The Importance of Audit Partners' Risk Tolerance to Audit Quality

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ABSTRACT: Relying on their history of legal infractions to measure individuals' risk tolerance, we examine the association between engagement partners' risk appetites and audit quality in the U.S. Criminology and economics research links criminal activity with enduring personality traits that capture an individual's risk tolerance. Our evidence supports the prediction that partners known to engage in risky off-the-job behaviors conduct lower quality audits. Specifically, we find that clients of partners with prior legal infractions exhibit greater propensity to misstate, fewer material weaknesses, and less timely loss recognition, while also paying lower audit fees and completing the audit earlier. We also document that risk-tolerant partners are more likely to pursue alternative sources of benefit by attracting larger non-audit fees from their audit clients. Reflecting that Big 4 firms have robust quality control systems and more standardized audit procedures that narrow the scope for partner characteristics to matter, we largely find that the Big 4 better constrain risk-tolerant partners from undermining audit quality. In additional cross-sectional analyses, we generally find supportive evidence that the impact of partners' risk tolerance on audit quality subsides in offices with industry expertise, offices that are closer to the audit firm's national office, and offices in the same city as the SEC. Collectively, our analysis contributes to emerging research on the role that individual partner characteristics play in shaping audit outcomes.

Keywords: audit partner; audit quality; risk tolerance; legal infractions.

1. Introduction

The lead engagement partner plays an integral role on the audit given their responsibility for making major decisions, ranging from whether to accept the client in the first place to rendering an opinion on whether the financial statements are free from material misstatement. Extant research documents the importance of individual partners' influence on audit quality relative to client, audit firm, and audit office effects; however, only a small portion of the partner effect is explained by observable demographic traits (Cameran et al. 2020; Gul et al. 2013). Further, the vast majority of prior partner-level research analyzes non-U.S. samples (Lennox and Wu 2018). In contrast, evidence on the determinants of variation in U.S audit partners' performance remains scarce. Indeed, recent research implies that observable lead partner characteristics hardly matter to audit quality in the U.S. (e.g., Aobdia et al. 2021; Burke et al. 2019, 2021; Gipper et al. 2021; Lee et al. 2019). Set against these findings, we analyze whether an innate personality trait—risk tolerance—helps explain the variation in audit quality across individual partners in the U.S. Mapping into prior economics and criminology research that connects an individual's legal infractions to their risk preferences, we rely on partner identity disclosures from the PCAOB and partners' criminal history to examine the association between partner risk tolerance and audit quality. Accordingly, our study responds to calls for evidence on the impact of partners' risk-taking profiles on audit quality (Cameran et al. 2020; Lennox and Wu 2018).

In a seminal study, Ehrlich (1973) links an individual's criminal record with their risk appetite evident in that the time spent on illegitimate activities rises with the person's risk tolerance. Criminology theory also posits that individuals' risk-taking is an important element of their self-control. Indeed, prior research implies that individuals with greater propensities to commit crimes typically have risk-taking, impulsive, and present-oriented natures (Gottfredson and Hirschi 1990; Wright et al. 2004). In particular, Gottfredson and Hirschi (1990) argue that poor self-control captures an individual's preference for short-term rewards over the potential for long-term losses. Consistent with these theories, empirical evidence suggests that personality traits such as impulsivity and poor self-control are positively correlated with various forms of risk-taking behaviors (e.g., Keane et al. 1993; Dohmen et al. 2011; Mishra and Lalumière 2011; Zuckerman and Kuhlman 2000). Further, individuals with a track record of legal infractions—including less severe infractions such as traffic violations—tend to be risk-takers (e.g., Burns and Wilde 1995; Iversen and Rundmo 2002).[1] Recent research extends this framework by generally documenting that executives, investors, and financial advisors known to exhibit risky off-the-job behavior undertake riskier investment and corporate activities (Davidson et al. 2015, 2020; Graham et al. 2013; Grinblatt and Keloharju 2009; Law and Mills 2019).

Audit partners' job responsibilities and the consequences of their decisions are considerably different than those of corporate executives (DeFond and Zhang 2014). In developing their opinion about clients' compliance with GAAP, partners' judgments are bounded by requirements in accounting and auditing standards. Moreover, strict disciplinary mechanisms such as peer and regulatory reviews, litigation, and reputational forces hold partners accountable for their decisions. In another monitoring layer, accounting firms are structured as partnerships in which partners act as both the owners (principals) as well as agents (Huddart and Liang 2005; Lennox and Li 2012). Despite incentive structures in these partnerships designed to motivate the desired level of effort and quality, the reality is that certain aspects of partners' performance are difficult to measure (Lennox and Wu 2018). Accordingly, partners may perceive the cost-benefit trade-off of delivering audit services to existing clients differently depending on their risk preferences. In particular, certain partners may weight immediate incentives (e.g., keeping

[1] Reinforcing that even relatively minor legal infractions can reflect differential behavioral norms, Fisman and Miguel (2007) report that the extent of corruption and legal enforcement in their home countries affects the amount of United Nations diplomats' unpaid parking tickets.

clients) more heavily than distant incentives related to avoiding litigation or reputational costs (Miller 1992; Nelson 2009). As a result, we expect risk-tolerant partners—identified based on their prior legal infractions—to be more apt to charge lower fees (and, in turn, expend less effort) to retain a client in the short-term relative to partners who exhibit greater risk aversion.

Although our prediction is grounded in theory and empirical research from other fields, several factors cast doubt on whether audit quality is sensitive to U.S. partners' risk appetites. First, extant archival research provides evidence that auditors are, on average, conservative, risk-averse individuals (Feng and Li 2014; Lennox and Kausar 2017), suggesting minimal variation in risk tolerance among partners. Second, risky behavior may be more constrained by audit firms' quality control mechanisms (El Ghoul et al. 2016), the strict regulatory and litigation institutions governing auditors in the U.S. (Cunningham et al. 2019), and discipline from within (e.g., financial analysts) and outside (e.g., the media) the capital markets (Dyck et al. 2010; Gipper et al. 2021). Third, public company audits are undertaken by large engagement teams, potentially diluting individual partners' impact on audit outcomes (Aobdia 2018; Carter and Spence 2014; Hu et al. 2021). Accordingly, it remains an empirical question whether partners in the U.S. exhibit variation in risk tolerance, and, if so, whether risk-tolerant partners supply lower quality audits.

Our sample of U.S. audit partners and their publicly-traded clientele is derived from the first year of mandatory partner disclosure under PCAOB Rule 3211, which became effective for audit reports issued on or after January 31, 2017. After identifying observations with available data for our analysis, we restrict the sample to only include partners with two or more clients during the year. Applying this screening process leaves a sample of 649 unique partners with 1,501 unique clients. Next, we extend our sample through the subsequent three years for clients of these same partners, resulting in a final sample comprised of 4,516 client-year observations. We rely on criminal background checks to develop our measure of risk tolerance that reflects whether the partner has committed any legal infractions. We hired an outside third party to conduct the federal, state, and county wide background checks after verifying the identity of each partner.[2] This process reveals a total of 223 infractions committed by 111 (17%) partners; the remaining 538 (83%) partners had no infractions. The legal infractions primarily involve risky traffic behavior such as speeding, reckless driving, and driving under the influence of alcohol.

