Auditors are Known by the Companies They Keep*

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Abstract

We study the role of client reputation in auditor-client matching. Using 1.2 million employment records from US broker-dealers, we find that broker-dealer clients of the same auditor have very similar financial adviser misconduct profiles. Misconduct is approximately half as important as client size in explaining auditor-client matches, and misconduct unrelated to misreporting or fraud risk is relevant to this matching. We link these matching patterns to auditors' heterogeneous preferences for client reputation. An auditor's track record for accepting high misconduct clients predicts future client misconduct, even after controlling for the client's misconduct record and characteristics. Additional results reveal that auditor-client reputation matching is widespread and generalizable to firms outside the investment industry. We interpret our results within a positive assortative matching framework, and conclude that auditors' differential reputation concerns relate to their client acceptance and continuance decisions.

JEL Classification: M21, M41, M42, G24, G28, D14, D18

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1. Introduction

Much research on audit relationships analyzes a client's selection of their auditor. For example, clients select auditors as a function of their size, industry, or desired audit quality (DeFond and Zhang, 2014). More recent work takes a nuanced view of audits as a "credence good" in which customers cannot fully understand the quality of the service purchased (Causholli and Knechel, 2012). As such, clients often rely on auditor reputation to assess quality. One implication of this reliance is that auditors deliver a sufficient level of audit quality to avoid fraud and misreporting incidents that harm their reputation and jeopardize their future rents (DeAngelo, 1981; Weber, Willenborg and Zhang, 2008). A second, less explored implication is that auditors protect their reputation by actively managing the clients they accept and keep in their portfolio. A market characterized by sellers and buyers screening one another is referred to as a two-sided matching market (Rysman, 2009; Azevedo and Leshno, 2016). In such a market, the benefit a customer receives from a seller is contingent, in part, on the number or types of other customers that seller has.[1]

In this paper, we investigate three empirical predictions of two-sided matching based on reputation in audit markets. First, an auditor's clients "look alike" in terms of their track record of behavior. Second, auditors doing business in reputation-sensitive markets will avoid clients having track records of misconduct; such clients will instead match with auditors not participating in reputation-sensitive markets. Third, when auditors gain access to more information about client misconduct, similarities among clients within auditors' portfolios will increase.

We investigate these predictions in the US broker-dealer (BD) market. BDs play a crucial role in financial intermediation by providing financial planning services to US households and executing over $40 trillion of transactions on their behalf annually. For our purposes of investigating the role of reputation in the matching between auditors and clients, the BD setting offers two

[1] By contrast, a prototypical one-sided market is a farmer selling grain. The farmer does not care who is buying the grain, and the buyer does not care who else has purchased grain from the farmer.

key advantages. First, *individual* financial advisers must register with the Financial Industry Regulatory Authority (FINRA), and their detailed employment history and misconduct records (if any) are public. The most common misconduct incidents involve the sale of unsuitable investments, misrepresentation, unauthorized activity, fraud, negligence, and excessive trading. For each incident, we observe the date, identity of the adviser and their employer, as well as a description of the misconduct behavior and outcomes including sanctions, employment terminations, and bans from the industry. We use the misconduct records for over 1.2 million financial advisers to develop a proxy for the reputation of BD firms, and henceforth use "reputation" and "misconduct" interchangeably.[2] Having objective, comprehensive information about advisers' misconduct records permits us to sidestep well known measurement issues that hamper research on misconduct in firms. Specifically, we do not have to restrict our analysis to the top officers of a given firm, or rely upon survey instruments to extract information about an employee's own misbehavior.

Second, all BDs must undergo audits and file their financial statements with the SEC, allowing us to observe the complete client portfolio for all audit firms in this market, as opposed to observing only the public clients. Each year, nearly 4,000 US BD firms contract with 700 audit offices of 400 auditors, ranging in size and BD client exposure. BDs have anywhere from one to tens of thousands of advisers. Twelve percent of the typical BD's advisers have a misconduct event on their record; however, some BDs have a zero tolerance policy, while others appear to specialize in misconduct (Egan, Matvos, and Seru, 2018). Thus, the BD setting is well suited to studying our predictions: we observe all auditor-client matches, we have an operational measure of client behavior, and there exists rich heterogeneity in BD characteristics that enables us to isolate the role of reputation in matching.

[2] In this respect our approach is similar to Davidson, Dey, and Smith (2015) and Pacelli (2018), who develop proxies for managerial style and corporate culture, respectively.

We find reputation plays an important role in the formation of auditor-client pairs: the misconduct record of a BD's advisers *prior to* the audit engagement is strongly related to the adviser misconduct records of the audit office's other clients.[3] We then document three ways in which auditor screening contributes to this matching. First, auditors with reputation concerns stemming from their (non-BD) publicly held and IPO client engagements are least likely to deal with high misconduct BDs. Second, low misconduct auditors appear to be the least inclined of all auditors to accept or continue with high misconduct clients. Third, auditors increase their concentration in a given client misconduct segment following an increase in transparency surrounding client behavior. Collectively, our results are consistent with positive assortative matching (Becker, 1973), where two parties, each with their own preferences, match based on a positive correlation of characteristics. Additional results reveal that positive assortative matching on misconduct is a widespread phenomenon found in BDs of all sizes, and extends to settings other than BDs.

To gauge the economic importance of misconduct matching, we begin by studying assortative matching based on size, which is somewhat mechanical given auditor resource constraints. We sort BDs into small, medium, and large terciles according to their size, and audit offices into small, medium, and large terciles according to the average size of their clients. If size is not important to matching, we should find that small BDs match with large auditors roughly as frequently as large BDs. However, we find small (large) BDs matching with large (small) auditors only 17.0% (18.3%) of the time; while the likelihood of a small (large) BD matching with a small (large) auditor is 48.9% (55.1%).

We then compare these size-based matching rates to those using misconduct rates. Following Egan et al. (2018), we measure the misconduct of BDs as the percent of a BD's advisers with

[3] We use the terms "audit office", "office", and "auditor" interchangeably throughout the paper.

a misconduct record. We use these percentages to assign BDs to low, medium, and high misconduct terciles. We then assign auditors to misconduct terciles using the average misconduct rates of their clients in the prior year. Controlling for BD size, we find relatively few "mismatched" pairs: high (low) misconduct BDs match with low (high) misconduct auditors only 19.2% (27.3%) of the time, compared to 42.0% (35.2%) with high (low) misconduct auditors.

We confirm these initial findings using a regression framework with year fixed effects for each BD size tercile, type, and district, along with controls for other client and audit characteristics. Notably, we find the association between a BD's misconduct record and the misconduct record of their auditor's other clients is roughly 50% as important to matching as the association for client size. Our results survive when we study BDs switching because their prior audit office exited the BD market, suggesting that unobservable BD business model shocks alone do not explain our results. We also find the same results after controlling for investment product offering x year fixed effects, indicating our findings do not stem from auditor specialization in high misconduct products or from product market conditions.

One might be concerned about the relevance of our reputation-based assortative matching results if they were limited to the smallest BDs. However, we find this matching in both large (including, for example, Charles Schwab, Citi, JPMorgan, Oppenheimer, and Wells Fargo) and small BDs. In addition, we find matching among BDs using Global Network Audit Firms as well as both privately and publicly held BDs. Finally, although the BD setting is well suited for our research question for reasons we highlight above, the BD industry has unique characteristics. Therefore, we develop firm-level misconduct measures based on the incidence of AAERs and meeting/beating analyst earnings forecasts to analyze all US public firms. We find significant auditor-client matching in public firms using these misconduct measures, and conclude that misconduct matching is relevant to a wide variety of audit relationships.

Next, we study the types of misconduct that explain our matching findings. One prediction motivated by prior literature (e.g., Lennox, 2000; Newton et al., 2016; Chen et al., 2016) is that financial reporting-related infractions drive misconduct matching. Indeed, many misconduct incidents in our sample do not indicate misreporting or problems with internal controls over reporting (e.g., client claims the adviser misrepresented the investment or the investment was unsuitable). However, when we omit reporting-related misconduct and study only BDs with inherently low audit risk, we continue to find statistically and economically significant misconduct matching.[4] This suggests that auditors screen clients based on both reporting *and non-reporting* behavior, a finding that we are not aware of being documented elsewhere.

We then demonstrate three ways in which auditor selectivity over their portfolio of clients, rather than client preferences over auditor characteristics alone, contributes to the positive assortative matching. First, we examine the relation between an auditor's non-BD portfolio and the misconduct profile of their BD clients. IPO clients are particularly sensitive to their auditor's reputation, given information asymmetry problems and litigation risk (Willenborg, 1999; Pittman and Fortin, 2004; Li, McNichols, and Raghunandan, 2018). We therefore expect auditors of IPO clients to be least inclined to accept high misconduct BDs. We find less misconduct among BD clients of auditors dealing with IPO firms. This finding applies even across offices within the same audit firm, indicating that both audit office and firm-level variation in reputation concerns are relevant to client portfolio decisions.

Second, we uncover an asymmetry in the matching pattern that is indicative of auditor selectivity. If client preferences alone explained our findings, then low misconduct clients should

[4] The fallout from the recent discovery of widespread sales misconduct at Wells Fargo's helps illustrate this result. Wells Fargo was caught opening millions of fake customer accounts, leading several lawmakers to publicly question the quality of their auditor's (KPMG) work and call for PCAOB investigation. While KPMG asserted that "not every illegal act has a meaningful impact on a company's financial statements", their awareness of sales misconduct could harm their reputation (McKenna and Riquier, 2017).

be as unlikely to pair with high misconduct auditors as vice-versa. However, we find that low auditor misconduct-high client misconduct pairs (19.2%) are significantly less common than high auditor misconduct-low client misconduct pairs (27.3%). In fact, the low auditor misconduct-high client misconduct pair's deviation from the null of no matching is *nearly double* that of the converse pair, suggesting that auditor preferences are potentially *more* important than client preferences in explaining our matching results. Reinforcing this, we show that the auditor-client relationship length among the most mismatched pairs is not uniformly shorter: low auditor misconduct-high client misconduct pairs separate significantly sooner than high auditor misconduct-low client misconduct pairs. Again, this asymmetry is consistent with audit firm portfolio management (Shu, 2000; Johnstone and Bedard, 2004) rather than solely a client preference.

