<i>FA corruption × FA misconduct</i>		0.0199 (0.721)		0.0637** (2.365)		0.1020*** (2.879)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	6,333,487	6,333,487	6,333,487	6,333,487	6,336,107	6,336,107
<i>R²</i>	0.5227	0.5227	0.5227	0.5227	0.5227	0.5227
Panel C: Reemployment						
<i>Dep. Var.:</i>	<i>Reemployment</i>					
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	0.0204*** (8.592)	0.0203*** (8.440)	0.0086*** (4.653)	0.0086*** (4.545)	0.0038 (1.367)	0.0037 (1.318)
<i>FA misconduct</i>	-0.1381*** (-14.069)	-0.1472*** (-9.632)	-0.1382*** (-14.071)	-0.1401*** (-13.142)	-0.1382*** (-14.024)	-0.1403*** (-12.559)
<i>FA corruption × FA misconduct</i>		0.0179 (0.844)		0.0066 (0.427)		0.0075 (0.416)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1,432,515	1,432,515	1,432,515	1,432,515	1,433,216	1,433,216
<i>R²</i>	0.5318	0.5318	0.5318	0.5318	0.5317	0.5317

Table 12. Brokers Versus Investment Advisors

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable in Panel A, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. The dependent variable in Panel B, *Separation*, equals one if the FA left the firm the following year and zero otherwise. The dependent variable in Panel C, *Reemployment*, equals one if the FA joined a new firm within one year and zero otherwise. In Panel C, we restrict the sample to FAs with job turnover in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Misconduct			
<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	<i>Brokers</i>	<i>Investment advisors</i>	<i>Dually registered brokers and investment advisors</i>
	[1]	[2]	[3]
<i>FA corruption</i>	0.0015*** (6.395)	0.0016*** (4.715)	0.0018*** (5.293)
<i>FA controls</i>	Yes	Yes	Yes
<i>Firm × County × Year FE</i>	Yes	Yes	Yes
<i>N</i>	6,044,030	3,344,995	3,044,341
<i>R</i> ²	0.0952	0.1150	0.1095

Table 12. (Cont.)

Panel B: Employment Separation						
<i>Dep. Var.:</i>	<i>Separation</i>					
	<i>Brokers</i>		<i>Investment advisors</i>		<i>Dually registered brokers and investment advisors</i>	
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	0.0004 (0.225)	-0.0003 (-0.150)	-0.0022 (-1.263)	-0.0026 (-1.426)	-0.0026 (-1.402)	-0.0029 (-1.534)
<i>FA misconduct</i>	0.2924*** (12.415)	0.2530*** (14.704)	0.2332*** (13.879)	0.2172*** (12.990)	0.2396*** (14.085)	0.2255*** (13.199)
<i>FA corruption</i> × <i>FA misconduct</i>		0.1202*** (3.027)		0.0512** (2.080)		0.0450* (1.796)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	6,044,030	6,044,030	3,344,995	3,344,995	3,044,341	3,044,341
<i>R</i> ²	0.5133	0.5133	0.5926	0.5926	0.5798	0.5798
Panel C: Reemployment						
<i>Dep. Var.:</i>	<i>Reemployment</i>					
	[1]	[2]	[3]	[4]	[5]	[6]
<i>FA corruption</i>	0.0069*** (2.903)	0.0070*** (2.858)	0.0189*** (8.065)	0.0192*** (7.936)	0.0180*** (7.124)	0.0183*** (7.049)
<i>FA misconduct</i>	-0.1398*** (-13.898)	-0.1377*** (-13.121)	-0.1574*** (-17.292)	-0.1502*** (-10.283)	-0.1601*** (-17.048)	-0.1511*** (-9.936)
<i>FA corruption</i> × <i>FA misconduct</i>		-0.0063 (-0.326)		-0.0224 (-0.808)		-0.0280 (-0.998)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1,376,122	701,868	701,868	642,866	642,866	1,376,122
<i>R</i> ²	0.5281	0.6514	0.6514	0.6495	0.6495	0.5281