To test our hypothesis, we evaluate the association between audit quality and the presence of partner infractions in a multivariate framework. We triangulate our analysis by specifying several output- and input-based audit quality proxies available in our setting, including the propensity to misstate the financial statements, reported material weaknesses, discretionary accruals, timely loss recognition, audit fees, and the timing of audit report release (Aobdia 2019a; Chou et al. 2021; Cunningham et al. 2019; Lamoreaux 2016).[3] We find that partners with prior legal infractions provide more lax monitoring of their clients' financial reporting process evident in a greater propensity to misstate, fewer reported material weaknesses, and less timely loss recognition, while also charging significantly lower audit fees and completing the audit earlier relative to reporting deadlines. It is important to stress that our evidence implies that the impact of partners' history of infractions is incremental to other partner traits (i.e., gender, experience, specialization, location, number of clients, and education), executive traits (i.e., gender, experience, and risk appetite), and characteristics related to the audit firm/office and client. In

[2] We employ the same third party as Davidson et al. (2015, 2020). It is important to note that these background checks focus on legal infractions and do not cover the individual's credit history. Our acquisition and use of data conforms to the provisions of the Driver's Privacy Protection Act, which stipulates this data may be used for research purposes provided that personal information is not published.

[3] Due to limited time-series data on partner name disclosures, we cannot meaningfully use restatements in our analysis because misstatements typically take at least two to three years from the fiscal year-end to become reliably known (Cunningham et al. 2019; Francis et al. 2013). Instead, we follow extensive recent research by relying on the F-score measure from Dechow et al. (2011) as a signal of a client firm's misstatement likelihood (Bradley et al. 2017; Cunningham et al. 2019; Fang et al. 2016; Ge et al. 2011; McGuire et al. 2012). Additionally, we explain later in the paper that we do not have sufficient variation in our data to reliably measure audit quality with going concern reporting accuracy.

contrast to the results for the other audit quality proxies, we fail to find that partner infractions have any perceptible link to clients' discretionary accruals. In additional analyses, we document that our core evidence holds under propensity score matching (PSM) and entropy balancing techniques, alternative measures of risk tolerance that focus on more severe or more recent infractions, and a falsification test that exploits mandatory partner rotation. Collectively, our results imply that the differential audit quality impact of risk-tolerant partners—identified based on their criminal histories—runs through a failure to constrain clients that pose a major threat of misstatement, rather than milder forms of earnings management within the scope of GAAP.

A lingering question from our primary analysis is whether risk-tolerant partners elicit any benefit for themselves or their firms from exerting less effort on their audit engagements. One issue that we are able to evaluate with our data is whether risk-tolerant partners supply more non-audit services to their public clients (e.g., DeFond et al. 2002). We find that partners with infractions are associated with significantly higher levels of non-audit services relative to their counterparts without infractions. These results reinforce the narrative underlying our findings that certain partners are more likely to engage in risky behavior to not only retain their clients, but also pursue alternative sources of benefit. This evidence also provides insight into why audit firms tolerate these partners: our results imply that although they conduct lower-quality audits, partners known to exhibit risky behaviors also attract more consulting revenue from these clients.

Finally, we deepen the analysis by examining settings where we expect to observe that partner risk tolerance plays a larger role. For starters, given that the Big 4 audit firms have more robust quality control systems, more standardized audit procedures, and larger engagement teams that potentially narrow the scope for partner traits to matter, we analyze whether our evidence varies systematically according to audit firm type. Consistent with this conjecture, our results imply that the positive (negative) association between partner infractions and propensity to misstate (reported material weaknesses, audit report timing, and timely loss recognition) is generally concentrated in the non-Big 4 subsample. Interestingly, the negative relation between partner infractions and audit fees holds in both subsamples. In another series of cross-sectional analyses, we generally find supportive evidence that the importance of partners' risk tolerance to audit quality subsides in offices with industry expertise, offices that are closer to the audit firm's national office, and offices located in the same city as an SEC office. Altogether, this evidence lends some support that governance and monitoring structures internal and external to audit firms moderate the impact of risk-tolerant partners in undermining audit quality.

In several ways, we contribute to extant research on the role that individual auditor characteristics play in audit quality. First, against the backdrop of prior evidence implying that partners exhibit wide variation in their auditing styles (Aobdia et al. 2015; Cameran et al. 2020; Gul et al. 2013; Li et al. 2017), we examine whether audit quality is sensitive to partners' risk tolerance. Rooted in economics and criminology research linking legal infractions with risk preferences, we explore whether a partner's risk appetite shapes their style. By design, prior research using partner fixed effects estimation presents a "black box" of potential determinants (Chou et al. 2021; Krische 2011). In gauging partner style with their off-the-job behavior, we improve identification of partner type relative to prior research that resorts to measuring style with on-the-job behavior (e.g., partner quality according to accruals in Aobdia et al. 2015; partner reporting decisions in Knechel et al. 2015). In contrast, focusing on their behaviors on the job leaves the analysis vulnerable to reflecting attributes of the audit firm such as its quality control structures and incentive plans (Davidson et al. 2015). Set against recent evidence implying that observable demographic characteristics are responsible for only a small fraction of the inter-partner variation in audit quality (Cameran et al. 2018; Gul et al. 2013), we add to the recent progression in research identifying the omitted individual traits that explain the variation (Chou et al. 2021; Kallunki et al. 2019). Consequently, we respond to calls for empirical research on the determinants of inter-partner differences in audit quality (Aobdia 2019b; Cameran et al. 2020; DeFond and Zhang 2014; Lennox and Wu 2018).

Second, we extend prior work on the links between partner risk profiles and audit outcomes. Amir et al. (2014) document that Swedish audit partners with criminal convictions compile riskier client portfolios. Although their study finds that risk-tolerant partners in Sweden tend to have riskier clients, recent field evidence implies that audit firms are primarily responsible for partner assignment in the U.S. (Dodgson et al. 2020); i.e., overarching audit firm policies and quality control structures in the U.S. likely prevent risk-tolerant partners from self-selecting into certain engagements (Kinney 2015). Additionally, rather than matching high-risk clients to high-risk auditors (Cook et al. 2020), descriptive statistics for our U.S.-based sample generally imply that partners with prior infractions tend to be assigned to *lower*-risk clients evident in that these firms exhibit less accounting reporting complexity, are more profitable, have less debt in their capital structures, and have larger and less volatile operating cash flows.[4] In any event, it is important to stress that Amir et al. (2014) focus on partners' portfolio management decisions, while we examine whether audit quality outcomes hinge on the presence of partners' legal infractions. Lennox and Wu (2018: 28) specifically call for research on this issue: "We are aware of only one study that uses data on partners' criminal records (Amir et al. 2014)...They do not examine the effect on audit quality. This is another research question that may be examined using the new data on U.S. partners."

[4] Nonetheless, to help dispel any lingering concern that our evidence reflects variation in observable firm-level characteristics, we verify that our core results are robust to applying PSM and entropy balancing to help confront the role that screening by auditors and selection by their clients play (Lawrence et al. 2011; Lennox and Pittman 2010b). In holding client and other partner characteristics fairly constant, we are in a better position to provide reliable inferences on whether audit quality varies systematically with partners' risk profiles. We also exploit the mandatory partner rotation rules in undertaking a falsification test to alleviate potential selection concerns.

Third, our research has several practical implications for audit committees, audit firms, regulators, investors, and the broader public policy discourse. In evaluating potential engagement partners (Dodgson et al. 2020; PCAOB 2015), audit committees may want to consider weighing candidates' risk profiles evident in their criminal histories since this may affect their performance. Similarly, our evidence may be relevant to audit firms' recruitment, promotion, and retention decisions as well as their development of optimal partner assignment policies (Campbell 2012; Lennox and Wu 2018). The PCAOB—in applying its risk-oriented inspection program—may consider partner risk tolerance when selecting engagements to inspect. From a policy standpoint, early research on the PCAOB Form AP disclosures fails to find evidence that partner identification matters to actual or perceived audit quality (Cunningham et al. 2019; Doxey et al. 2021). However, an important consideration when evaluating the usefulness of these disclosures is that sufficient background information at the partner level is not straightforward to process or free to obtain on the Form AP issuance date, which may affect investors' initial reactions. Our analysis lends empirical support to publicly identifying engagement partners.