Third, we study the 2007 modernization of the BrokerCheck website, which significantly reduces the cost of identifying BD misconduct, but provides no new information to clients about audit firms. Prior to the modernization, the website primarily contained BD-level registration information. A user could make a phone or written request for a summary report about any individual adviser, and FINRA would respond to requests via mail or email. If a summary report revealed misconduct, the user would then need to file a subsequent request to obtain relevant details of the disclosure (NASD, 2007). The modernized website provides free, instantaneous, readily searchable information about all financial advisers and their misconduct. We show that post-modernization, auditors increasingly concentrate their client portfolios in a given misconduct segment, suggesting that transparency of BD behavior intensifies misconduct matching.

From our collection of findings, we infer that auditors have heterogeneous preferences over client reputation, leading to positive assortative matching based on misconduct. An alternative explanation for our findings is that misconduct is correlated with clients' financial constraints, and these constraints lead to price sensitivity that explains the matching. However, we view price rationing as a mechanism contributing to our results, not a separate factor. Specifically, higher reputation auditors are able to charge more precisely because they have earned their reputation, in part, by screening lower quality clients. Similarly, there are other auditors lacking reputation who match with clients with no preferences over auditor quality, only price. Therefore, price, in part, serves as the rationing mechanism. However, we lack pricing data to formally establish this rationing mechanism.

We conclude our analyses by highlighting an important implication of our matching results: the identity of a BD's new auditor predicts the BD's future misconduct over-and-above the BDs' own misconduct record. We model a BD's future misconduct as a function of their current and past misconduct, their new auditor's misconduct profile, as well as the controls and fixed effects from our main specification. We find that those BDs matching with a high misconduct auditor subsequently engage in significantly more misconduct than otherwise similar BDs matching with a low or medium misconduct auditor.

We offer two contributions. First, we document how auditor reputation preferences shape auditor-client matching and the structure of audit markets. Except for a handful of field studies examining acceptance decisions of a single audit firm (e.g., Johnstone and Bedard, 2003, 2004), there is little evidence on screening efforts by auditors specifically or the relevance of client misconduct (reporting-related or otherwise) to audit markets generally. The strong size and misconduct selection effects we document are relevant to research attempting to investigate how auditors affect client behavior. Second, by linking auditor-BD matches to future misconduct, we offer early evidence of an investor protection function for auditors in overseeing BD intermediaries. While BD misconduct has real effects on investor participation and has attracted much attention from academics and regulators, auditors' role in this setting is not well understood.

2. Theoretical Framework and Prior Literature

We study auditor-client matches using the theoretical framework of assortative matching, which refers to a process by which buyers and sellers match with one another (Gale and Shapley, 1962; Becker, 1973). *Positive* assortative matching describes the tendency of parties to match with their peers—"birds of a feather." Examples of positive assortative matching include partners of similar income, education, or age being more likely than random to marry one another. *Negative* assortative matching describes cases where parties avoid matching with those similar to themselves—"opposites attract."

In studying auditor-client relationships, the audit literature focuses on several *client* preferences over auditors, such as auditor size or industry specialization. In terms of size, clients seek auditors with sufficient resources (e.g., labor and capital) to conduct the audit, remain independent, and accept any litigation risk (DeAngelo, 1981; Dye, 1993; Lennox, 1999). Clients with complex operations may prefer an auditor with expertise in their industry (Hogan and Jeter, 1999; Gerakos and Syverson, 2015). Moreover, firms relying on public financing or accessing the public markets for the first time are more likely to seek a reputable auditor because public capital providers lack private information about the firm and are poorly positioned to monitor it (Bills and Jensen, 2010; Weber and Willenborg, 2003; Mansi, Maxwell, and Miller, 2004; Pittman and Fortin, 2004).

A client's preference for a reputable auditor can strengthen the *auditor's* preferences for reputable clients. Recent literature arguing that audits are a credence good illustrates this point (Causholli and Knechel, 2012). A credence good is one in which the quality is not known to the buyer, even after consumption, due to information asymmetries between the producer and consumer (Darby and Karni, 1973). For example, many medical services are credence goods because the patient lacks the expertise ex-ante to evaluate the quality of the care provider or the effectiveness of their treatment ex-post. In the case of audits, clients do not observe the extent or quality of work performed as this work takes place. Absent an obvious ex-post failure (e.g., revelation of fraud linked to weak internal controls), the client may still lack the ability to assess audit quality after it was performed. In credence good markets, consumers often rely on a producer's reputation to help evaluate the quality of services they provide. The central hypothesis of our paper is that an auditor's reputation is in part formed by their client portfolio—auditors are known by the companies they keep. Producers with a reputation for providing high quality services to high quality clients can, in turn, charge a premium for their output.

Since DeAngelo's (1981) canonical work, the literature has focused on how the existence of quasi-rents creates an incentive for auditors to deliver audit quality and maintain their reputation (e.g., Becker, DeFond, and Jiambalvo, 1998; Dechow Ge, and Schrand, 2010). However, DeAngelo also discusses how an auditor's quasi-rents provides them with "an incentive to design their client portfolios" (pp. 197). While DeAngelo was concerned with the issue of auditor independence, her argument broadly applies to the auditor's overall portfolio strategy: quasi-rents will discipline client acceptance and continuation decisions. For our purposes, auditors whose clients have strong reputation preferences face the strongest incentives to screen—to decline new clients with track records of misconduct and separate from existing clients with such records.

Much of the empirical evidence on auditor screening comes from field and experimental work. Johnstone and Bedard (2003, 2004) use data from a large audit firm to test a model of portfolio management decisions, including client acceptance, continuance, and billing. They find that this firm sheds riskier clients and that newly accepted clients are less risky than continuing clients (particularly in terms of characteristics related to audit risk, including management culture).[5] Johnstone (2000) conducts an experiment with 137 audit partners, and finds that these partners are more inclined to manage client risk by avoiding risky clients than by adapting to the risks the clients present. Bell, Landsman, and Shackelford (2001) access survey data from a large audit firm, and report that auditors adapt to client-related risks by billing for additional effort.

[5] See also Bell, Bedard, Johnstone, and Smith (2002).

In the IPO market, Li et al. (2018) find matching between clients and auditors on reporting quality, and that Big 4 auditors provide higher audit quality. Another stream of literature finds that auditor portfolios changed following Sarbanes-Oxley (Landsman, Nelson, and Rountree, 2009) and AS5 (Schroeder and Hogan, 2013), and attributes these portfolio changes to shifts in auditor preferences for misreporting risk.[6]

Collectively, we argue that auditors have heterogeneous preferences for client reputation, leading to auditor selectivity having a significant role in matching. While some prior (primarily field) work has investigated auditor selectivity, difficulties associated with measuring client reputation specifically and auditor portfolio decisions generally have prevented researchers from using large sample archival methods to confirm and extend this line of work. As a result, the extent and importance of auditor screening based on client reputation to the audit market as a whole is not well understood.

3. Setting, Data, and Summary Statistics

3.1 Setting: Broker-Dealers in the US

We study auditor-client relationships in the US broker-dealer market. Brokers execute securities transactions for their customers, whereas dealers execute securities transactions for themselves. When selling a proprietary holding to a customer, the entity is acting as both a broker and a dealer. Because brokers and dealers participate in the same market for investors, face the same audit regulations, and the literature studies them as a group, we follow the convention and study brokers and dealers together.

BDs deal in a variety of investment products, including exchange-traded equities, debt, options, variable life insurance, mutual funds, mortgage-backed securities, and other securities.

[6] See also the research on auditor resignations (Shu, 2000), litigation (Krishnan and Krishnan, 1997; Venkataraman, Weber, and Willenborg, 2008), auditor dismissals (Francis and Wilson, 1988; Johnson and Lys, 1990; Haskins and Williams, 1990), and regulation (Duguay, Minnis, and Sutherland, 2018; Ferguson, Pinnuck, and Skinner 2018).

They can trade on the floor of the exchange, transact in privately-placed securities, or underwrite and create markets for securities. BD customers range from individual households to large institutional investors. In 2017, BDs executed over $42 trillion of transactions and generated over $308 billion of revenue (FINRA, 2018). That year, there were 3,726 BDs in the US employing over 630,000 FINRA-registered advisers.

BDs are regulated by the SEC under Rule 17a-5 of the 1934 Act. BDs are required to submit audited annual reports, which identify the auditor but not the audit price. BD audits provide reasonable assurance that the financial statements and required regulatory calculations are fairly stated, in all material respects, in conformity with US GAAP.[7] In 2017, there were 431 BD auditors with 690 offices. Audit firm sizes range from sole proprietors to Big N firms.

In addition to SEC regulation, BDs are subject to FINRA oversight. FINRA is a self-regulated enforcement agency tasked with protecting investors in the US securities industry. In this role, FINRA oversees firm and adviser licensing, writes and enforces rules, performs periodic examinations, and facilitates industry transparency with the overarching aim of protecting investors and market integrity. To facilitate industry transparency, FINRA compiles and publicly reports customer complaints and adviser infractions in its BrokerCheck database. This database is the source of our misconduct and employment data.

Our use of the BrokerCheck data follows recent work investigating the causes and consequences of financial adviser misconduct. This literature focuses on how the past behavior of financial advisers and the compliance culture of BDs predict misconduct (Dimmock and Gerken, 2012; Qureshi and Sokobin, 2015; Egan et al., 2018; Dimmock, Gerken, and Graham, 2018; Honigsberg and Jacob, 2018; Law and Mills, 2018; Parsons, Sulaumen, and Titman, 2018). In terms of conse-

[7] See Bedard et al. (2014) and Kowaleski et al. (2018), for detailed discussion of mandatory regulatory capital calculations, reporting requirements, and attestation.

quences, Pacelli (2018) finds firm-level misconduct is associated with less accurate analyst forecasts and less informative reports. Gurun, Stoffman, and Yonker (2017) find that residents of communities experiencing investment fraud withdraw funds from BDs and increase bank deposits.