Table 13. Additional Controls

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. *Trust*, *Hierarchy*, and *Individualism* are FA cultural variables calculated using the same approach as *FA corruption*. *Client facing* equals one if the job title category requires the FA to directly interact or contact the client and zero otherwise. *High rating* equals one if a FA has a high rating in Discovery Data and zero otherwise. Discovery Data classifies a FA as high-rating if he/she possesses a Series 6 or 7 license for at least seven years and is currently registered in at least nine states. *Ln(AUM)* is the natural logarithm of FA's self-reported AUM in millions. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Misconduct								
<i>Dep. Var.:</i>	<i>FA misconduct</i>							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
<i>FA corruption</i>	0.0014*** (6.027)	0.0014*** (5.758)	0.0014*** (5.691)	0.0013*** (4.457)	0.0007*** (3.568)	0.0010*** (3.103)	0.0012*** (2.276)	0.0015** (2.252)
<i>Trust</i>	0.0005** (2.197)			0.0001 (0.134)				
<i>Hierarchy</i>		0.0008*** (3.196)		0.0007** (2.347)				
<i>Individualism</i>			0.0002 (0.785)	0.0002 (0.564)				
<i>Client facing</i>					0.0012*** (10.554)			0.0009*** (2.795)
<i>High rating</i>						0.0006** (2.442)		0.0003 (0.735)
<i>Ln(AUM)</i>							0.0002** (2.739)	0.0002** (2.472)
<i>FA controls</i>				Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	6,317,812	5,881,060	6,317,812	5,881,060	3,900,105	2,303,754	1,314,738	1,104,449
<i>R²</i>	0.0991	0.1015	0.0991	0.1015	0.1063	0.1008	0.1162	0.1188

Table 13. (Cont.)

Panel B: Employment Separation				
<i>Dep. Var.:</i>	<i>Separation</i>			
	[1]	[2]	[3]	[4]
<i>FA corruption</i>	0.0040 (1.611)	0.0032 (1.274)	-0.0015 (-1.014)	-0.0019 (-1.193)
<i>FA misconduct</i>	0.2876*** (12.299)	0.2393*** (14.168)	0.1027*** (9.952)	0.0884*** (7.015)
<i>FA corruption × FA misconduct</i>		0.1510*** (3.424)		0.0458* (1.737)
<i>Trust</i>	0.0072* (1.709)	0.0072* (1.718)		
<i>Hierarchy</i>	-0.0018 (-1.176)	-0.0018 (-1.194)		
<i>Individualism</i>	-0.0047 (-1.631)	-0.0047 (-1.637)		
<i>Client facing</i>			-0.0050* (-1.749)	-0.0050* (-1.750)
<i>High rating</i>			-0.0261*** (-6.897)	-0.0261*** (-6.896)
<i>Ln(AUM)</i>			-0.0021*** (-4.809)	-0.0021*** (-4.808)
<i>FA controls</i>	Yes	Yes	Yes	Yes
<i>Firm × County × Year FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	5,881,060	5,881,060	1,107,025	1,107,025
<i>R²</i>	0.5229	0.523	0.7727	0.7727

Table 13. (Cont.)

Panel C: Reemployment				
<i>Dep. Var.:</i>	<i>Reemployment</i>			
	[1]	[2]	[3]	[4]
<i>FA corruption</i>	-0.0022 (-0.691)	-0.0021 (-0.662)	0.0038* (1.647)	0.0035 (1.480)
<i>FA misconduct</i>	-0.1378*** (-13.889)	-0.1360*** (-12.886)	-0.0107* (-1.817)	-0.0194 (-1.322)
<i>FA corruption × FA misconduct</i>		-0.0056 (-0.253)		0.0267 (0.677)
<i>Trust</i>	-0.0435*** (-7.509)	-0.0435*** (-7.508)		
<i>Hierarchy</i>	0.0045** (2.002)	0.0045** (2.002)		
<i>Individualism</i>	0.0210*** (4.899)	0.0210*** (4.898)		
<i>Client facing</i>			0.0034** (2.419)	0.0034** (2.419)
<i>High rating</i>			0.0074*** (5.755)	0.0074*** (5.753)
<i>Ln(AUM)</i>			0.0007** (2.399)	0.0007** (2.400)
<i>FA controls</i>	Yes	Yes	Yes	Yes
<i>Firm × County × Year FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	1,326,327	1,326,327	160,552	160,552
<i>R²</i>	0.5341	0.5341	0.9394	0.9394