2. Prior research and hypothesis development

Prior research

Individual audit partner characteristics

Recent research documents that audit partners provide systematically different levels of audit quality, presumably driven by varying partner-level incentives, workloads, client relationships, and innate characteristics (Lennox and Wu 2018). Comprehensive data on U.S. engagement partners' identities was unavailable until the PCAOB imposed Rule 3211. Accordingly, extant research at the partner level is predominantly set in other countries. Several studies establish the overall importance of partner characteristics using a fixed effects approach. Gul et al. (2013) observe Chinese audit partners over time and across at least two clients to isolate partner effects from client, audit office, and audit firm effects. They conclude that partner fixed effects exhibit statistically and economically significant associations with audit quality. However, Gul et al. (2013) also report that these results are not consistently driven by observable demographic characteristics available in their setting, including gender, work experience, age, education, and political affiliation; indeed, their evidence implies that observable characteristics explain only a small fraction of an auditor's style. In extending this analysis to the U.K., Cameran et al. (2020) find that partner fixed effects have more explanatory power than the combined fixed effects of audit firms and offices. Relatedly, Aobdia et al. (2015) measure partner quality in Taiwan using partner fixed effects in a discretionary accruals model. In subsequent regressions, they document that capital market participants value the presence of high-quality audit partners. Collectively, prior evidence supports that individual partners matter to audit quality.

Examining specific partner characteristics is constructive for opening the "black box" by identifying which traits shape audit quality. Extant research primarily focuses on more readily observable characteristics that are acquired from education or experience. For example, Gul et al. (2013) find that partners with graduate degrees are associated with marginally more aggressive reporting outcomes, while Li et al. (2017) find no such relationship. Studies also show that partners with more client-specific experience and pre-client experience are associated with improved audit quality (Chi et al. 2009, 2017). Finally, industry expertise at the partner level is associated with higher audit quality and fees, and these expert partners accept fewer high-risk clients (Chi and Chin 2011; Goodwin and Wu 2014; Hsieh and Lin 2016; Zerni 2012).

However, prior work seldom focuses on partners' innate personality traits which are typically more difficult to measure (DeFond and Zhang 2014).[5] In examining Swedish partners'

[5] In an exception, Chou et al. (2021) find that audit quality in Taiwan improves in the presence of a narcissistic partner. Kallunki et al. (2019) report that audit quality is higher for more intelligent Swedish audit partners, although, rather than an intrinsic personality trait, intelligence reflects cognitive ability.

behavior over time, Knechel et al. (2015) find that an auditor's style in the form of exhibiting higher (lower) levels of aggressive (conservative) behavior on prior audits is predictive of behavior on future audits. He et al. (2018) provide evidence that Chinese auditors undergo "imprinting" in the formative early years of their career when they experience major negative events that shape their style long afterward. Arguably most relevant to our analysis, Amir et al. (2014) detect a link between audit partners' risk preferences and riskier client portfolios. These studies infer the persistence in auditors' behaviors to reflect evidence of innate or acquired personal characteristics (Lennox and Wu 2018). Given that evidence on the role that partners' personality traits play in shaping audit outcomes remains scarce, DeFond and Zhang (2014: 304) encourage future research to: "consider additional individual auditor characteristics, such as professional skepticism [and] personality traits." Indeed, Cameran et al. (2020: 5) stress the "insufficiency of using solely publicly-available partner demographic variables such as gender, age, and experience" and call for research exploring other sources of inter-partner variation such as "partners' attitudes to risk and their risk-taking behavior."

Individuals' preference for risk

Becker's (1968) seminal economic theory holds that individuals undertake a cost-benefit analysis when deciding whether to commit a crime. In other words, an individual is willing to take the risk of being caught for a criminal act if the expected gain exceeds the expected cost. Given that the evaluation of both the benefits and costs of an illegal act are highly subjective, they likely depend on the personality and attitudes (such as risk tolerance) of the individual. For example, in linking the risk appetites of an individual to their criminal behavior, Ehrlich (1973) shows that individuals with higher risk tolerance commit more crime than risk-neutral or risk-avoiding individuals. Criminal propensity theories also assert that criminally prone individuals typically have risk-taking, impulsive, and present-oriented natures (Wright et al. 2004). In demonstrating the connection between delinquent behavior and poor self-control, Gottfredson and Hirschi (1990) consider risk-taking an important element of self-control. They argue that low self-control captures an individual's preference for short-term rewards over the potential for long-term losses. Indeed, prior research implies that personality traits such as impulsivity and poor self-control are positively correlated with various forms of risk-taking behaviors (e.g., Keane et al. 1993; Mishra and Lalumière 2011; Samuels et al. 2004; Schwebel et al. 2007).

Subsequent studies on criminal behavior also provide evidence consistent with these theories that individuals with a prior history of legal infractions tend to be risk-takers (Collins and Schmidt 1993; Grinblatt and Keloharju 2009; Iversen and Rundmo 2002). Extant research implies that these individuals refuse to accept that the rules apply to them and are either able to justify the negative ramifications if they are caught (Becker 1968; Ehrlich 1973), or underestimate the likelihood of detection (Eide et al. 2006; Garoupa 2003; Palmer and Hollin 2004; Walters 2009). Although these studies focus on criminal activity in general, other research implies that risk tolerance is also evident in less severe legal infractions such as traffic violations (Burns and Wilde 1995; Castillo-Manzano et al. 2015; Fisman and Miguel 2007; Junger et al. 2001; Wilde 1982). In analyzing large-sample survey data, Dohmen et al. (2011) provide evidence that individuals' general assessment of their own willingness to take risks exhibits a strong, positive correlation with both their willingness to take risks when driving a car and in their careers.

Extending prior work on risky behavior to the corporate testing ground, finance and accounting research documents the importance of individuals' risk profiles to various economic outcomes. Grinblatt and Keloharju (2009) provide evidence that investors with a history of speeding violations pursue riskier investment strategies. Several studies also report that riskier behaviors of CEOs and CFOs captured by legal infractions, personality surveys, or pilot licenses are associated with increased financial reporting risk and riskier corporate activity (Cain and

McKeon 2016; Davidson et al. 2015, 2020; Graham et al. 2013). Finally, Law and Mills (2019) find that financial advisors with a track record of prior legal infractions pose a greater threat of misbehavior in handling their clients' accounts.

Hypothesis development

We expect that engagement partners' risk tolerance will affect their perceptions of the benefits and costs of providing a high-quality audit. In accounting firm partnerships, partners act as both the owners (principals), who share the firm's profits, as well as agents, who generate the profits (Knechel et al. 2013a; Lennox and Li 2012). Although partnerships are the common structure when human capital primarily affects service quality, they can also engender moral hazard problems since each partner assumes the full cost of their own effort but collects only a fraction of the firm-wide earnings (Lennox and Wu 2018). Despite that accounting firm partnerships develop various incentive structures to encourage the desired level of effort and quality (Knechel et al. 2013a), challenges remain since certain aspects of partners' performance are difficult to measure. For example, Lennox and Wu (2018) highlight how certain factors such as attracting new business (or retaining existing business) are much easier to observe than other factors such as partners' independence and effort. As a result, incentive systems can induce risk-seeking behavior that benefits the individual partner in the short-term at the expense of potential long-term reputation or litigation costs shouldered by all partners (Francis 2004; Miller 1992).