3.2 Data and Summary Statistics

We construct our sample using the intersection of two datasets. Audit Analytics' BD database compiles company, financial statement, and audit report information from EDGAR between 2001 and 2017. For misconduct records, we turn to FINRA's BrokerCheck database of individuals employed by BDs. In January 2018, we accessed BrokerCheck's database of BD adviser records. The database contains all registered advisers currently employed in the US securities industry, as well as individuals employed up to ten years prior.[8] Each record contains information about the individual's current employment, previous employment, exams passed, state licenses, as well as disclosures of customer complaints, arbitrations, regulatory actions, employment terminations, bankruptcy filings, and any civil or criminal proceeding involving them. Figure 1 contains an example report from an individual in our sample. We aggregate the 1,228,778 adviser records in our sample to the BD-year level using the firm's unique central registration database number.

Table 1 details the construction of our sample using the Audit Analytics and FINRA data. Accessing all available Audit Analytics records between 2001 and 2017 yields 83,823 observations. Following Kowaleski (2017), we identify and remove 2,551 incomplete filings, and 3,561 filings with duplicate balance sheet, audit report, or attestation report variables, leaving us with 77,711 observations. After eliminating 1,763 observations missing FINRA data, 1,169 observations from foreign BDs, and 375 missing leverage, we arrive at our final sample of 74,404 BD-

[8] Following Egan et al. (2018), we use the term "financial adviser" and "adviser" interchangeably to refer to all FINRA-registered brokers, including those that are also registered investment advisers.

years.[9] For our main tests studying only new auditor-client relationships and requiring lagged variables, we have 6,855 BD-years. Table 2, Panel A presents summary statistics for the BD variables used in our analysis. The mean (median) *Total Assets* is \$1.00B (\$0.56M). We measure *Leverage* as the ratio of *Total Liabilities* to *Total Assets* and find that the mean ratio is 0.30. The average *BD Adviser Count* is 155. Seven percent of BDs are publicly traded. We categorize twenty percent of BDs as carrying BDs—those maintaining custody of ("carrying") investors' assets, while 48% are retail-focused.[10] The average BD firm age is 13.86 years. At the typical BD, the average adviser has 14.46 years of experience and has passed 2.12 of the six most common qualification exams (Series 6, 7, 24, 63, 65, and 66).

Panel B describes our audit variables. Nineteen percent (21%) of BDs have a *Big N* auditor, defined as the Big 4 plus Arthur Andersen (*Big N* plus BDO, Grant Thornton, and RSM). Five percent (2%) of BDs have an *IC Material Weakness (Going Concern* opinion). The typical audit office (defined as the intersection of an Auditor Name and an Opinion City in Audit Analytics) has 19.73 BD clients.[11] We observe audit offices with as few as one and as many as 144 clients.

Panel C presents summary statistics for our misconduct measures, which are based on Egan et al. 2018. Egan et al. classify six types of disclosures on advisers' records as relating to misconduct: Civil-Final, Criminal-Final Disposition, Customer Dispute-Award/Judgment, Customer Dispute-Settled, Employment Separation after Allegations, and Regulatory-Final. Appendix B provides a definition and example for each misconduct disclosure type. For each adviser each year,

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[9] We use the applicable SEC filing number or the BD's name to merge these files. Although the SEC requires each registered BD to annually file an audited report as if it were an independent entity, a number of BDs are affiliated with each other. We use Audit Analytics to identify BD affiliates on four dimensions: matching across parent ticker, parent name, parent CIK, and both address and auditor. We include affiliates in our analysis because affiliates often choose different auditors than one another, and because misconduct differs across affiliates. Nevertheless, when we drop all affiliates, we find the same results.

[10] BDs must maintain at least \$250,000 of Net Capital if they have custody of customer assets or clear trades. We define retail BDs as those where the typical adviser is registered in more than three states, following Qureshi and Sokobin (2015) and Honigsberg and Jacob (2018).

[11] Our main results are the same if we conduct our analysis at the auditor level, or if we eliminate auditors with more than one office.

we create an indicator for whether they have any misconduct that year, and an indicator for whether they had any misconduct on their record to date (i.e., this year or prior years, including with other employers). Then for each BD, similar to Qureshi and Sokobin (2015) and Egan et al. (2018) we take the average of each indicator across all of the BD's current advisers.

At the typical BD, 1% of advisers are involved in misconduct in the current year (*BD Misconduct Current*), while 12% have been involved at any point in their career (*BD Misconduct Ever*). We observe many BDs—including dozens with over 100 advisers—with not one single adviser with a misconduct record. For example, State Employees' Credit Union Brokerage Services (560 advisers), and Rothschild, Inc. (164 advisers) have zero advisers with a misconduct record. Other BDs have large concentrations of advisers with misconduct records. Two percent (15%) of the average BD's advisers have a current (prior) disclosure statement detailing a misconduct event, or a less serious infraction or dismissed complaint.

3.3 Non-parametric Analysis

In Table 3, Panel A, we partition auditor-BD pairs into terciles based on the size of the BD and the average size of the auditor's BD clients, both measured in the year before they matched. We form terciles rather than study raw figures in order to facilitate comparisons across size and misconduct characteristics, and to illustrate the degree of segmentation in the audit market. Measuring size with a lag relative to the match year ensures that our auditor size and BD size tercile assignments are not mechanically correlated.

Our non-parametric analysis involves three steps. First, we assign BDs to terciles each year according to their *Adviser Count* last year, with tercile 1 being the smallest and tercile 3 being the largest (*BD Size Tercile*).[12] Second, for each BD, we assign their *auditor* to terciles, based on the average size tercile of their BD clients (*Auditor Size Tercile*). Our choice to define an auditor based

[12] Assigning BDs to each size terciles based on Total Assets produces similar evidence, as shown in Table A1 of our online appendix.

on the size of their clients rather than on their own size is motivated by our matching hypothesis that clients match with auditors who deal with clients similar to them. However, we arrive at similar conclusions if we define auditors based on their own size (e.g., client count, or Global Network auditor vs. rest). Third, we include only the first year of each BD x auditor relationship, such that we assess the importance of size in the year of the "match". Using this approach, the number of small, medium, and large BDs is 2,364, 2,226, and 2,265 while the number for auditors is 2,365, 2,204, and 2,286, respectively.[13]

This simple non-parametric approach allows us to gauge the degree to which BDs and auditors match on size, and provides a benchmark for studying other characteristics (e.g., Berger, Minnis, and Sutherland, 2017). For example, the bottom row of Panel A shows the probability of each match type under the null hypothesis that size is not relevant to matching. Based on our size classifications, the null hypothesis is that 34.5% of BDs (regardless of their own size) match with small auditors, 32.2% with medium auditors, and 33.3% with large auditors.

However, actual matches do not follow this pattern. For the smallest BDs (tercile 1), 48.9% match with an auditor focusing on small clients; compared to 34.1% focusing on medium-sized clients and just 17.0% focusing on large clients. We uncover a similar pattern for medium (tercile 2) and large (tercile 3) BDs: BDs most often match with auditors concentrated in their size tercile. Opposite matches ("mismatches") are particularly rare: large BDs are least likely (18.3%) to match with small client auditors, just as small BDs are least likely to match with large auditors (17.0%). The Pearson's chi-squared test reported at the bottom of the panel rejects the null hypothesis of independence in auditor size and BD size at the 1% level. This evidence suggests that there is positive assortative matching between BDs and auditors with respect to size.

[13] Studying only the first year of each audit relationship and requiring lagged variables reduces our sample size from 74,404 to 6,855.

Panel B performs a similar exercise (again for only new relationships, and lagging BD and auditor characteristics), but studies misconduct records rather than size. We focus on *BD Misconduct Ever*, for two reasons. First, as Table 2, Panel C shows, misconduct events are rare, and counting only events occurring within the year significantly restricts the across-BD variation we can document. Second, there is significant persistence in misconduct at the individual level: Egan et al. (2018) report that prior offenders are five times as likely as the average adviser to engage in new misconduct.

We assign BDs to misconduct terciles *within* their size tercile (i.e., relative to their peers in *BD Size Tercile* 1, 2, or 3) last year (*BD Misconduct Tercile*). We then assign auditors to misconduct terciles based on the average misconduct terciles (1, 2, or 3) of their clients last year (*Auditor Misconduct Tercile*). We control for BD size in our misconduct analysis, for two reasons. First, size may be correlated with misconduct, because BDs with a reputation for misconduct may experience difficulty growing. Second, because we measure misconduct rates per adviser, the distribution of misconduct rates will differ between small BDs with few advisers and large BDs with many.

Panel B presents the results. The bottom row shows the null hypothesis for each match type: 30.7%, 37.9%, and 31.5% for matches with low, medium, and high misconduct auditors, respectively. In terms of actual matches, we find a similar, though less pronounced positive assortative matching pattern as in Panel A. BDs tend to match to an auditor belonging to the same misconduct tercile or a neighboring tercile. Opposite matches occur infrequently, with the least common of all matches being the high misconduct BD-low misconduct auditor pair. This latter finding suggests auditors avoid clients with misconduct records when they have reputations to protect.

Overall, Table 3 suggests that both size and misconduct are important drivers of auditor-client matches. However, we caution against interpreting the relative magnitudes of each characteristic from this analysis, for two reasons. First, many factors beyond size and misconduct can influence matching. Our next section develops a formal regression framework for isolating the contributions of size and misconduct to matches. Second, size and misconduct have distinct distributions, and despite similarities in how we assign parties to size and misconduct terciles, across-tercile changes in size and misconduct may not be directly comparable. Therefore, when we assess magnitudes in Section 4.2, we study raw size and misconduct rates, in addition to terciles.

4. Tests and Results

4.1 Empirical Specification

We study auditor-client matches using the following OLS specification:

$$y_{i,t-1} = \beta_1 \times BD\ Misconduct\ Tercile_{i,t-1} + \alpha_{c,t-1} + \alpha_{r,t-1} + \alpha_{s,t-1} + \gamma \times Controls_{i,t-1} + \varepsilon_{i,t-1}, \quad (1)$$

where the unit of observation is BD x year. Because we are interested in the match between BDs and auditors, we restrict our sample to the first year of each BD-auditor pair in our sample. $y_{i,t-1}$ is *Auditor Misconduct Tercile*, while our variable of interest is *BD Misconduct Tercile*$_{t-1}$. Both terciles are measured the year before BD *i*'s relationship with their auditor forms. We study these tercile measures in an OLS specification to facilitate economic interpretation and to include the set of fixed effects described below. Table 4 columns 3 and 4 and Appendix C show our inferences are the same using continuous measures and multinomial logit, respectively.