Table 14. Controlling for FAs' Demographics, Interests, and Lifestyle Attributes

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable in Panel A, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. The dependent variable in Panel B, *Separation*, equals one if the FA left the firm the following year and zero otherwise. The dependent variable in Panel C, *Reemployment*, equals one if the FA joined a new firm within one year and zero otherwise. In Panel C, we restrict the sample to FAs with job turnover in a given year. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

Panel A: Misconduct										
<i>Dep. Var.:</i>	<i>FA misconduct</i>									
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
<i>FA corruption</i>	0.0009*** (3.198)	0.0007* (1.910)	0.0010*** (2.757)	0.0007*** (3.540)	0.0010*** (3.337)	0.0010*** (4.617)	0.0010*** (4.619)	0.0010*** (4.644)	0.0009*** (4.305)	0.0024* (1.699)
<i>Age</i>	-0.0000*** (-3.667)									-0.0000 (-0.153)
<i>Marital status</i>		-0.0004*** (-3.258)								-0.0007* (-1.880)
<i>No. of children</i>			0.0000 (0.543)							0.0001 (0.480)
<i>No. of firms associated</i>				0.0008*** (3.237)						0.0013** (2.231)
<i>Education</i>					-0.0002*** (2.631)					-0.0007** (-2.307)
<i>General interests</i>						-0.0001 (-0.904)				-0.0027 (-1.571)
<i>Music interests</i>						-0.0001 (-1.231)				0.0003 (0.847)
<i>Reading interests</i>						-0.0001 (-1.205)				-0.0001 (-0.387)
<i>Sport interests</i>						-0.0000 (-0.020)				-0.0002 (-0.632)
<i>Contribution</i>							0.0002*** (3.283)			0.0004 (0.999)
<i>Investments</i>								-0.0003*** (-4.018)		-0.0000 (-0.069)
<i>Wealth</i>									0.0002*** (3.197)	0.0001 (0.365)
<i>FA controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm×County×Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2,854,789	967,706	1,192,779	3,951,527	1,971,724	3,794,398	3,794,398	3,794,398	3,387,673	199,559
<i>R²</i>	0.1086	0.1578	0.1507	0.1062	0.1330	0.1141	0.1141	0.1141	0.1168	0.1992

Table 14. (Cont.)

Panel B: Employment Separation		
<i>Dep. Var.:</i>	<i>Separation</i>	
	[1]	[2]
<i>FA corruption</i>	-0.0007 (-0.194)	-0.0012 (-0.340)
<i>FA misconduct</i>	0.1288*** (6.838)	0.0887*** (2.726)
<i>FA corruption</i> × <i>FA misconduct</i>		0.1249* (1.659)
<i>Age</i>	-0.0003*** (-2.775)	-0.0003*** (-2.777)
<i>Marital status</i>	-0.0040** (-2.434)	-0.0040** (-2.431)
<i>No. of children</i>	0.0005 (0.925)	0.0005 (0.916)
<i>No. of firms associated</i>	0.0137 (1.292)	0.0136 (1.290)
<i>Education</i>	0.0026** (2.427)	0.0026** (2.425)
<i>General interests</i>	-0.0145** (-2.443)	-0.0145** (-2.452)
<i>Music interests</i>	-0.0011 (-0.753)	-0.0011 (-0.746)
<i>Reading interests</i>	0.0007 (0.451)	0.0007 (0.451)
<i>Sport interests</i>	-0.0018 (-1.382)	-0.0018 (-1.379)
<i>Contribution</i>	-0.0006 (-0.454)	-0.0007 (-0.470)
<i>Investments</i>	-0.0068*** (-3.095)	-0.0068*** (-3.101)
<i>Wealth</i>	-0.0073*** (-3.748)	-0.0073*** (-3.749)
<i>FA controls</i>	Yes	Yes
<i>Firm × County × Year FE</i>	Yes	Yes
<i>N</i>	199,559	199,559
<i>R²</i>	0.7025	0.7025

Table 14. (Cont.)