Given this structure, partners may perceive the cost-benefit trade-off of delivering audit services to existing clients differently depending on their risk preferences. Specifically, partners are rewarded for not only conducting high-quality audits, but also for generating revenues (Lennox et al. 2020). Since client retention is a readily observable performance metric, partners may be eager to keep audit fees low to reduce the incidence of client defections. To maintain engagement profitability metrics, the partner could exert less effort, which raises the expected costs of poor audit quality through litigation or reputation concerns that may be eventually revealed over time.[6] Indeed, Nelson (2009: 21) stresses that auditors may exercise insufficient professional skepticism after discounting disciplinary incentives (e.g., litigation exposure, regulatory enforcement, and reputation loss for deficient audits) that are: "…probabilistic and far in the future." In short, partners may weight immediate incentives (e.g., keeping clients) more heavily than these distant incentives.[7] Partners may also consider the time savings on the audit a personal benefit that facilitates focusing on other activities such as acquiring new clients, selling non-audit services, or even enjoying additional leisure. We expect risk-tolerant partners to be more apt to lower fees (and, in turn, expend less effort) to retain a client in hopes that they will avoid detection, especially since such behavior is difficult for the audit firm to monitor because the partner accumulates superior information about his/her clients (Miller 1992).

Collectively, prior theory and evidence motivates the intuition underlying our prediction that partners exhibiting higher levels of risk tolerance will be more lenient in monitoring their clients' financial reporting (stated in the alternative form):

H_1**:** Audit partners with a higher risk tolerance are associated with lower audit quality.

However, injecting tension into our analysis, several factors suggest that partners' risk tolerance may be irrelevant to audit quality in the U.S. Although prior work suggests that executives' off-the-job behavior influences corporate outcomes (e.g., Davidson et al. 2015; Law and Mills 2019), executives are known to be more risk seeking and enjoy fewer constraints on their behavior relative to audit partners (Graham et al. 2013). In contrast, auditors are generally conservative, risk-averse individuals (Davidson and Dalby 1993; Swain and Olsen 2012),

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[6] Individual partners may be tempted to shirk when the effort that they exert is unobservable (Balachandran and Ramakrishnan 1987; Lennox and Li 2012).

[7] Nelson (2009: 4) explains that: "…an auditor who has high professional skepticism needs relatively more convincing (in the form of a more persuasive set of evidence) before concluding that an assertion is correct." Insufficient professional skepticism is partly responsible for many PCAOB audit deficiencies, SEC enforcement actions, and malpractice lawsuits against auditors (Beasley et al. 2001; PCAOB 2012).

implying minimal variation in partners' risk profiles.[8] For example, Feng and Li (2014) report that auditors in the bankruptcy setting assign a lower weight to management forecasts thought to be overly optimistic. Similarly, Lennox and Kausar (2017) find that auditors respond to different levels of estimation risk in making going concern decisions, consistent with their ample risk aversion. Amir et al. (2014) also observe that Swedish auditors have, on average, far fewer legal infractions than CEOs, directors, and owners.

Moreover, executives have wide discretion in the decision-making process (Hambrick and Mason 1984; Montanari 1978), such that they continue to wield substantial power even in the presence of oversight by, for example, the board of directors (e.g., Adams et al. 2005; Cohen et al. 2010; Hermalin and Weisbach 1998). In contrast, auditors of public companies are required to follow PCAOB auditing standards to evaluate their clients' compliance with GAAP, restricting auditors' judgment processes within this framework. Reflecting that they are kept on a short leash, auditors are held responsible for their decisions through strict disciplinary mechanisms, including peer review, litigation, and reputation protection forces (DeFond and Zhang 2014). Public company audits are also undertaken by large engagement teams that are subject to rigorous quality controls such as internal consultations and engagement quality reviews, potentially diluting individual partners' impact on audit outcomes (Aobdia 2018; Hu et al. 2021).[9] Consistent with these differences, recent research implies that the impact of personality traits on

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[8] Besides that more risk-averse individuals are drawn to public accounting (Swain and Olsen 2012), experience in public practice likely increases their risk aversion in decisions made under uncertainty (Brief 1975; Hoitash et al. 2016; Trotman et al. 2009). Indeed, prior research implies that certified public accountants are typically risk averse (Newton 1977). This risk aversion manifests in companies with accountant CFOs exhibiting a lower incidence of restatements (Aier et al. 2005), stronger internal controls (Li et al. 2010), and milder earnings management via discretionary accruals (Rakhman 2009).

[9] In another contrast with corporations, litigation exposure provides audit partners with strong incentives to cross-monitor each other's work and to improve quality control structures (e.g., investing in training programs and adopting rigorous staff recruiting and promotion policies) that prevent deficient audits in the first place (Dye 1993, 1995; Lennox and Li 2012). Naturally, these incentives are magnified in larger audit firms (e.g., Big 4) with more partners handling audits (Huddart and Liang 2005), particularly given that they are more vulnerable to "deep-pocket" lawsuits in the event of audit failure.

economic outcomes diverges for executives and audit partners; e.g., financial reporting quality is lower (higher) in the presence of a narcissistic CEO (partner) (Ham et al. 2017; Chou et al. 2021).

Additionally, while partner research set in other countries suggests that partners matter to audit quality, recent work in the U.S. setting provides contrasting evidence. Specifically, Cunningham et al. (2019) and Doxey et al. (2021) document that actual and perceived audit quality, respectively, are insensitive to partner identity. In analyzing proprietary PCAOB data, Aobdia et al. (2021) and Gipper et al. (2021) also find that observable lead partner characteristics are irrelevant to audit quality in the U.S. These findings may be driven by strict internal (e.g., engagement quality reviews) and external (e.g., PCAOB inspections) governance structures that limit the role that individual level characteristics play in shaping audit quality.[10] Another constraint is that partners' objective functions may discount the importance of focusing intently on protecting audit quality. Rather, individual partners have incentives to expand their clientele, retain valuable clients, and conduct more profitable audits (Aobdia 2019b). If compensation structures align with these varying incentives (Huddart 2013; Knechel et al. 2013a), then the influence of partners on audit quality may be minimal. Accordingly, examining the audit quality implications of partners' risk tolerance amounts to a joint test of: whether their risk profiles affect their performance, and whether partner-level variation in risk tolerance manifests in audit outcomes despite the presence of various constraining forces.

2. Sample and research design

Sample

Our sample of lead engagement partners for publicly-traded companies is selected from audit reports issued in the first year after PCAOB Rule 3211 became effective. We follow prior research

[10] Along with the tough public and private enforcement institutions governing auditors in the U.S. (El Ghoul et al. 2016; Francis and Wang 2008; Guedhami and Pittman 2006; Lamoreaux 2016), they experience strict discipline from various market forces (Dyck et al. 2010; Gipper et al. 2021)

by restricting our sample to include only non-financial U.S. issuers with assets exceeding $1 million with available data (Cunningham et al. 2019). We also restrict our sample to audit partners with at least two clients during the fiscal year for several reasons: (i) most audits in a given year are performed by partners with multiple clients (i.e., 57% in the first year according to Table 1 [1,501 / 2,633]); (ii) requiring at least two clients per partner alleviates concerns that the results are solely driven by the client; and (iii) this approach balances the benefits of assembling a large sample of partners against the high costs of data collection.[11] Table 1 summarizes the selection process that leads to our sample initially containing 649 unique audit partners with 1,501 clients. Next, we extend the sample to 4,651 firm-year observations by including additional client firm observations with fiscal year ends through October 31, 2020 for these same partners.

Compiling the sample from first-time disclosures of audit partner identities has several advantages and disadvantages. For starters, the analysis benefits from the fact that audit firms and companies may not have had sufficient time to endogenously change partner assignments in the first year under the Form AP regime. Another advantage is that practically all of the legal infractions (see below) were committed prior to our sample period such that the public revelation of partner identities almost certainly did not materially affect partner behaviors captured in our risk tolerance measures. In contrast, a potential downside is that there may be a learning process during the early years of the disclosures such that behaviors may be different in later years as audit firms and their clients adjust to the new regime (Lennox and Pittman 2010a). In another disadvantage, our sample has a restricted time-series, which prevents us from, for example, reliably examining whether switching to or from a risk-tolerant partner affects audit quality.

[11] Apart from dropping a single partner during data collection because this person is a non-U.S. citizen, the sample is comprehensive since we do not rely on voluntary participation (e.g., posting to LinkedIn or other professional websites), avoiding selection bias.