$\alpha_{c,t-1}$, $\alpha_{r,t-1}$, and $\alpha_{s,t-1}$ are carrying firm x year, FINRA district x year, and *BD Size Tercile* x year fixed effects. These fixed effects allow us to absorb trends in audit relationships within BD business type (carrying or not), district, and size tercile, as well as general economic conditions and auditing standards that are constant within a year.[14] The district x year fixed effects also help account for heterogeneity in the audit supply across different parts of the country.[15]

[14] The 11 districts include San Francisco, Los Angeles, Denver, Kansas City, New Orleans, Dallas, Atlanta, Chicago, Philadelphia, New York, and Boston. See http://www.finra.org/industry/finra-district-offices for district definitions.
[15] We use districts rather than states because 30% of BD-auditor pairs are not in the same state. Using a state x year design does not affect our inferences.

In addition to these fixed effects, we also employ a set of controls (all lagged) including the BD's *Leverage*, and whether the BD has an IC material weakness or going concern opinion that year (*IC Weakness*; *Going Concern*). To account for the possibility that, all else equal, more experienced advisers are more likely to have been involved with a misconduct event, we control for average adviser experience (*Log Average Adviser Experience*). We include a measure of the average number of qualifications for the BD's advisers (*Average Qualifications*). We also control for BD age (*Log BD Age*), ownership type (*Public Parent*), and business model (*Retail BD*). Last, although we control for *BD Size Tercile* x year fixed effects, we also include *Log Total Assets* and *Log BD Adviser Count* in our regressions, to ensure we are isolating the roles of size and misconduct in auditor-BD matching. We cluster our standard errors at the audit office level; clustering instead by auditor does not affect our inferences.

4.2 Auditor-Client Matching by Size and Misconduct

We begin by modeling *Auditor Size Tercile*. In this initial analysis, we use equation (1) but omit our controls for *Log Total Assets* and *Log BD Adviser Count*, as well as our size tercile x year fixed effects. Doing so facilitates a comparison between the effects of a one unit change in *BD Size Tercile* and a one unit change in *BD Misconduct Tercile*. As with section 3.4, starting with size provides a benchmark for assessing the relative importance of misconduct to matching.

Column 1 of Table 4 shows a significantly positive relation between *BD Size Tercile* and *Auditor Size Tercile*. The 0.204 coefficient on *BD Size Tercile* implies that a one tercile increase in BD size is associated with a 0.204 tercile increase in auditor size. Interestingly, the BD's *Misconduct Tercile* is negatively related to the *Auditor's Size Tercile*, indicating that high misconduct BDs match with smaller auditors. BDs with internal control weaknesses choose auditors with smaller clients. Publicly owned, retail, and carrying BDs choose auditors with larger clients.

Column 2 studies the relation between a BD's misconduct and the misconduct tercile of the auditor. We find the coefficient on *Misconduct Tercile* is significantly positive, and at 0.107, more than half the magnitude of *BD Size Tercile* from column 1. Columns 3 and 4 study size and misconduct using the log number of advisers and log misconduct rate, respectively. Using this approach rather than our terciling approach produces similar inferences. Moreover, considering the standard deviation of the log variables, misconduct is 43% as important as size in explaining matches. Thus, while size constraints are first order (a one-person audit firm lacks the resources to accept the largest BD), misconduct also plays an economically important role in the formation of audit relationships.

Column 5 presents the results from estimating specification (1).[16] We refer to this as our main result hereafter. We find a positive and significant relation between the BD's misconduct tercile and the auditor's misconduct tercile. The 0.100 coefficient implies that a one unit increase in the BD's misconduct tercile (e.g., from *Misconduct Tercile* 1 to 2 or 2 to 3) is associated with a 0.100 unit increase in the *Auditor Misconduct Tercile*.

We then conduct a series of robustness tests in Table A2 to verify these main findings. We begin by investigating the concern that the relation between auditor and BD misconduct arises from an omitted variable associated with the BD's business model. For example, BDs are undergoing business model changes when they match with their auditor, as prior literature has linked auditor switches to management turnover and client performance (Schwartz and Menon, 1985; Johnson and Lys, 1990; DeFond, 1992). Yet another concern is that some BD product offerings may attract more misconduct complaints than others, and auditors may specialize in certain product offerings. Then, our results would reflect specialization in product offerings by auditors, rather than misconduct matching.

We address these concerns in two ways. First, we study a subsample of auditor switches instigated by the BD's prior auditor exiting the BD market. These exits force the BD to find a new

[16] Our results slightly differ from column 2, because unlike this column specification (1) includes size tercile x year fixed effects and controls for total assets and adviser count.

auditor, and we study whether their new auditor's clients have a similar misconduct profile to them. We construct our subsample using the set of audit offices with at least three BD clients last year, and none this year. We find 113 (79) audit office (audit firm) exits fit these criteria, leaving 513 BD clients to find new auditors.[17] Exits occur for a range of reasons, including the death of a sole proprietor, the demise of Arthur Andersen, and disciplinary action from the SEC or PCAOB. Notably, these audit market exits affect clients of all districts, size terciles, ownership types, and in all years. We estimate specification (1) on this sample in column 1. We find a positive relation between a BD's misconduct and that of their new auditor's clients.

Second, we collect information, when available, on the BDs' types of product offerings that generate more than one percent of their annual revenue as indicated on SEC Form BD. Adapting Graham (2015), we create an indicator variable for each of the following six product offerings: Debt Security, Investment Advisory, Mortgage Backed Securities, Mutual Fund Retailer, Private Placement, and Variable Life Insurance and Annuity Dealer. We then interact these indicators with year fixed effects, such that our specification accounts for time-varying conditions in each product market and their effect on BD-auditor matches. Column 2 shows that our results remain when we control for product group x year fixed effects, indicating that product specialization is not behind our findings. Our results also remain if we control for product group x district x year effects, or if we run our tests separately for retail and non-retail BDs, or BDs who sell investment advice and those who do not.[18]

We then examine the sensitivity of our results to alternative misconduct measures. Many misconduct records result from customer complaints, and customers may not report all incidents

[17] We eliminate cases where over two-thirds of the exiting auditing firm's clients flock to the same new auditor, to ensure we are not capturing acquisitions rather than exits.

[18] Finally, in Appendix C we employ a multinomial logit specification that explicitly compares how realized matches compare to other feasible matches. This addresses concerns regarding the availability of auditors in certain areas or geographic differences in misconduct that are not captured by our district x year effects. We find similar results in this specification.

given their own awareness of or willingness to use FINRA's complaint filing process. Because BDs differ in the types of customers they serve, two BDs with identical misconduct behavior may have different *reported* misconduct if they serve different customer types. We therefore assign BDs and auditors to terciles based only on regulator-reported misconduct, because we expect regulators to be more consistent in reporting misconduct across our BDs. Column 3 shows our results are statistically and economically similar to our original results. Last, Column 4 counts all disclosure events on the adviser's record, rather than just the serious incidents classified as misconduct by Egan et al. (2018). Our results remain.[19] Overall, it does not appear that our misconduct matching inference is sensitive to accounting for investment product specialization or to the type of misconduct incidents we consider.

Table 5 evaluates the generalizability of our misconduct matching findings, in two ways. First, in Panel A we investigate the auditor and client pairs where misconduct matching is relevant. If the misconduct matching we document is not found in the larger BDs responsible for the majority of assets and employment in the industry, it would raise questions about the importance of our findings. Column 1 limits the sample to size tercile 3 BDs. The coefficient on *Misconduct Tercile* is significantly positive, and nearly 70% larger than in our main results. We continue to find results for the two remaining size categories (not tabulated for brevity). Column 2 studies pairs involving a Global Network Audit Firm, and finds a significantly positive coefficient on *Misconduct Tercile*. Column 3 studies publicly held BDs. As with the first two columns, we find evidence of misconduct matching, despite substantial sample attrition.

When then extend our sample to all US public firms. To study the broadest set of firms possible, we use AAERs and meet-or-beat as a proxy for misconduct behavior relevant to auditor-

[19] Our findings are also the same if we consider only *BD Misconduct Current* instead of *BD Misconduct Ever*.

client matching.[20] We assign firms to misconduct terciles by industry-year according to their prior incidence of AAERs and meeting or beating analyst expectations, and estimate a modified version of specification (1).[21] Columns 4 and 5 find a positively significant relation between a public firm's AAER and meet-or-beat history and the history of their auditor's other clients. Combined with our BD subsample analyses, these results suggest that misconduct matching is a common phenomenon in audit markets.

In our second set of generalizability tests, we explore whether misconduct matching stems solely from financial reporting-related infractions, as the "opinion shopping" literature might suggest, or is instead relevant to other types of misconduct. Column 1 forms BD and auditor misconduct terciles after omitting events plausibly related to misreporting or fraud. Specifically, we perform a textual analysis of our 1,228,778 adviser records, and omit disclosures containing the phrases "fraud", "forgery", "misappropriate", "unregistered", or variants of these phrases. The remaining disclosures primarily relate to unsuitable investments, misrepresentation, unauthorized activity, and commission-related complaints. If reporting risk is solely responsible for our main results, then we expect much weaker or null results when we study these remaining disclosures. However, our results are statistically and economically similar to our main result.[22]

Column 2 continues with this modified misconduct measure, and omits several types of BD-year observations where reporting risk is ex-ante expected to be greatest. Specifically, we exclude publicly held BDs and carrying BDs, whose audits are more complicated and the audit risk is greater. We also omit any BDs with IC material weaknesses or going concern opinions in

[20] Our analysis is related to Raghunandan (2018), who accesses a dataset on federal agency penalties, and studies the relation between financial and non-financial misconduct in public firms.
[21] Specifically, we study only new auditor-client relationships, and control for log revenue, log total assets, sales growth, cash flow volatility, profit margin, return on assets, leverage, market-to-book, log market value, and log firm age.
[22] We also find similar results if we exclude criminal events on an adviser's record. FINRA collects and reports criminal background information about each adviser, including DUIs and drug-related offenses that may not be relevant to the BD's operations or reputation (Law and Mills, 2018).

the past or present. Last, we omit BDs with exposure to mortgage-backed securities. For the remaining observations, we expect audit risk to be inherently low because the BD is not public, does not encounter the regulatory complexity and misappropriation risk that comes with taking custody of clients' assets, has not reported IC material weaknesses or going concern opinions, and does not participate in the riskiest investment products. Column 2 shows that for the remaining BD-year observations, our results are similar to our main findings. Thus, when auditors are making client acceptance decisions, they appear to consider not only the financial reporting risk of the client, but also other aspects of management behavior not directly pertaining to financial reporting.