Panel C: Reemployment		
<i>Dep. Var.:</i>	<i>Reemployment</i>	
	[1]	[2]
<i>FA corruption</i>	0.0211*** (2.928)	0.0208*** (2.853)
<i>FA misconduct</i>	-0.0861*** (-3.351)	-0.1060** (-2.437)
<i>FA corruption</i> × <i>FA misconduct</i>		0.0601 (0.416)
<i>Age</i>	-0.0002 (-1.116)	-0.0002 (-1.114)
<i>Marital status</i>	0.0018 (0.745)	0.0018 (0.749)
<i>No. of children</i>	-0.0015 (-1.438)	-0.0015 (-1.447)
<i>No. of firms associated</i>	0.0059 (1.375)	0.0059 (1.373)
<i>Education</i>	-0.0026 (-1.297)	-0.0026 (-1.299)
<i>General interests</i>	-0.0029 (-0.278)	-0.0029 (-0.280)
<i>Music interests</i>	0.0011 (0.444)	0.0011 (0.447)
<i>Reading interests</i>	0.0041* (1.751)	0.0041* (1.753)
<i>Sport interests</i>	-0.0007 (-0.347)	-0.0008 (-0.349)
<i>Contribution</i>	0.0018 (0.707)	0.0018 (0.703)
<i>Investments</i>	-0.0016 (-0.380)	-0.0016 (-0.377)
<i>Wealth</i>	0.0021 (1.304)	0.0021 (1.301)
<i>FA controls</i>	Yes	Yes
<i>Firm</i> × <i>County</i> × <i>Year FE</i>	Yes	Yes
<i>N</i>	30,706	30,706
<i>R</i> ²	0.8941	0.8941

Appendix A. The Sample

This table reports the data filter process to obtain the sample for our baseline regression.

	<i>No. of FAs</i>	<i>No. of Surnames</i>
Number of FAs extracted from BrokerCheck and IAPD	1,529,115	270,567
Exclude FAs with missing cultural origin information	1,428,602	201,355
Exclude FAs with missing FA-level information	1,043,102	169,158

Appendix B. Variable Definition

<i>Variable</i>	<i>Definition</i>	<i>Source</i>
<i>FA misconduct</i>	Dummy variable equals one if the FA has at least one misconduct disclosure in a year and zero otherwise.	BrokerCheck; IAPD
<i>FA corruption</i>	FAs' corruption value. The corruption value is based on the Corruption Perception Index of FAs' cultural origins inferred from their surnames using the immigration records of passengers who arrived at the port of New York from foreign ports between 1820 and 1957.	BrokerCheck; IAPD; <i>Ancestry.com</i> ; Transparency International
<i>Prior misconduct</i>	Dummy variable equals one if the FA has a misconduct record prior to the current year and zero otherwise.	BrokerCheck; IAPD
<i>Experience</i>	The number of years since the FA passed the first qualification exam.	BrokerCheck; IAPD
<i>Female</i>	Dummy variable equals one if the FA is female and zero otherwise.	GenderChecker; <i>genderize.io</i> ; Discovery Data
<i>Investment Adviser (65/66)</i>	Dummy variable equals one if the FA passed the <i>Investment Adviser Exam</i> in or before the current year and zero otherwise.	BrokerCheck; IAPD
<i>Securities Agent State Law (63)</i>	Dummy variable equals one if the FA passed the <i>Securities Agent State Law Exam</i> in or before the current year and zero otherwise.	BrokerCheck; IAPD
<i>General Securities Rep. (7)</i>	Dummy variable equals one if the FA passed the <i>General Securities Representative Exam</i> in or before the current year and zero otherwise.	BrokerCheck; IAPD
<i>Investment Company Product Rep. (6)</i>	Dummy variable equals one if the FA passed the <i>Investment Company Product Representative Exam</i> in or before the current year and zero otherwise.	BrokerCheck; IAPD