Measuring audit partners' risk tolerance

We develop a measure of audit partners' risk-tolerance based on the presence of prior legal infractions. After compiling a list of audit partner names from Form AP for our final sample, we hired an outside third-party specializing in criminal background checks to perform two services for $28 per person. First, the third-party conducted a person search to confirm the identity of each audit partner. Any partner with multiple or uncertain matches were sent to the research team for additional analysis. For these observations, separate co-authors performed independent searches to ascertain the correct individual based on identifiable demographics such as age, geographic information, education history, and self-reported addresses from publicly available sources (e.g., LinkedIn, audit firm websites and press releases, and state licensing board websites).[12] Second, after finishing the person search, the company performed a federal-, state-, and county-wide criminal background check. The data reported for each partner includes legal infractions such as traffic violations, driving under the influence of alcohol, and other charges.[13]

Rather than relating to the audit partners' work, these infractions represent off-the-job behaviors that reflect a greater propensity for risk-taking (Amir et al. 2014), which we predict will be associated with auditors' performance. In discussions with several partners and human resource representatives from U.S. accounting firms, we learned that a rigorous background check is part of the typical new partner promotion process at the Big 4 firms. In some instances, background checks are also undertaken at these firms at regular intervals or when a triggering event (e.g., potential rotation to a large client) occurs. This reliance on background checks as a means to identify and "protect themselves" from behaviors of individual partners lends

[12] Out of the 649 audit partners in the sample, we were able to match 647 with almost absolute certainty. For the remaining two partners, we were able to isolate the likely match with only a small amount of residual uncertainty. Predictably, our results hold if we remove these two partners from the analysis.
[13] We follow Amir et al. (2014) and Law and Mills (2019) to ensure that the sample is comprehensive by including all instances of actual and suspected legal infractions such that our measures are not sensitive to alternative retributions permitted for infractions to be dismissed or expunged from an individual's record.

credibility to specifying legal infractions to capture risk tolerance. Although we do not expect audit firms to discipline individuals with a history of traffic violations, this behavior is indicative of a person's tendency to push the boundaries of formal rules and social norms.[14]

Table 2 reports descriptive statistics on the quantity and type of infractions reported in the criminal background checks. A total of 223 infractions were committed by 111 (17.1%) partners; in contrast, 538 (82.9%) partners had no infractions, reinforcing that most auditors are risk-averse individuals. Of the 111 partners with at least one infraction, 59 (53.2%) of them are repeat offenders (i.e., recidivists), including one partner who committed 11 infractions. The vast majority of infractions, 215 out of 223 (96.4%), relate to traffic tickets: eight involve driving under the influence; 22 involve reckless driving, red light violations, or other safety related incidents; 101 are speeding tickets; and 84 are parking and other less severe traffic tickets. A small number of infractions, four out of 223 (1.8%), relate to severe crimes, including drug offences, assault, and evading arrest, while another four (1.8%) infractions involve sport and leisure activities.

Our primary measure of risk tolerance is an indicator variable (*INFRACTION*) set to one if the audit partner has committed at least one legal infraction, and zero otherwise.[15] For sensitivity analysis reported in Section 4, we construct three additional measures. First, we exclude less severe infractions such that the resulting measure, *SEVERE_INFRACTION*, is an indicator variable set equal to one if the partner committed at least one infraction outside of those

[14] For example, background checks are also becoming more common in other monitoring processes such as those implemented by boards of directors. Specifically, in discussing data obtained from background checks, Bower (2020: 20-21) states that: "everything is scrutinized" and that "a pattern of speeding violations suggests risky behavior."

[15] We considered whether the audit partner has a pilot license as an alternative measure of risk tolerance by searching the database maintained by the Federal Aviation Administration (FAA). We identified only five partners in our entire sample with a pilot license (0.77%). Relative to prior research reporting that approximately 6 to 8% of CEOs are pilots (Cain and McKeon 2016; Sunder et al. 2017), the low frequency of pilot licenses among partners provides indirect evidence that partners are generally more risk averse than corporate executives. However, the scarcity of pilot licenses among partners prevents us from meaningfully analyzing our research question with this measure.

related to parking and less severe traffic violations, and zero otherwise.[16] Second, we narrow the focus to reflect more recent infractions, which are more likely to occur during the individual's time as a partner, by assigning another indicator variable, *RECENT_INFRACTION*, the value one if a partner has any legal infractions in the past seven years, and zero otherwise. We follow Law and Mills (2019) in setting the cutoff at seven years since they find that recidivism steeply subsides when the last infraction was at least seven years ago. Finally, we specify a continuous measure, *NUM_INFRACTION,* which equals the natural logarithm of one plus the total number of infractions. Our four measures of partner risk tolerance are all highly positively correlated (ranging from 0.63 to 0.93), reflecting that they capture the same underlying construct.

Table 3 reports descriptive statistics for all partners in our sample (Panel A) and by subsample based on whether the partner has committed an infraction (Panel B). Specifically, our models reflect several additional partner characteristics that may affect the partner assignment process. Given that prior research suggests that female auditors are more risk-averse (Burke et al. 2019; Hardies et al. 2015; Lee et al. 2019) and auditors become more conservative in their decision-making over time in public practice (Trotman et al. 2009), we include control variables for partner gender (*FEMALE*) and experience (*AGE*). Reassuringly from an identification standpoint, these characteristics appear to be relatively similar for partners with and without infractions. Partners with prior infractions have, on average, slightly fewer clients (*NUM_CLIENTS*) relative to non-infraction partners. Partners with legal infractions are also marginally less likely to be affiliated with larger audit firms (*BIG4*), reconciling with the intuition that the Big 4 impose tougher quality control, including in the form of recruiting and retaining partners with characteristics conducive to flourishing in the public accounting profession (El Ghoul et al. 2016). Additionally, partners

[16] We consider traffic violations not related to moving charges as less severe (e.g., expired registration or expired license), consistent with common practice by insurance companies to exclude these non-moving infractions when setting insurance rates.

with a history of prior infractions are more likely to be non-local partners (*PTR_NONLOCAL*), defined as partners with a home office that is more than 100 kilometers from the client's headquarters (Francis et al. 2020). Interestingly, partners with infractions are also more likely to be industry experts in their local market (*PTR_EXPERT*), reinforcing the importance of controlling for these determinants in the multivariate regressions.

3. Empirical models

To analyze our prediction, we examine whether partners with greater risk tolerance are associated with lower audit quality after controlling for other auditor and client firm characteristics. Since actual audit quality is unobservable, we use multiple proxies that suit our testing ground, capturing both outputs and inputs of the audit process (DeFond and Zhang 2014), in estimating this model:

$$AQ_{it} = \beta_0 + \beta_1 INFRACTION_j + \sum\beta_k Controls_{kit} + \textit{Industry and Year Fixed Effects} + \varepsilon_{it} \quad (1)$$

We describe each of the regression variables in separate subsections below.[17]

Propensity to misstate

A natural output-based measure would reflect the incidence of material misstatements evident in subsequent restatement announcements. However, our setting does not allow us to identify subsequent restatement announcements due to limited time-series data (Cunningham et al. 2019; Francis et al. 2013). As an alternative, we use the propensity to misstate financial statements as

[17] Going concern reports are a direct measure of audit quality since the report is the auditor's responsibility (DeFond and Zhang 2014). Consistent with prior research (Chou et al. 2021; Kallunki et al. 2019), we considered using a measure of auditor reporting accuracy. After we follow prior work by limiting our sample to financially distressed clients (n=2,128), we identified 356 (126) instances in which the client received a (first-time) going concern opinion. Based on Audit Analytics data related to bankruptcies, we identified 328 cases that were Type I (false positive) errors and only 20 cases of a Type II (false negative) error. Moreover, there are 41 observations with a fiscal year end after May 31, 2021 for which we cannot yet make a determination. As such, we cannot reliably use auditor reporting accuracy as an alternative proxy. Although this approach does not suit the small samples under study (DeFond and Zhang 2014), we find that *INFRACTION* exhibits a negative relation with the likelihood of reporting a first-time going concern opinion, implying that risk-tolerant partners are less conservative in their reporting decisions.

captured by the F-score from Dechow et al. (2011: 18) given that it provides a "signal of the likelihood of earnings management or misstatement." An advantage of this measure is that it is correlated with the incidence of SEC enforcement actions, which is an *ex post* indicator for earnings manipulation (Fang et al. 2016). Several recent studies use this measure in a similar manner (Bradley et al. 2017; Cunningham et al. 2019; Fang et al. 2016; Ge et al. 2011; McGuire et al. 2012). *FSCORE* is the predicted probability of an accounting misstatement in Dechow et al. (2011), scaled by the unconditional probability of having a misstatement. We expect this measure to reflect more egregious issues related to the quality of audits. The propensity to misstate would rise with partner risk tolerance under H_1, which would be evident in a positive coefficient for β_1.