Overall, our findings present consistent evidence of auditor-client matching on misconduct. This matching is not an artifact of size, location, BD type, or investment product-specific developments. Our findings are not limited to privately held BDs or small BDs, and stem from both reporting and non-reporting misconduct incidents.

4.3 Misconduct Clients and Auditor Reputation

In this section, we study how an auditor's non-BD client portfolio relates to the misconduct profile of the BD clients they deal with. We predict that auditors dealing with reputation-sensitive clients are more likely to ration high misconduct BDs, resulting in a lower misconduct profile for these auditors. To test this, we develop two auditor portfolio measures. First, *No Public Client* is an indicator equal to one for auditors with no publicly held clients that year. Second, we measure the audit office's exposure to IPO markets using an indicator for whether the auditor has an IPO client this year or a surrounding year (*IPO Exposure*). We then model *Auditor Misconduct Tercile* as a function of these variables, as well as auditor district x year fixed effects and the controls from equation (1) averaged across the audit office's clients. The unit of observation is audit office-year.

Table 6 presents the results. Column 1 shows that when an auditor has publicly held clients, their average misconduct tercile is significantly lower. The 0.155 coefficient implies that having a public client is associated with a 0.155 unit reduction in the auditor's misconduct tercile. Column

2 shows an incremental effect for IPO exposure. That is, while we continue to find that auditors with publicly held clients have lower misconduct BD clients, those with IPO clients have yet lower misconduct BD clients. Column 3 limits the sample to audit firms with at least two offices, and adds an audit firm x year fixed effect. By studying variation in IPO exposure and client misconduct across offices of the *same audit firm*, this specification allows us to identify differential reputation preferences across offices and how these preferences affect client portfolios. We continue to find a significant coefficient on *IPO Exposure* (albeit, a smaller coefficient than our original result, indicating that across-audit firm variation is an important factor). Overall, our evidence indicates that both audit firms and individual audit offices avoid high misconduct BDs when they have reputation-sensitive clients in non-BD markets.

4.4 Relationship Length

Thus far, our tests have offered evidence on client acceptance decisions and how these decisions relate to auditor reputation. In this section, we study how misconduct relates to the length of BD-auditor relationships, to provide insight into auditors' continuance decisions.

We measure auditor-client relationship length as the number of years between the first and last appearance in our dataset for the auditor-client pair. The average relationship length in our sample is 3.99 years.[23] We model relationship length as a function of the BD-auditor misconduct match using specification (1), in two ways. First, we measure the absolute difference between the BD's *Misconduct Ever* rate and the average rate for the auditor's clients (*Difference in Misconduct*). Second, we create indicator variables for exact misconduct matches (i.e., *Match* $1_A, 1_{BD}$, *Match* $2_A, 2_{BD}$, and *Match* $3_A, 3_{BD}$ pairs where the auditor and client both belong to tercile 1, 2, or 3) and mismatches (*Match* $1_A, 3_{BD}$ and *Match* $3_A, 1_{BD}$ pairs where the auditor is in tercile 1 and the client is in tercile 3, or vice-versa). We characterize the match as of the last year of the data for

[23] Because we only observe the 2001-2017 period, our relationship length estimates are likely biased downward.

each relationship. Other types of pairs (matches between 2s and 3s or between 1s and 2s) form the holdout sample. Intuitively, our second specification allows us to measure whether exact matched pairs stay together longer and poorly matched pairs separate sooner, relative to other pairs.

Table 7 presents the results. Column 1 shows a significantly negative relation between *Relationship Length* and *Difference in Misconduct*. The coefficient on the latter variable implies a one standard deviation increase in the difference in BD and auditor misconduct rates being associated with a 0.22 year decrease in relationship length.

We then study our indicators for exact and mismatched pairs. Column 2 shows that relationships where the BD and auditor both belong to misconduct tercile 1 (2) last 0.729 years (0.373 years) longer than the holdout group. High misconduct BD-high misconduct auditor pairs have weakly longer relationships (the t-statistic on *Match* $3_A,3_{BD}$ is 1.35). Column 2 also shows that mismatched pairs dissolve sooner. Notably, the shortest of all relationships are those involving low misconduct auditors and high misconduct BDs (*Match* $1_A,3_{BD}$), who dissolve 1.061 years earlier than the holdout group. By comparison, high misconduct auditors and low misconduct BD pairs (*Match* $3_A,1_{BD}$) dissolve just 0.442 years earlier. The difference between the *Match* $1_A,3_{BD}$ and *Match* $3_A,1_{BD}$ coefficients is economically and statistically significant (the p-value of the difference is 0.044). This finding is consistent with low misconduct auditors declining continuance to high misconduct clients, either because these clients' misconduct behavior has not improved, worsened, or was not fully known to the auditor at the time of acceptance. This finding also complements our Table 3, Panel B evidence showing that *Match* $1_A,3_{BD}$ pairs are the least likely to form in the first place.

Column 3 adds indicators for each type of size match from Table 3, Panel A and finds similar results. Last, we address an omitted variable concern about variation in the availability of auditors in various parts of the country, which could explain why certain pairs last longer than others. Specifically, we control for the log number of auditors within 100 miles of the BD.[24] Our results remain. We also find this control is negatively associated with relationship length (though the association is marginally insignificant); suggesting that relationship length is decreasing in "market thickness" –the opportunity for participants to meet and form new matches.

4.5 Misconduct Matching and Transparency

In 2006, Congress passed the Military Personnel Financial Services Protection Act, which required the expansion of publicly available information about the professional background and conduct of advisers. The information was made available by the National Association of Securities Dealers (a predecessor of FINRA) on the BrokerCheck website, detailed as follows (NASD, 2007; emphasis added):

> Today's launch marks the first major modernization of NASD BrokerCheck since the service was first introduced online in 1998. *The public disclosure program has been responding to written inquiries since 1988 and to telephone inquiries since 1990*. Beginning today, NASD BrokerCheck is available online 24 hours a day, seven days a week. Vastly improved search options make finding an individual broker or firm faster and easier. When they find that a broker or firm has "disclosure events" such as criminal actions, customer complaints and disciplinary actions by regulators, *investors no longer have to make a separate request for a disclosure report to be sent via email at a later time. Instead, the disclosure report is available online within seconds*.

Our assumption is that the website reform made it easier for auditors to evaluate client misconduct profiles, and that increased transparency should change matching patterns (e.g., Hao 2008).[25]

We study the composition of auditors' client portfolios around the March 2007 website modernization. If auditors differ in their tolerance of client misconduct, then the availability of client misconduct information should increase auditors' portfolio concentration with respect to client misconduct. To assess this, we measure the standard deviation of misconduct rates (*Std Dev*

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[24] We are unable to calculate this variable for some observations missing longitude and latitude data.

[25] Discussions with several audit partners in the BD market confirm that the website informs their acceptance and continuance decisions.

Client Misconduct) across each audit office's clients each year.[26] We model this dispersion measure as a function of *Transparency* (an indicator equal to one after 2007), the controls from equation (1) averaged across the office's clients, and office fixed effects. We limit our sample to the two years before and after the 2007, to reduce the threat of other developments entering our results. We omit 2007 because we do not observe the exact timing of auditor-BD matches, just the year-end audit report date.

Table 8 presents the results. Column 1 shows a significant post-modernization reduction in portfolio dispersion. Considering the pre-period *Std Dev Client Misconduct* of 13.6%, our -1.5% coefficient implies an economically significant 11% decline in portfolio dispersion. Of course, one limitation of this particular analysis is that it relies upon a simple pre-post comparison around a single event. Specific to our setting, one might be concerned that our post period coincides with the onset of the financial crisis. To reduce this concern, column 2 adds time-varying controls for the office's exposure to clients participating in each of the six product offerings. Further, column 3 eliminates offices with any clients participating in the Mortgage Backed Securities market, which experienced considerable turmoil during the crisis. In both columns, we arrive at economically and statistically similar results.

4.6 Auditor-Client Matches and Future Misconduct

Our final set of tests sheds light on the consequences of misconduct matching for investor protection. Specifically, we examine whether a BD's auditor match is relevant to future misconduct. We study *BD Misconduct Current* (i.e., new misconduct incidents) in the years after auditor matches. We estimate future misconduct as a function of *High Misconduct Auditor*, equal to one for misconduct tercile 3 auditors, and zero for tercile 1 or 2 auditors. We also control for the BD's misconduct in the year before the match, and the controls and fixed effects from equation (1). The

[26] We find similar results using the interquartile range as our dispersion measure.

coefficient of interest is *High Misconduct Auditor*. A positive coefficient on this variable indicates worse future behavior after matching with a high misconduct auditor. A negative coefficient indicates the opposite, and would be more consistent with auditor specialization. In a specialization story, those auditors with the most experience dealing with high misconduct clients should be best positioned to help them reform behavior and reduce misconduct.

Table 9 presents the results. Column 1 shows a positive coefficient on *High Misconduct Auditor*, indicating that those BDs matching with lower reputation auditors experience a higher rate of *BD Misconduct Current* over the next year. Measuring future misconduct over the next two years (column 2) or adding a control for *BD Misconduct Ever* (column 3) does not affect the results. Column 4 repeats our test on high misconduct BDs—those who are tercile 3 BDs in the year before they match with their auditor. We find the same results for this sample: those BDs choosing a *High Misconduct Auditor* experience a significantly higher rate of misconduct over the next two years.

We caution that these tests are not intended to be interpreted causally. Specifically, prior work (e.g., Lawrence, Minutti-Meza, and Zhang, 2011) and our own main findings illuminate the challenges associated with identifying auditor treatment effects in the presence of matching. Nevertheless, we note that our findings are consistent with three non-mutually exclusive mechanisms involving auditors' heterogeneous preferences for reputation. First, because we control for public information about BD misconduct, our findings are consistent with high reputation auditors developing private information to screen potential clients (*screening*). Second, high reputation auditors, through their audit procedures and oversight of internal controls, could reduce the scope for BD misconduct (*treatment*). Third, those BDs intending to root out misconduct may seek to match with high reputation auditors (*selection*).