<i>General Securities Principal (24)</i>	Dummy variable equals one if the FA passed the <i>General Securities Principal Exam</i> in or before the current year and zero otherwise.	BrokerCheck; IAPD
<i>Number of other qualifications</i>	The number of qualifications other than Series 6, 7, 24, 63, 65, and 66 that the FA possesses.	BrokerCheck; IAPD

Online Appendix:

Corruption Culture and Financial Advisor Misconduct

Online Appendix A: Additional Tables

Table A1. List of Frequency Distribution of Cultural Origin

Table A2. Semiparametric Control Function

Table A3. Validate the Epidemiological Approach

Online Appendix B: Disclosure Definitions

Online Appendix C: Semiparametric Control Function

Table A1. List of Frequency Distribution of Cultural Origin

This table presents the list of the frequency distribution (%) of each cultural origin across all FAs in our sample.

<i>Cultural Origin</i>	<i>Frequency (%)</i>
<i>United Kingdom</i>	21.4313
<i>Germany</i>	12.9241
<i>Italy</i>	11.6759
<i>Ireland</i>	7.1532
<i>Scandinavia</i>	3.7250
<i>France</i>	2.8576
<i>Spain</i>	2.5697
<i>Netherlands</i>	2.3410
<i>Jewish</i>	2.1916
<i>Poland</i>	1.7932
<i>Sweden</i>	1.3568
<i>Russia</i>	1.3247
<i>Hungary</i>	1.2319
<i>Norway</i>	1.1705
<i>Austria</i>	0.8009
<i>China</i>	0.7823
<i>Greece</i>	0.7352
<i>Denmark</i>	0.7345
<i>Canada</i>	0.6871
<i>Switzerland</i>	0.5614
<i>India</i>	0.5508
<i>Portugal</i>	0.5049
<i>Belgium</i>	0.4752
<i>Slovakia</i>	0.4306
<i>Cuba</i>	0.3983
<i>Puerto Rico</i>	0.3544
<i>Czechia</i>	0.3417
<i>Finland</i>	0.3288
<i>Japan</i>	0.2810
<i>Latin America</i>	0.2415
<i>Croatia</i>	0.2411
<i>Romania</i>	0.2044
<i>Mexico</i>	0.1851
<i>Syria</i>	0.1820
<i>Slovenia</i>	0.1396
<i>Brazil</i>	0.1284

<i>Philippines</i>	0.1131
<i>Africa</i>	0.1101
<i>Lithuania</i>	0.0847
<i>Venezuela</i>	0.0830
<i>Armenia</i>	0.0610
<i>Turkey</i>	0.0608
<i>Chile</i>	0.0598
<i>Polynesia</i>	0.0588
<i>Australia</i>	0.0554
<i>Argentina</i>	0.0533
<i>Latvia</i>	0.0410
<i>Serbia</i>	0.0404
<i>Bulgaria</i>	0.0382
<i>Israel</i>	0.0376
<i>Arab World</i>	0.0351
<i>Colombia</i>	0.0348
<i>Malta</i>	0.0291
<i>Estonia</i>	0.0290
<i>Honduras</i>	0.0276
<i>Egypt</i>	0.0218
<i>Yugoslavia</i>	0.0189
<i>Dominican Republic</i>	0.0184
<i>Asia</i>	0.0183
<i>Albania</i>	0.0181
<i>Panama</i>	0.0141
<i>North Macedonia</i>	0.0128
<i>Bosnia and Herzegovina</i>	0.0120
<i>Peru</i>	0.0119
<i>Malaysia</i>	0.0110
<i>South Africa</i>	0.0099
<i>Pacific Islander</i>	0.0096
<i>Montenegro</i>	0.0095
<i>Ecuador</i>	0.0091
<i>West Indies</i>	0.0087
<i>Iceland</i>	0.0084
<i>Costa Rica</i>	0.0078
<i>Bermuda</i>	0.0074
<i>Iran</i>	0.0072
<i>Lebanon</i>	0.0063
<i>Jamaica</i>	0.0056