Discretionary accruals

Our second output-based measure of audit quality is performance-matched discretionary accruals (Kothari et al. 2005). We estimate each firm's residual from a cross-sectional modified Jones model for each two-digit SIC industry and year with at least 10 observations. Afterward, we calculate the difference between a firm's residual and the residual from a firm with the closest *ROA* in the same two-digit industry and year. The absolute value of this difference is our measure of discretionary accruals (*ABSDA*), which we use to capture "within GAAP" earnings manipulation. We expect to observe a positive coefficient for β_1 given the prediction in H_1 that risk-tolerant partners provide their clients with wider scope to manipulate earnings via accruals.

Likelihood of material weakness

For our third audit quality measure, we specify the likelihood of a client having a material weakness in internal control over financial reporting (*MW*) under SOX Section 404. Consistent with prior research (e.g., Lamoreaux 2016; Lamoreaux et al. 2019), we expect that auditors who conduct higher quality audits are both: (i) more fully able to evaluate internal controls and, accordingly, are in a better position to identify material weaknesses; and (ii) less susceptible to succumbing to management's pressure to reduce the severity of control deficiency reporting. Importantly, this specification aligns with DeAngelo's (1981) theory that audit quality stems from auditor competence and independence. We examine the impact of partner risk profiles on the incidence of material weaknesses using a logit model. We predict under H_1 a negative coefficient for β_1, reflecting that risk-tolerant partners are less likely to identify and report material weaknesses in internal controls over financial reporting.

Audit fees

In examining the role that partner risk tolerance plays in an input-based measure of audit quality, we specify the natural logarithm of audit fees (*LN_AUDFEES*) since fees are highly correlated with audit effort (Aobdia 2019a). The prediction in H_1 implies a negative coefficient for β_1 since audit partners with greater risk tolerance exert less effort.[18]

Audit report timing

We also use the timing of audit report release as another proxy for audit effort. In particular, we gauge the audit delay as the number of days that the audit report is issued ahead of the client's SEC filing date (*DELAY*). Large accelerated filers, accelerated filers, and non-accelerated filers are required to submit their annual reports within 60, 75, and 90 days after their fiscal year end, respectively (Lambert et al. 2017).[19] Accordingly, we expect that auditor effort is decreasing in the duration between the date the audit report is issued and the filing deadline. We predict under H_1 a negative coefficient for β_1, capturing that risk-tolerant partners exert less effort evident in finishing the audit earlier.

[18] Audit fees can also reflect that partners may charge their clients a risk premium, although this impact would run in the same direction; i.e., we expect that audit fees will be cheaper for clients with risk-tolerant partners who may both expend less effort and require smaller risk compensation (e.g., Simunic 1980).

[19] We verify that our results on this front hold when we replace *DELAY* with the standard measure of audit report lag based on the number of days between the fiscal year end and the audit report date (e.g., Knechel and Payne 2001). Given that Glover et al. (2020) highlight that this becomes a noisier proxy after 2009, we also verify that our results are robust to using the earnings announcement lag that reflects the duration between the fiscal year end and the earnings announcement date.

Asymmetric timely loss recognition

Finally, we examine timely loss recognition based on the Basu (1997) model, which is routinely used in evaluating audit quality (DeFond and Zhang 2014; Knechel et al. 2013b). This output-based measure facilitates gauging whether risk-tolerant partners are associated with less conservative financial reporting. Ettredge et al. (2012) find that restatement firms exhibit significantly lower levels of conservatism during the period of misstatement relative to non-restatement firms, suggesting that less timely loss recognition maps into more egregious forms of misreporting. Consistent with extant research (Cunningham et al. 2019; Ettredge et al. 2012), we extend Basu's (1997) model to include an interaction with partner infractions as follows:

$$
\begin{aligned}
EARN_{it} = {} & \beta_0 + \beta_1 RET_{it} + \beta_2 NEG_{it} + \beta_3 RET_{it} \times NEG_{it} + \beta_4 INFRACTION_j \\
& + \beta_5 INFRACTION_j \times RET_{it} + \beta_6 INFRACTION_j \times NEG_{it} \\
& + \beta_7 INFRACTION_j \times RET_{it} \times NEG_{it} + \beta_8 SIZE_{i,t-1} + \beta_9 SIZE_{i,t-1} \times RET_{it} \\
& + \beta_{10} SIZE_{i,t-1} \times NEG_{it} + \beta_{11} SIZE_{i,t-1} \times RET_{it} \times NEG_{it} + \beta_{12} MB_{i,t-1} + \beta_{13} MB_{i,t-1} \times RET_{it} \\
& + \beta_{14} MB_{i,t-1} \times NEG_{it} + \beta_{15} MB_{i,t-1} \times RET_{it} \times NEG_{it} + \beta_{16} LEVERAGE_{i,t-1} \\
& + \beta_{17} LEVERAGE_{i,t-1} \times RET_{it} + \beta_{18} LEVERAGE_{i,t-1} \times NEG_{it} \\
& + \beta_{19} LEVERAGE_{i,t-1} \times RET_{it} \times NEG_{it} + \textit{Industry and Year Fixed Effects} + \varepsilon_{it} \qquad (2)
\end{aligned}
$$

where *EARN* is earnings divided by the lagged market value of equity; *RET* is the 12-month cumulative return for the fiscal year; and *NEG* is an indicator variable equal to one if *RET* is negative, and zero otherwise. A client firm is considered to exhibit greater conservatism if its earnings are more sensitive to bad news than to good news, which would manifest as a positive coefficient for *RET*NEG*. Accordingly, if audit partners with greater risk tolerance are associated with less timely loss recognition, then this would translate into a negative coefficient for β_7.

Control variables

Besides the Basu model in Equation (2) that requires a unique approach, we closely follow prior research in the choice and specification of controls in Equation (1) that represent audit partner, audit office, audit firm, and client firm characteristics (Aobdia 2019a; Chou et al. 2021; Cunningham et al. 2019; Kallunki et al. 2019). This involves controlling for partner characteristics, including gender (*PTR_FEMALE*), experience (*PTR_AGE*), industry specialization (*PTR_EXPERT*), location status (*PTR_NONLOCAL*), and the number of clients (*NUM_CLIENTS*). We also control for audit firm size (*BIG4*), audit office industry specialization (*CITY_EXPERT*), first-year audit engagements (*AUDITOR_CHG*), and audits with a December year end (*BUSY*).