5. Conclusion

We study auditor-client matching in the BD market. Using a comprehensive dataset of financial adviser employment records and BD-auditor relationships, we find significant evidence of positive assortative matching on misconduct. Specifically, a BD's past misconduct record is highly related to the misconduct record of their new auditor's clients. Auditors' involvement in other reputation-sensitive markets reduces their willingness to accept high misconduct BDs. BDs and auditors that are mismatched with respect to misconduct stay together the least amount of time. Furthermore, once FINRA improved the transparency surrounding adviser misconduct, auditors increased their concentration in a given misconduct clientele. Our findings suggest that auditor reputation concerns contribute to selectivity in the clients they choose to accept and continue serving.

Finally, we show that an auditor's portfolio misconduct rate is predictive of a BD's future misconduct behavior, over-and-above the BD's own historical misconduct level. While this finding does not discern between sorting and treatment mechanisms, it could provide a useful reference point for the 56% of Americans who rely on financial advisers as their conduit to engage the financial markets.

Overall, our matching findings carry two implications for future research. First, research investigating an auditor's effect on client behavior should consider the auditor and client preferences that contributed to their matching. Second, in markets where auditor reputation is important, the identity of a client's auditor can be informative about the client's future behavior.

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Appendix A: Variable Definitions

Variable	Description
BD Size Tercile	The size tercile (1=small, 2=medium, 3=large) of the BD. We assign BDs to terciles each year according to their number of advisers.
Auditor Size Tercile	The size tercile (1=small, 2=medium, 3=large) of the BD's auditor. We assign auditors to terciles each year according to the average size tercile of their BD clients.
BD Misconduct Tercile	The misconduct tercile (1=low, 2=medium, 3=high) of the BD. We assign BDs to terciles each year according to *BD Misconduct Ever*. These misconduct terciles are assigned within *BD Size Tercile*, to control for size.
Auditor Misconduct Tercile	The misconduct tercile (1=low, 2=medium, 3=high) of the BD's auditor. We assign auditors to terciles each year according to the average *BD Misconduct Tercile* of their clients.
Audit Office	The intersection of auditor name and opinion city in Audit Analytics.
Total Assets	The total assets reported at the end of the BD's fiscal year.
Leverage	The ratio of total liabilities to total assets reported at the end of the BD's fiscal year.
Adviser Count	The number of FINRA-registered advisers in the BD-year.
Publicly Held BD	An indicator equal to one for BD subsidiaries of publicly traded companies, and zero otherwise. We classify a BD as publicly traded if it has a ticker symbol in Audit Analytics.
Retail BD	An indicator equal to one for BDs that serve individual rather than institutional customers. Following Qureshi and Sokobin (2015) and Honigsberg and Jacob (2018), we classify BDs as retail when their average adviser is registered in more than three states.
Carrying BD	An indicator equal to one for BDs that execute trades or maintain custody of investors' assets as indicated by minimum required net capital of at least $250,000, and zero otherwise. As our public data does not identify these Carrying BDs, we proxy for the BD type when Audit Analytics reports a Minimum Required Net Capital of at least this amount, following Schnader et al. (2018).
BD Age	The number of years since the BD's first appearance in the FINRA data.

Average Adviser Experience	The average number of years of experience across the BD's advisers. We use the earliest year of FINRA registration for each adviser to calculate experience.
Average Qualifications	The average number of qualification exams passed by the BD's advisers. Following Egan et al. (2018), we consider the six most common qualification exams (Series 6, 7, 24, 63, 65, and 66)
Big N Auditor	An indicator equal to one for BD-years audited by PwC, EY, Deloitte, KPMG, or Arthur Andersen.
Global Network Auditor	An indicator equal to one for BD-years audited by a Big 4 auditor, Arthur Andersen, BDO, Grant Thornton, RSM, or variations thereof (e.g., McGladrey & Pullen).
IC Material Weakness	An indicator equal to one if the BD has an internal control material weakness that year, and zero otherwise.
Going Concern	An indicator equal to one if the BD has a going concern opinion that year, and zero otherwise.
Audit Office Client Count	The number of BD clients for the audit office that year.
Auditors Near BD	The number of audit offices within 100 miles of the BD.
BD Misconduct Current	The percent of the BD's advisers with a misconduct event that year. We use the Egan et al. (2018) definition of misconduct, which includes the following six categories of FINRA disclosures: Civil-Final, Criminal-Final Disposition, Customer Dispute-Award/Judgment, Customer Dispute-Settled, Employment Separation after Allegations, and Regulatory-Final as described in Appendix B.
BD Misconduct Ever	The percent of the BD's advisers with a misconduct event that year or any prior year.
BD Disclosure Current	The percent of the BD's advisers with a FINRA disclosure that year. Disclosures can include Misconduct events or less serious complaints and infractions (including those that were dismissed).
BD Disclosure Ever	The percent of the BD's advisers with a FINRA disclosure that year or any prior year.
Auditor Median Client Size	The number of advisers at the auditor's median client.

Auditor Misconduct Rate	The average BD Misconduct Ever rate across the audit office's clients.
No Public Client	An indicator equal to one if the audit office has no publicly held clients.
IPO Exposure	An indicator equal to one if the audit office has an IPO client last year, this year, or next year.
Relationship Length	The number of years between the first and last appearance in the data for the BD-auditor pair.
Difference in Misconduct	The absolute value of the difference between the BD's Misconduct Ever rate and the average rate of BD Misconduct Ever across the auditor's clients.
Match $\#_{A}$,$\#_{BD}$	An indicator equal to one for a pairs with an auditor from misconduct tercile # and a BD from misconduct tercile #. For example, Match 1_{A}-3_{BD} equals one for pairs with an auditor from misconduct tercile 1 and a BD from misconduct tercile 3.
Transparency	An indicator equal to one in year 2008 and 2009, and zero in year 2005 and 2006.
Std Deviation Client Misconduct	The standard deviation of BD Misconduct Ever across the audit office's clients.
High Misconduct Auditor	An indicator variable equal to one for BD-auditor pairs where the auditor belongs to the highest *Auditor Misconduct Tercile*, and zero when the auditor belongs to the lowest two *Auditor Misconduct Terciles*.

Appendix B: Examples of Each Misconduct Type

This table provides definitions for each of the six misconduct categories, as well as example disclosures. In some cases, excerpts are provided for brevity. We have redacted the names of individuals and firms involved in the example misconduct disclosures.

Misconduct Category	**Example**
Civil-Final This type of disclosure event involves (1) an injunction issued by a court in connection with investment-related activity, (2) a finding by a court of a violation of any investment-related statute or regulation, or (3) an action brought by a state or foreign financial regulatory authority that is dismissed by a court pursuant to a settlement agreement.	The Securities and Exchange Commission ("Commission" or "SEC") today charged a California-based investment adviser and its owner with fraud for failing to disclose a material conflict of interest when recommending that their clients invest in a hedge fund that made undisclosed subprime and other high-risk investments. The SEC alleges that investment adviser company ("Company") and its Principal recommended that more than 60 of their clients invest approximately $40 million in equity options fund ("Fund"), a hedge fund managed by consulting firm ("Firm"). According to the SEC's complaint, Company and owner failed to disclose a side agreement in which company received a portion of the performance fee that fund paid firm for all the company assets invested in the hedge fund. From April 2005 to September 2007, the company received more than $350,000 in performance fees from the firm. The fund collapsed in August 2007, and company clients lost nearly all of the money they invested. Resolution: Judgment Rendered Sanctions: Injunction
Criminal- Final Disposition This type of disclosure event involves a criminal charge against the broker 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.	Charges Count #1 attempt stealing $500.00 by deceit Amended Charges: Making a false report Amended Charge Type: Misdemeanor Amended Charge Disposition 2 yrs. probation & $500.00 fine
Customer Dispute- Award/Judgment	Allegations Clients allege that recommendation of Freddie Mac and Fannie Mae preferred shares were unsuitable for their account and represented as "safe".

This type of disclosure involves a final, consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the broker that resulted in an arbitration award or civil judgment for the customer.	Damage Amount Requested $25,000.00 Damages Granted $25,000.00
Customer Dispute- Settled This type of disclosure event involves a consumer-initiated, investment-related complaint, arbitration proceeding or civil suit containing allegations of sale practice violations against the broker that resulted in a monetary settlement to the customer.	Allegations Customers alleged the representative's recommendation to invest in a limited partnership, in February 2009, was not appropriate. Customers have alleged damages as noted below. Damage Amount Requested $175,000.00 Settlement Amount $145,000.00
Employment Separation after Allegations This type of disclosure event involves a situation where the broker voluntarily resigned, was discharged, or was permitted to resign after being accused 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.	Adviser's affiliation was terminated for his failure to disclose a regulatory inquiry and subsequent consent order by the Ohio Department of Insurance to the firm.
Regulatory- Final This type of disclosure event may involve (1) a final, formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulatory such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation of investment-related rules or regulations; or (2) a revocation or suspension of a broker's authority to act as an attorney, accountant, or federal contractor.	At the time of an on-site examination of the adviser in 2008 by the Office of Compliance Inspections and Examinations ("OCIE"), the adviser had violated securities laws by failing to complete an annual compliance review in 2006, making misleading statements on the adviser's website regarding the adviser's exclusive access to an investment firm's funds, omitting disclosures in its performance information that were required by the adviser's own policies and procedures, and making misleading statements in its performance information by providing model results that did not deduct the adviser's advisory fees. Following the examination, OCIE staff sent the adviser a letter concerning these violations. Despite assurances that it would take corrective action to remedy these violations, the adviser continued to violate

	securities laws at the time of OCIE's 2011 examination by failing to complete an annual compliance review in 2009 and by continuing to make misleading statements regarding its access to an investment firm's funds in its marketing materials. The adviser also misleadingly represented in one location on its website that it had over $600 million in assets when it reported in its Form ADV that it had less than $325 million in assets under management as of September 2011.

Appendix C: Matching Regression

This appendix describes the results of a matching regression that explicitly models how all realized matches compare to other feasible matches. We use a multinomial logit to estimate the matching process between BDs and auditors. Each BD is matched to the audit office that provides the best match of all potential auditors. This setup allows us to test variables that affect the probability of matching while considering other feasible matches.