<i>Ukraine</i>	0.0049
<i>Czechoslovakia</i>	0.0046
<i>Haiti</i>	0.0042
<i>Palestine</i>	0.0034
<i>Uruguay</i>	0.0029
<i>Jordan</i>	0.0028
<i>Nicaragua</i>	0.0027
<i>New Zealand</i>	0.0027
<i>Indonesia</i>	0.0021
<i>Muslim</i>	0.0020
<i>Guatemala</i>	0.0019
<i>Pakistan</i>	0.0015
<i>Iraq</i>	0.0013
<i>Bolivia</i>	0.0011
<i>South Korea</i>	0.0011
<i>Sudan</i>	0.0008
<i>Ethiopia</i>	0.0007
<i>Morocco</i>	0.0007
<i>Algeria</i>	0.0006
<i>Barbados</i>	0.0006
<i>Liberia</i>	0.0006
<i>El Salvador</i>	0.0005
<i>Senegal</i>	0.0005
<i>Burma</i>	0.0004
<i>Mongolia</i>	0.0004
<i>Paraguay</i>	0.0004
<i>Hispanic</i>	0.0004
<i>Tunisia</i>	0.0003
<i>Afghanistan</i>	0.0003
<i>Cyprus</i>	0.0003
<i>Vietnam</i>	0.0003
<i>Central America</i>	0.0003
<i>Somalia</i>	0.0002
<i>Suriname</i>	0.0002
<i>Sri Lanka</i>	0.0002
<i>Thailand</i>	0.0001
<i>Luxembourg</i>	0.0001

<i>United States</i>	13.0455
<i>Unclear</i>	2.5711

Table A2. Semiparametric Control Function

This table presents the regression results of a linear probability model that estimates the relation between corruption culture and FA misconduct. Observations are at the FA-year level. The dependent variable, *FA misconduct*, equals one if the FA has at least one misconduct disclosure in a year and zero otherwise. *FA corruption* is FAs' corruption value based on the Corruption Perception Index of FAs' cultural origins inferred from the surname. We address the sample selection concern using a two-step semiparametric control function. We restrict the sample to FAs with an initial misconduct record but did not experience a job separation following misconduct. Variables definitions are described in Appendix B. Robust t-statistics corrected for clustering by the firm are reported in parentheses. ***, **, or * next to the coefficients indicates that the coefficients significantly differ from zero at the 1%, 5%, or 10% levels, respectively.

<i>Dep. Var.:</i>	<i>FA misconduct</i>		
	[1]	[2]	[3]
<i>FA corruption</i>	0.0637** (2.406)	0.0631** (2.396)	0.0138* (1.878)
<i>FA controls</i>		Yes	Yes
<i>Firm FE</i>			Yes
<i>County FE</i>			Yes
<i>Year FE</i>			Yes
<i>N</i>	305,610	305,610	305,610
<i>R</i> ²	0.0012	0.0022	0.0693

Table A3. Validate the Epidemiological Approach

This table reports the individual-level ordered probit regression results on the relation between the corruption value of the country of ancestry and the corruption attitudes of respondents in the U.S. General Social Survey between 1972 and 2021. The number of observations in each regression is the number of valid respondents in the corresponding survey question. *Corruption survey* is the CPI of the ancestry country reported by the respondent. *Female* equals one if the respondent is female and zero otherwise. *Age* is the age of the respondent at the time of the survey. *Education* is the number of years of formal education of the respondent. *Income* is the family income of the respondent scaled by 10,000 in constant 1986 U.S. dollars. *Married* equals one if the respondent was married at the time of the survey and zero otherwise. *White (Black)* equals one if the race of the respondent is white (black) and zero otherwise. *Employed* equals one if the respondent works full time and zero otherwise. z-statistics reported in parentheses are calculated based on heteroskedasticity-consistent standard errors.