To mitigate concerns that our findings reflect executive-level rather than audit partner-level risk tolerance, we include measures of the CEO's and the CFO's risk tolerance. Given that cost constraints prevent us from gauging executive risk profiles using legal infractions, we resort to measuring this construct with whether the executive holds a pilot license (Cain and McKeon 2016; Sunder et al. 2017). We begin by retrieving CEO and CFO data for our sample observations from ExecuComp. Since ExecuComp does not provide executive data for most of our sample (2,161 out of 4,516 observations), we hand-collect CEO and CFO information for the specific firm and year from SEC proxy filings, annual reports, and other online sources when available. Afterward, we follow prior research by matching the CEO and CFO names in our sample to the FAA database of pilot licenses (*CEO_PILOT* and *CFO_PILOT*). Since gender and age may also reflect executives' risk tolerance (e.g., Ge et al. 2011), we include additional control variables that capture CEO and CFO gender and age using data downloaded from ExecuComp and hand-collected from SEC filings (*CEO_FEMALE*, *CEO_AGE*, *CFO_FEMALE*, and *CFO_AGE*).

Since the financial statements are the joint outcome of both the client's financial reporting and the audit process (Antle and Nalebuff 1991), we include client characteristics that are associated with lower financial reporting quality and greater financial reporting risk. These controls include client size (*SIZE*), financial condition (*LOSS, LEVERAGE,* and *MB*), cash flow levels and volatility (*OCF* and *VOLATILITY*), accounting reporting complexity (*ARC* and *PERC_EXTEND*), and other characteristics that reflect operating complexity and risk (*GROWTH*, *SEGMENTS*, and *FOREIGN_INC*). Finally, we include industry and year fixed effects to capture variations in audit quality across industries and over time. All continuous variables are winsorized at the 1st and 99th percentiles, and standard errors are clustered at the client firm level. In the Appendix, we provide detailed definitions for all variables.

4. Results

Descriptive statistics

Table 4 reports descriptive statistics for the regression variables in the client firm sample. This univariate analysis provides some initial evidence consistent with our prediction; specifically, we find that the mean values for *FSCORE* (*MW*, *LN_AUDFEES*, and *DELAY*) are significantly higher (lower) in the subsample where *INFRACTION*=1, although the differences are statistically indistinguishable from zero in the *ABSDA* comparison. Among the control variables, we find that clients in the *INFRACTION*=1 subsample are less likely to be affiliated with a Big 4 firm (*BIG4*), although they are more likely to engage a local industry expert (*CITY_EXPERT*). Also, these clients are slightly smaller (*SIZE*) and are more likely to have a younger CEO (*CEO_AGE*) and a pilot CFO (*CFO_PILOT*). Further, they report higher earnings and operating cash flows (*EARN*, *LOSS*, and *OCF*), exhibit less accounting reporting complexity (*ARC* and *PERC_EXTEND*), have less debt in their capital structures (*LEVERAGE*), exhibit less volatility and growth (*VOLATILITY* and *GROWTH*), and have smaller market-to-book ratios (*MB*). These descriptive statistics generally suggest that the clients of infraction partners enjoy less operating and reporting risk.

Multivariate evidence on audit quality

In Table 5, we report our primary evidence. Panel A presents the results for the propensity to misstate, discretionary accruals, reported material weaknesses, audit fees, and audit report delay estimations, while Panel B tabulates the results for the Basu (1997) model of timely loss recognition. Overall, we find consistent evidence at the 5% level or better across five of the six audit quality proxies supporting the prediction in H_1 that partners with greater risk tolerance conduct lower quality audits. Specifically, partners with prior infractions (*INFRACTION*) exhibit a positive and statistically significant association with *FSCORE* ($p < 0.05$); reflecting its economic materiality, the coefficient on *INFRACTION* indicates a 9% greater propensity to misstate, on average. In the *MW* model, we find that *INFRACTION* enters negatively ($p < 0.05$); its coefficient implies that the odds of identifying and reporting a material weakness is 33% lower for partners with infractions relative to their counterparts without prior infractions. Further, the asymmetric timeliness coefficient for *INFRACTION* in the Basu model is negative and significant ($p < 0.05$); in terms of economic magnitude, this result translates into partners with infractions experiencing a 22% reduction in timely losses for their clients' recognition of negative news. Finally, the significant inverse relations between *INFRACTION* and both *LN_AUDFEES* ($p < 0.01$) and *DELAY* ($p < 0.01$) reveals that partners with risky off-the-job behavior exert less effort on their engagements; economically, partners with an infraction, on average, charge audit fees that are 7% lower and issue audit reports 27% earlier.[20] In contrast, the *ABSDA* regression results suggest that *INFRACTION* is irrelevant to less severe forms of within-GAAP earnings management.[21]

Besides our focus on audit quality instead of client portfolio considerations, these findings differ from prior research. In particular, Amir et al. (2014) document a *positive* association between partner infractions and audit fees in Sweden, which they attribute to partners expanding the scope of the audit to manage the elevated risk. In contrast, we report a *negative* association between partner infractions and audit fees, consistent with our prediction that risk-tolerant

[20] In a separate series of re-estimations, we incorporate audit firm fixed effects into the models and find that our core results remain consistent.

[21] Since some prior research implies that auditors are more eager to constrain upward earnings management (Lennox et al. 2014; Nelson et al. 2002), we separately analyze positive abnormal accruals using a tobit model and continue to find that partner risk tolerance has no perceptible impact. In interpreting these insignificant results, it is important to stress that it may be hard to justify gauging audit quality with general earnings management since this construct is difficult to reliably measure (e.g., Aobdia 2019a; Dechow et al. 2010; Hribar and Collins 2002).

partners tend to charge lower fees (and, in turn, expend less effort evident in the negative association with the audit quality proxies) in striving to retain the client in the short-term.

It is important to stress that our findings for partner infractions are incremental to other audit firm, office, and partner traits. Specifically, partners' demographic characteristics (*PTR_FEMALE*, *PTR_AGE*) and number of clients (*NUM_CLIENTS*) generally have statistically insignificant coefficients in our models, reflecting that these variables do not explain variation in audit quality. Consistent with Goodwin and Wu (2014), we find that partner industry expertise (*PTR_EXPERT*) is positively associated with audit fees, subsuming any effect of office-level expertise. *PTR_EXPERT* is also positively associated with the likelihood of material weaknesses, although it has no discernible impact on F-score or discretionary accruals. We also find that *PTR_NONLOCAL* exhibits positive associations with both the likelihood of material weaknesses and audit report delay, but a negative association with audit fees. Focusing on the other auditor characteristics, we find that Big 4 auditors (*BIG4*) are associated with a lower propensity to misstate and higher fees, while *CITY_EXPERT* is insignificant in each specification. Finally, *AUDITOR_CHG* is associated with a lower propensity to misstate, a higher likelihood of material weaknesses, and a longer audit report delay.

In additional tests (untabulated), we evaluate whether our earlier results are robust to using the alternative risk tolerance measures. Using the same models as in Table 5, we continue to find supportive evidence in almost all cases when we replace *INFRACTION* with *SEVERE_INFRACTION*, *RECENT_INFRACTION* and *NUM_INFRACTION* in successive regressions; in the lone exception, the coefficient on *NUM _INFRACTION* becomes insignificant when we focus on timely loss recognition in Equation (2). Further, to confront the concern that our findings are driven by extreme partner observations, we re-estimate our regressions after separately and jointly removing observations for clients engaging partners with these infraction types listed in Table 2: (i) reckless, red light, and safety related traffic tickets; (ii) driving under the influence (DUI) tickets; (iii) drugs, assault, and evading arrest tickets; and (iv) four or more infractions. We find that our core results hold in all cases except that *INFRACTION* becomes insignificant when we no longer include DUI infractions in the timely loss recognition model. In short, these re-specifications reinforce that our evidence reflects pervasive economic phenomena.