We define feasible matches based on whether the BD carries customer funds. We presume that carrying BDs can only be matched with auditors that have at least one carrying client, and that non-carrying BDs can be matched with any auditor. We define the latent quality of the match between BD i and auditor j at time t as

$$V_{i,j,t} = \alpha_{i,t} + \beta x_{i,j,t} + \varepsilon_{i,j,t} \ ,$$

where the vector x contains characteristics of the match and ε follows the usual i.i.d. extreme value distribution. We allow the intercept to vary by BD type and year to capture time effects that may vary for carrying and non-carrying BDs. The probability that BD i and auditor j are matched is equal to the probability that

$$V_{i,j,t} > V_{i,k,t} \ \text{for all feasible matches } k \neq j.$$

For the characteristics of the match, we include the difference in misconduct between the BD and the auditor's other clients, the distance between the broker-dealer and the auditor's office, and the difference in size between the BD and the auditor's other clients. All characteristics are lagged by one year, as in Table 4.

The difference in misconduct is measured as the absolute value of the difference between the BD's record of misconduct (*Misconduct Ever*) and average value of this variable for the auditor's clients. Distance is measured as the square root of the miles between the BD and the auditor (measured using spherical trigonometry). The square root is taken to reduce the right skew. The difference in size is measured as the absolute value of the difference between the BD's *Log Adviser Count* and average *Log Adviser Count* of the auditor's clients. As in Table 4, we estimate this regression using only new matches.

The results of this estimation are presented below. In column 1, we see that all of the variables have a statistically significant effect on the probability of matching. The coefficient of negative 0.137 on distance tells us that each additional 100 miles between a BD and an auditor reduces the odds of them matching by 75%.[27] A one standard deviation increase in the difference in misconduct (size) of 0.2 (1.6) reduces the odds of a match by 27% (45%).

Column 2 separates the differences in misconduct based on whether the BD or auditor has relatively more misconduct. While we find a larger effect when the auditor's clients have greater misconduct, we also find a significant effect when the BD has more misconduct.

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[27] Calculated using the odds ratio: $\exp[-0.137\text{x}(100)^{.5}] - 1 = -.75$.

This table models the probability of a BD-auditor match based on the similarity of the BD and the auditor's clients and the geographic distance between them. The difference in misconduct is based on *BD Misconduct Ever*. The difference in size is based on *Log BD Adviser Count*. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Difference in Misconduct	-1.587***	
	[-10.65]	
Difference in Misconduct (BD higher)		-1.238***
		[-4.38]
Difference in Misconduct (Auditor higher)		-1.754***
		[-4.33]
Distance	-0.137***	-0.137***
	[-20.42]	[-20.41]
Difference in Size	-0.375***	-0.377***
	[-15.95]	[-16.09]
Bayesian information criterion	68,036	68,038
BD observations	6,218	6,218

Figure 1: Example Investment Adviser Record on FINRA

Table 1: Sample Selection

This table describes the construction of our sample using Audit Analytics and FINRA's BrokerCheck database.

Total observations in Audit Analytics (2001-2017)	83,823
Less:	
Incomplete filings	(2,551)
Duplicates	(3,561)
BD-Years	77,711
Less:	
Unable to match to FINRA BrokerCheck data	(1,763)
Non-U.S. or missing location	(1,169)
Missing Leverage	(375)
Final Sample: BD-Years	74,404
New Relationship Sample (Tables 3-5): BD-Years	6,855

Table 2: Summary Statistics

This table summarizes the BD, audit, and misconduct variables for observations in our sample.

Panel A: Broker-Dealer Variables

	Mean	Std Dev	25%	50%	75%	N
Total Assets ($000s)	1,002,167	15,127,860	121	556	3,776	74,404
Leverage	0.30	0.27	0.07	0.22	0.46	74,404
Adviser Count	155.41	1,132.08	4.00	10.00	32.00	74,404
Publicly Held BD	0.07	0.26	0.00	0.00	0.00	74,404
Carrying BD	0.20	0.40	0.00	0.00	0.00	74,404
Retail BD	0.48	0.50	0.00	0.00	1.00	74,404
BD Age	13.86	11.33	5.00	11.00	20.00	74,404
Average Adviser Experience	14.46	6.93	9.62	13.20	18.00	74,404
Average Qualifications	2.12	0.67	1.79	2.16	2.50	74,404

Panel B: Audit Variables

	Mean	Std Dev	25%	50%	75%	N
Big N Auditor	0.19	0.39	0.00	0.00	0.00	74,404
Global Network Auditor	0.21	0.41	0.00	0.00	0.00	74,404
IC Material Weakness	0.05	0.22	0.00	0.00	0.00	74,404
Going Concern	0.02	0.13	0.00	0.00	0.00	74,404
Audit Office Client Count	19.73	26.07	2.00	7.00	26.00	74,404

Panel C: Misconduct Variables

	Mean	Std Dev	25%	50%	75%	N
BD Misconduct Current	0.01	0.05	0.00	0.00	0.00	74,404
BD Misconduct Ever	0.12	0.19	0.00	0.05	0.17	74,404
BD Disclosure Current	0.02	0.06	0.00	0.00	0.00	74,404
BD Disclosure Ever	0.15	0.20	0.00	0.07	0.22	74,404

Table 3: Auditor-Client Matching by Size and Misconduct

This table provides non-parametric analysis of size and misconduct matches between BDs and auditors. In Panel A, we assign BDs to size terciles based on their *Adviser Count*, and auditors to size terciles based on the size terciles of their average client. In Panel B, we assign BDs to misconduct terciles within their size tercile based on their rate of *BD Misconduct Ever*. We assign auditors to misconduct terciles based on the misconduct tercile of their average client. We tabulate BD and auditor terciles from the year before their match, to avoid a spurious positive correlation between BD and auditor tercile assignments. Each cell in the 3 x 3 table reports the percent of BDs in their size or misconduct tercile that matched with a particular auditor size or misconduct tercile. For example, the first row of Panel A shows that for size tercile 1 BDs, 48.6% (34.5%; 16.8%) have an auditor in size tercile 1 (2; 3). The row below each table reports the expected probability of each type of match under null hypothesis that there is no matching on size or misconduct. We report the Pearson's chi-squared test statistic for independence in auditor and BD characteristics at the bottom of the panel.

Panel A: Size Matching

		Auditor Size Tercile		
		1	2	3
BD	1	48.9%	34.1%	17.0%
Size	2	35.7%	35.7%	28.6%
Tercile	3	18.3%	26.7%	55.1%
	Null	34.5%	32.2%	33.3%

Test of independence for auditor and BD size:
Chi-square: 872.07
P-value: 0.000

Panel B: Misconduct Matching

		Auditor Misconduct Tercile		
		1	2	3
BD	1	35.2%	37.5%	27.3%
Misconduct	2	38.3%	37.5%	24.2%
Tercile	3	19.2%	38.7%	42.0%
	Null	30.7%	37.9%	31.5%

Test of independence for auditor and BD misconduct:
Chi-square: 265.72
P-value: 0.000

Table 4: Auditor-Client Matching by Size and Misconduct

This table models auditor-client matches as a function of BD size, misconduct, and other characteristics. The dependent variable in column 1 (2 and 5) is *Auditor Size Tercile* (*Auditor Misconduct Tercile*), the size (misconduct) terciles assigned in Table 3. The dependent variable in column 3 (4) is *Log Auditor Median Client Size* (*Log Auditor Misconduct Rate*), the natural logarithm of the advisor count of the auditor's median client (*BD Misconduct Ever* averaged across clients). The sample is restricted to the first year of each audit office-BD relationship. The unit of observation is BD x year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Auditor Size Tercile	(2) Auditor Misconduct Tercile	(3) Log Auditor Median Client Size	(4) Log Auditor Misconduct Rate	(5) Auditor Misconduct Tercile
BD Size Tercile	0.204***	-0.086***			
	[11.79]	[-4.66]			
BD Misconduct Tercile	-0.087***	0.107***			0.100***
	[-6.91]	[8.26]			[8.08]
Log BD Adviser Count			0.200***	-0.006***	-0.021
			[12.26]	[-5.52]	[-1.54]
Log BD Misconduct Ever			-0.615***	0.071***	
			[-6.58]	[6.92]	
Leverage	0.004	0.043	-0.163***	0.004	0.121***
	[0.10]	[1.12]	[-3.13]	[0.92]	[3.15]
IC Weakness	-0.222***	0.083	-0.261***	0.020**	0.057
	[-4.88]	[1.30]	[-4.37]	[2.15]	[1.06]
Going Concern	-0.011	0.02	-0.108	-0.001	-0.030
	[-0.17]	[0.31]	[-1.48]	[-0.15]	[-0.47]
Log BD Age	0.017	-0.02	0.015	-0.002	-0.007
	[1.31]	[-1.53]	[0.98]	[-1.33]	[-0.52]
Log Average Adviser Experience	-0.119***	0.134***	-0.176***	0.018***	0.104***
	[-3.97]	[4.91]	[-4.31]	[4.97]	[4.02]
Average Qualifications	0.015	0.023	0.013	0.003	0.013
	[0.89]	[1.42]	[0.61]	[1.37]	[0.81]
Publicly Held BD	0.439***	-0.270***	0.868***	-0.023***	-0.207***
	[11.59]	[-6.63]	[8.80]	[-6.82]	[-4.98]
Retail BD	0.066***	-0.096***	0.061*	-0.012***	-0.072***
	[3.03]	[-4.38]	[1.94]	[-4.38]	[-3.36]
Carrying BD	0.336***	-0.251***	0.407***	-0.022***	
	[9.83]	[-7.13]	[7.48]	[-7.58]	
Log Total Assets					-0.045***
					[-7.04]
Adj R-Sq.	0.229	0.171	0.291	0.157	0.189
N	6,855	6,855	6,855	6,855	6,855
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes	Yes
BD Size Tercile x Year FEs	No	No	No	No	Yes
Carrying BD x Year FEs	No	No	No	No	Yes