<i>Dep. Var.:</i>	<i>Govcheat</i> [1]	<i>Taxcheat</i> [2]	<i>Anomia3</i> [3]	<i>Anomial</i> [4]	<i>Wrkearn</i> [5]	<i>Hiinc</i> [6]
<i>Corruption survey</i>	-0.3529** (-2.0792)	-0.4520*** (-2.8350)	-0.7789*** (-6.0484)	-0.7494*** (-5.9026)	-0.5229*** (-4.6163)	-0.5524*** (-4.8221)
<i>Female</i>	0.1657*** (2.6013)	0.1884*** (3.1703)	0.1098* (1.9289)	0.004 (0.0720)	0.0950** (2.4396)	-0.0252 (-0.6220)
<i>Age</i>	0.0001 (0.0696)	0.0040** (2.1486)	0.0031* (1.8294)	-0.0126** (-7.9157)	0.0010 (0.8829)	0.0038*** (3.0760)
<i>Education</i>	0.0567*** (4.6285)	0.0381*** (3.3461)	0.0866*** -8.4089	0.0923*** -9.3936	0.0937*** -12.7121	0.0566*** -7.5695
<i>Income</i>	0.0149 (1.0034)	-0.0117 (-0.9019)	0.0581*** (3.9972)	0.0249* (1.9097)	0.0305*** (4.0773)	-0.0187*** (-2.6389)
<i>Married</i>	0.1307** (1.9608)	0.1759*** (2.812)	0.0299 (0.5042)	-0.0601 (-1.0268)	-0.0244 (-0.6032)	0.0727* (1.7259)
<i>White</i>	-0.0831 (-0.4607)	-0.1491 (-0.8342)	0.1958 (0.7081)	0.2517 (0.9236)	0.0923 (1.0521)	0.1894** (1.9862)
<i>Black</i>	-0.2271 (-0.8670)	-0.2344 (-0.9421)	-0.1219 (-0.4012)	-0.6123** (-2.0317)	-0.2768** (-2.2680)	-0.2659* (-1.8425)
<i>Employed</i>	0.0175 (0.2556)	-0.0864 (-1.3440)	-0.0109 (-0.1812)	0.0092 (0.1591)	0.0294 (0.7151)	-0.066 (-1.5240)
<i>N</i>	1502	1475	2976	3032	3183	3176
<i>Pseudo R²</i>	0.0191	0.0146	0.0649	0.1052	0.0393	0.0229

Online Appendix B. Disclosure Definitions

This table presents the definitions of 23 disclosure categories in FINRA (<http://brokercheck.finra.org>). * indicates the misconduct disclosure categories defined by Egan, Matvos, and Seru (2019).

Disclosure Category	Definition
<i>*Civil – Final</i>	This type of disclosure event involves (1) an injunction issued by a court in connection with the 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.
<i>Civil - On Appeal</i>	This type of disclosure event involves an injunction issued by a court in connection with the investment-related activity or a finding by a court of a violation of any investment-related statute or regulation currently on appeal.
<i>Civil - Pending</i>	This type of disclosure event involves a pending civil court action that seeks an injunction in connection with any investment-related activity or alleges a violation of any investment-related statute or regulation.
<i>Civil Bond</i>	This type of disclosure event involves a civil bond for the adviser that has been denied, paid, or revoked by a bonding company.
<i>*Criminal - Final Disposition</i>	This type of disclosure event involves a criminal charge against the adviser that has resulted in a conviction, acquittal, dismissal, or plea. The criminal matter may pertain to any felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property.
<i>Criminal - On Appeal</i>	This type of disclosure event involves a conviction for any felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property that is currently on appeal.
<i>Criminal - Pending Charge</i>	This type of disclosure event involves a formal charge for a crime involving a felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property is currently pending.
<i>*Customer Dispute - Award/Judgment</i>	This type of disclosure event involves a final, consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the adviser that resulted in an arbitration award or civil judgment for the customer.

<i>*Customer Dispute - Settled</i>	<p>This type of disclosure event involves a consumer-initiated, investment-related complaint, arbitration proceeding, or civil suit containing allegations of sales practice violations against the adviser that resulted in a monetary settlement to the customer.</p>
<i>Customer Dispute - Closed - No Action/Withdrawn/Dismissed/Denied/Final</i>	<p>This type of disclosure event involves (1) a consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the individual adviser that was dismissed, withdrawn, or denied or (2) a consumer-initiated, investment-related written complaint containing allegations that the adviser engaged in sales practice violations resulting in compensatory damages of at least \$5,000, forgery, theft, or misappropriation, or conversion of funds or securities, which was closed without action, withdrawn, or denied.</p>
<i>Customer Dispute - Pending</i>	<p>This type of disclosure event involves (1) a pending consumer-initiated, investment-related arbitration or civil suit that contains allegations of sales practice violations against the adviser or (2) a pending, consumer-initiated, investment-related written complaint containing allegations that the adviser engaged in sales practice violations resulting in compensatory damages of at least \$5,000, forgery, theft, or misappropriation, or conversion of funds or securities.</p>
<i>*Employment Separation After Allegations</i>	<p>This type of disclosure event involves a situation in which the adviser voluntarily resigned, was discharged, or was permitted to resign after being accused of (1) violating investment-related statutes, regulations, rules, or industry standards of conduct; (2) fraud or the wrongful taking of property; or (3) failure to supervise in connection with investment-related statutes, regulations, rules, or industry standards of conduct.</p>
<i>Financial - Final</i>	<p>This type of disclosure event involves a bankruptcy, compromise with one or more creditors, or Securities Investor Protection Corporation liquidation involving the adviser or an organization the adviser controlled that occurred within the last ten years.</p>
<i>Financial - Pending</i>	<p>This type of disclosure event involves a pending bankruptcy, compromise with one or more creditors, or Securities Investor Protection Corporation liquidation involving the adviser or an organization the adviser controlled that occurred within the last ten years.</p>
<i>Investigation</i>	<p>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.</p>
<i>Judgment/Lien</i>	<p>This type of disclosure event involves any unsatisfied and outstanding judgments or liens against the adviser.</p>

**Regulatory - Final*

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

Regulatory - On Appeal

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

Regulatory - Pending

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

Online Appendix C. Semiparametric Control Function

There is a potential selection issue when we examine recidivism for FAs with different corruption values. This is because we can only observe the repeat offenses for those FAs who find new jobs in another FA firm. It could be the case that the FAs with a higher recidivism rate but a lower corruption value leave the industry. We address the sample selection issue using a two-step semiparametric control function. In the first-step regression, we estimate the propensity of the FA to experience a job separation following the initial misconduct using the following model:

$$Separation_{i,t+1} = \lambda \mathbf{X}_{i,t} + \mu_j + \mu_l + \mu_t + \varepsilon_{i,t+1}, \quad (OA1)$$

where $Separation_{i,t+1}$ indicates whether FA i left the firm in year $t+1$. We include the same set of FA controls as in Equation (2), as well as firm, county, and year fixed effects. The parameters are allowed to vary across different corruption values. We extract the predicted values from the first-step regression as the propensity of the FA to experience a job separation, denoted as $\widehat{Separation}$.

In the second step, we estimate the following recidivism model controlling the fourth-order polynomial of $\widehat{Separation}$:

$$FA\ misconduct_{i,t} = \lambda \mathbf{X}_{i,t} + \sum_{n=1}^4 \delta_n \widehat{Separation}^n + \mu_j + \mu_l + \mu_t + \varepsilon_{i,t}, \quad (OA2)$$

where $\sum_{n=1}^4 \delta_n \widehat{Separation}^n$ denotes the fourth-order polynomial of $\widehat{Separation}$. We restrict the sample to FAs with an initial misconduct record but did not experience a job separation following misconduct. We use the FA's past characteristics at the time of misconduct as the exclusion restriction, which is required by the semiparametric model. The exclusion restriction requires that the past characteristics (determining whether the FA experiences a job separation following misconduct) are unrelated to recidivism, conditional on the FA's current characteristics. The results of the semi-parametric control function are reported in Table A2. It shows a positive and significant relation between the FA's corruption value and the propensity of misconduct regardless of model specifications, suggesting that FAs with a higher corruption value tend to be repeat offenders.