Table 5: Auditor-Client Matching Generalizability Analysis

This table performs robustness analyses of our Table 4, column 5 results using specification (1). The dependent variable is *Auditor Misconduct Tercile*, the misconduct tercile assigned in Table 3. Panel A studies alternative samples of BDs or auditors based on their business type, whereas Panel B employs alternative misconduct measures. In Panel A, column 1 (2; 3) limits the sample to relationships involving large BDs (Global Network Audit Firms; publicly held BDs). Column 4 (5) estimates specification (1) on public firms using the incidence of AAERs (meet-or-beat) as our misconduct measure. In Panel B, column 1 we exclude misconduct events related to financial reporting. Column 2 excludes misconduct events related to financial reporting and omits BDs that are publicly held, carry customer assets, have experienced an IC material weakness or going concern opinion, or participate in the MBS market. The sample in all columns is restricted to the first year of each audit office-BD relationship. The unit of observation is BD firm x year. Our tests include the controls from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

Panel A: Business Type Analysis

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile	(3) Auditor Misconduct Tercile	(4) Auditor Misconduct Tercile	(5) Auditor Misconduct Tercile
	Large BDs	Global Network Auditors	Public BDs	Public Firms AAERs	Public Firms Meet or Beat
BD Misconduct Tercile	0.171***	0.039*	0.119*		
	[6.82]	[1.96]	[1.89]		
Firm Misconduct Tercile				0.071**	0.036*
				[2.01]	[1.82]
Adj R-Sq.	0.210	0.174	0.209	0.139	0.172
N	2,265	1,608	500	6,080	6,080
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	No	No
Census Region x Year FEs	No	No	No	Yes	Yes
BD Size Tercile x Year FEs	No	Yes	Yes	No	No
Firm Size Tercile x Year FEs	No	No	No	Yes	Yes
Carrying BD x Year FEs	Yes	Yes	Yes	No	No

Panel B: Misconduct Type Analysis

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile
	No Reporting Misconduct	Low Audit Risk, No Reporting Misconduct
BD Misconduct Tercile	0.100***	0.110***
	[7.96]	[6.93]
Adj R-Sq.	0.154	0.100
N	6,855	4,048
Cluster by Audit Office	Yes	Yes
Controls	Yes	Yes
District x Year FEs	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes
Carrying BD x Year FEs	Yes	Yes

Table 6: Misconduct Client Focus and Auditor Reputation

This table models the auditor's misconduct tercile as a function of their portfolio exposure using the *Auditor Misconduct Tercile* assigned in Table 3 as the dependent variable. *No Public Client* is an indicator for auditors with no publicly held clients. *IPO Exposure* is an indicator for auditors with an IPO client last year, this year, or next year. The unit of observation is audit office x year. The sample in column 3 is restricted to audit firms with at least two offices. Our tests include the controls for the average client characteristics from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile	(3) Auditor Misconduct Tercile
No Public Client	0.155***	0.102***	0.032
	[5.33]	[3.46]	[0.63]
IPO Exposure		-0.307***	-0.126***
		[-7.98]	[-2.98]
Adj R-Sq.	0.161	0.167	0.297
N	22,905	22,905	7,149
Cluster by Audit Office	Yes	Yes	Yes
Controls (Average of Clients)	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes
Audit Firm x Year FE	No	No	Yes

Table 7: Misconduct Mismatch and Relationship Length

This table models auditor-client relationship length as a function of the BD-auditor misconduct match. The dependent variable is *Relationship Length*, the number of years between the first and last appearance of the BD-auditor pair in the data. *Difference in Misconduct* is the absolute value of the difference between the BD's *Misconduct Ever* rate and the average rate for the auditor's clients. *Match* $1_A, 1_{BD}$ is an indicator for instances where an auditor and BD both belong to the '1' misconduct tercile. Other 'Match' indicators follow the same convention. *Log # Auditors Near BD* is the log number of audit offices within 100 miles of the BD. The sample is limited to the latest year that each BD-auditor pair appears in the data. The unit of observation is BD x year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Relationship Length	(2) Relationship Length	(3) Relationship Length	(4) Relationship Length
	Full Sample	Drop 2001	Full Sample	Full Sample
Difference in Misconduct	-1.853***			
	[-5.70]			
Match 1_A, 1_{BD}		0.729***	0.682***	0.759***
		[5.96]	[5.70]	[5.51]
Match 2_A,2_{BD}		0.373***	0.310**	0.329**
		[2.76]	[2.34]	[2.17]
Match 3_A,3_{BD}		0.217	0.168	0.196
		[1.35]	[1.05]	[1.03]
Match 1_A,3_{BD}		-1.061***	-0.993***	-1.039***
		[-4.70]	[-4.44]	[-4.20]
Match 3_A,1_{BD}		-0.442*	-0.495**	-0.539*
		[-1.78]	[-2.00]	[-1.86]
Log # Auditors Near BD				-0.068
				[-1.41]
Adj R-Sq.	0.211	0.218	0.221	0.186
N	14,656	14,656	14,656	12,119
Cluster by Audit Office	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Size Match Indicators	No	No	Yes	No
District x Year FEs	Yes	Yes	Yes	No
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes
Carrying BD x Year FEs	Yes	Yes	Yes	Yes

Table 8: Misconduct Transparency and Audit Office Portfolio Concentration

This table models audit office portfolio concentration as a function of misconduct transparency. The dependent variable is *Std Deviation Client Misconduct*, the dispersion of misconduct rates across clients within an audit office-year. *Transparency* is an indicator variable equal to one for 2008 and 2009, and zero for 2005 and 2006. We limit the sample to these years. Column 3 omits auditors with BD clients participating in the Mortgage Backed Securities market. The unit of observation audit office x year. Reported below the coefficients are t-statistics calculated with standard errors are clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Std Dev Client Misconduct	(2) Std Dev Client Misconduct	(3) Std Dev Client Misconduct
	+/-2 years	+/-2 years	+/-2 years
Transparency	-0.015***	-0.015***	-0.015***
	[-3.42]	[-3.38]	[-2.71]
Adj R-Sq.	0.751	0.755	0.751
N	2,541	2,345	1,925
Cluster by Audit Office	Yes	Yes	Yes
Controls (Average of Clients)	Yes	Yes	Yes
Audit Office FEs	Yes	Yes	Yes
Client Product Offering FEs	No	Yes	Yes
Omit Offices with MBS Clients	No	No	Yes

Table 9: Auditor Type and Future Misconduct

This table models the BD's future misconduct as a function of the auditor they match with. The dependent variable is the average rate of *BD Misconduct Current* over future years, as labeled. *BD Misconduct Current*$_{Year0}$ is measured the year before the audit relationship formed. *High Misconduct Auditor* is an indicator equal to one (zero) for BDs with a tercile 3 (1 or 2) misconduct auditor. The sample in all columns is restricted to the first year of each audit office-BD relationship. Column 4 further restricts the sample to audit relationships with high misconduct BDs. The unit of observation is BD x year. Our tests include the controls from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)
		Full Sample of BDs		High Mis. BDs
	BD Misconduct Current Year 1	BD Misconduct Current Years 1-2	BD Misconduct Current Year 1	BD Misconduct Current Year 1
High Misconduct Auditor	0.005***	0.006***	0.005***	0.009**
	[3.16]	[4.15]	[2.86]	[2.23]
BD Misconduct Current$_{Year0}$	0.245***	0.188***	0.224***	0.249***
	[2.90]	[2.71]	[2.59]	[2.67]
BD Misconduct Ever$_{Year0}$			0.022***	
			[4.04]	
Adj R-Sq.	0.117	0.097	0.122	0.136
N	4,797	4,797	4,797	1,512
Cluster by Audit Office	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes
Carrying BD x Year FEs	Yes	Yes	Yes	Yes

Online Appendix to:

Auditors are Known by the Companies They Keep

January 2019

This online appendix tabulates additional analyses not reported in the paper.

Table A1: Auditor-Client Matching by Size and Misconduct- Total Assets Basis

This table repeats our Table 3 analysis using an alternative size classification scheme. In Panel A, we assign BDs to size terciles based on their *Total Assets*, and auditors to size terciles based on the size terciles of their average client. In Panel B, we assign BDs to misconduct terciles within their size tercile based on their rate of *BD Misconduct Ever*. We assign auditors to misconduct terciles based on the misconduct tercile of their average client. We tabulate BD and auditor terciles from the year before their match, to avoid a spurious positive correlation between BD and auditor tercile assignments. Each cell reports the percent of BDs in their size or misconduct tercile that matched with a particular auditor size or misconduct tercile. The row below each table reports the expected probability of each type of match under null hypothesis that there is no matching on size or misconduct. We report the Pearson's chi-squared test statistic for independence in auditor and BD characteristics at the bottom of the panel.

Panel A: Size Matching

		Auditor Size Tercile		
		1	2	3
BD	1	53.1%	33.4%	13.5%
Size	2	37.3%	38.0%	24.7%
Tercile	3	11.6%	26.5%	62.0%
	Null	34.3%	32.6%	33.1%

Test of independence for auditor and BD size:
Chi-square: 1500.00
P-value: 0.000

Panel B: Misconduct Matching

		Auditor Misconduct Tercile		
		1	2	3
BD	1	34.1%	34.6%	31.3%
Misconduct	2	35.2%	35.7%	29.1%
Tercile	3	23.3%	34.6%	42.1%
	Null	30.8%	34.9%	34.3%

Test of independence for auditor and BD misconduct:
Chi-square: 124.44
P-value: 0.000

Table A2: Auditor-Client Matching Robustness Analysis

This table provides robustness analyses of our Table 4 results. The dependent variable is *Auditor Misconduct Tercile*, the misconduct tercile assigned in Table 3. Column 1 provides our main result of estimating equation (1). Column 2 limits the sample to BDs whose prior auditor exited the BD market. Column 3 adds product group x year fixed effects. The misconduct variables in column 4 (5) consider only regulator-reported incidents (all incidents reported to BrokerCheck, regardless of their severity). The sample is restricted to the first year of each audit office-BD relationship. The unit of observation is BD x year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile	(3) Auditor Misconduct Tercile	(4) Auditor Misconduct Tercile
	Forced Exits	Product-Year FE	Regulator Ever	Disclosure Ever
BD Misconduct Tercile	0.111***	0.077***	0.091***	0.114***
	[3.13]	[5.19]	[6.72]	[9.15]
Adj R-Sq.	0.231	0.192	0.094	0.192
N	514	4,942	6,853	6,853
Cluster by Audit Office	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes
Carrying BD x Year FEs	Yes	Yes	Yes	Yes
BD Product Offering x Year FEs	No	Yes	No	No