Propensity score matching (PSM) and entropy balancing

Extant audit research stresses the inherent challenges in distinguishing audit quality from the client's underlying accounting transparency (Lawrence et al. 2011; Minutti-Meza 2013). Although PSM does not alleviate the endogeneity concern related to selection on unobservable factors, we complement our primary regression models by relying on this approach to mitigate observable confounding effects.[22] Specifically, we predict the propensity of a partner having prior infractions using a logistic regression where the dependent variable is *INFRACTION* and the independent variables are the control variables from Table 5. We also modify the matching model depending on the number of observations available for each dependent variable. Consistent with recommendations in prior research (Lennox and Pittman 2010b; Shipman et al. 2017), we implement both 1:1 and 1:3 matching in successive analyses. The 1:1 (1:3) matched sample involves matching each observation with *INFRACTION*=1 to an observation (three observations) with *INFRACTION*=0 by propensity score, within common support, without replacement (with replacement), using a caliper distance of 0.03. To conserve space, we only tabulate findings under

[22] Ideally, we would identify an exogenous variable that is an important determinant of a partner's legal infractions but not correlated with audit quality in a two-stage Heckman selection model. However, similar to Davidson et al. (2015), we struggle to locate a suitable exogenous determinant that meets both criteria. Another approach is to include client fixed effects in the models to capture unobservable time-invariant client characteristics not controlled in our multivariate analysis (Lennox et al. 2012; Pittman and Fortin 2004). Naturally, we cannot sensibly apply this design given that our test variables suffer from poor time-series variation in that client firms seldom change auditors in the short period under study. As a result, including firm fixed effects that remove cross-sectional variation would leave the analysis susceptible to failing to identify an impact even if present (deHaan 2021; El Ghoul et al. 2016; Zhou 2001).

1:1 matching, although all core results hold under 1:3 matching. To provide an example, Panel A of Table 6 reports the descriptive statistics for the control variables in the *FSCORE* matched sample. The differences in means between the treated (*INFRACTION*=1) and control (*INFRACTION*=0) samples are statistically insignificant at conventional levels for all independent variables ($p > 0.10$). We also verify that we reach covariate balance in each of the remaining matched samples. In the multivariate regression results tabulated in Panel B, we find that our core evidence remains at the 1% level after applying a PSM procedure to control for variation in observable characteristics between partners with and without infractions.

In a separate set of tests, we also employ entropy balancing to reduce covariate imbalance between clients with partners with and without infractions (Hainmueller 2012). Whereas PSM assigns a weight of either zero or one to each control observation, entropy balancing estimates continuous weights for observations in the control sample to achieve covariate balance, ensuring that we retain all observations in the full sample. In Panel B of Table 6, we report the multivariate regression results after weighting observations by their corresponding entropy weights. We require covariate balance on the first, second, and third moments of the distributions of all covariates. In doing so, we note that the maximum weight and the weight ratio are quite low, indicating that entropy balancing did not assign excessively high weights to a large number of control observations (McMullin and Schonberger 2020, 2021). In all estimations, we find that our core evidence holds at the 1% level after applying this entropy balancing technique to control for variation in observable characteristics between partners with and without infractions. Set against Amir et al.'s (2014) evidence that risk-tolerant partners assemble riskier clienteles, these analyses reinforce our earlier evidence implying that these partners provide more lenient external monitoring of their clients' financial reporting. In other words, the audit quality impact of partner risk tolerance appears to run through two channels: imposing more lax client screening in the first place (Amir et al. 2014) and conducting lower quality audits afterward.

Partner rotation analysis

Recent field evidence implies that audit firms are responsible for partner assignment in the U.S. (Dodgson et al. 2020), making it difficult to accept that risk-tolerant partners self-select into certain engagements.[23] However, consistent with extensive prior research that relies on mandatory partner rotation as an exogenous shock that disrupts the assignment of partners to client engagements (e.g., Firth et al. 2012; Lennox et al. 2014; Sharma et al. 2017), we exploit these mandatory partner rotation rules in undertaking a falsification test. Specifically, we capture each unique partner-client combination in our sample and then determine the partner's tenure according to the most recent Form AP filings. This data enables us to approximate the prior period in which a different partner would be assigned to each company. In this analysis, we focus on year *t*-6 to avoid confounding stemming from the incoming partner shadowing the outgoing partner in their last year on the engagement (Dodgson et al. 2020) and the outgoing partner working harder in their last year (Lennox et al. 2014). Accordingly, we construct a sample including the set of companies for which we have data for both year *t* and year *t*-6 that also continue to engage the same audit firm in both periods. We then apply our risk tolerance measures to the data in year *t*-6; since the partner would be different during that time period, we would not expect our results to hold using year *t*-6 data. Reassuringly, of the six audit quality variables under study in Table 5, we find that *INFRACTION* enters significantly at conventional

[23] In any event, any potential threat that selection bias poses likely runs in the opposite direction with more risk-tolerant partners assigned to lower-risk engagements (Hardies et al. 2020; Kinney 2015), making it harder for our analysis to reject the null hypothesis. Indeed, the descriptive statistics in Table 4 generally support that partners with prior infractions audit lower-risk clients evident in their lower accounting reporting complexity, higher earnings, lower leverage, and larger and less volatile operating cash flows.

levels in only one specification (untabulated).[24] Collectively, this falsification analysis helps dispel the concern that time-invariant client characteristics are spuriously behind our core results.[25]

Additional sensitivity analysis

Next, we undertake several additional sensitivity tests (untabulated). Since some research suggests that education is a determinant of audit quality (Gul et al. 2013), we analyze whether our inferences are sensitive to controlling for partner education. This involves constructing several measures of partners' education (*PTR_EDUCATION*) using data from LinkedIn and other online sources. Specifically, we identify whether the partner was an accounting major in their undergraduate program (75.6%), holds a graduate degree (16.7%), or graduated from a top accounting program (7.5%). We exclude these variables from the main analyses to minimize attrition in our small samples. However, in these additional tests, our core results for partner risk tolerance persist. Also, we generally find that these education variables are insignificant, corroborating prior work on U.S. audit partners (e.g., Burke et al. 2019; Francis et al. 2020).

In an alternative approach to dispelling any remaining concern that our evidence reflects executive-level instead of partner-level risk tolerance, we control for the risk-seeking nature of CEOs using the risk-taking activities of their firms. Specifically, we include separate controls for research and development (*R&D*), capital expenditures (*CAPEX*), and acquisitions (*ACQUISITION*) (Davidson et al. 2015). After adding these various controls for executives' risk

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[24] Regrettably, data constraints prevent us from controlling for executive-level characteristics in these falsification tests. Our results are qualitatively similar when we use *t*-5 or successively replace *INFRACTION* with the three alternative proxies for partner-level risk tolerance.

[25] Exceedingly poor variation prevents us from reliably analyzing partner changes. This lack of variation reflects that audit firms eager to minimize disruptions to the client relationship and avoid transition costs seldom replace the incumbent partner until the engagement reaches the mandatory rotation stage (Dodgson et al. 2020; Litt et al. 2014). Further, for the short time-series under study, we can only identify 206 partner changes in our sample—after excluding those stemming from an audit firm switch—with available data to determine changes in risk tolerance. Importantly, nearly 85% (=174/206) of these changes represent lateral moves (i.e., *INFRACTION*=1 to *INFRACTION*=1 or *INFRACTION*=0 to *INFRACTION*=0) such that we are left with only 5% (=11/206) that involve moving from a non-infraction to an infraction partner and 10% (=21/206) that involve moving from an infraction to a non-infraction partner.

preferences to the estimations, our core evidence holds except that *INFRACTION* is just outside conventional levels of statistical significance in the *FSCORE* regression. However, *INFRACTION* remains positive and significant if we use model (1) in Dechow et al. (2011) to measure *FSCORE*.

Although we could not identify any reason *ex ante* why unobservable variation in law enforcement across different locations is spuriously behind our evidence, we nonetheless examine its potential role in two ways. First, we find that our results are robust to re-estimating the regressions after controlling for the population of the Metropolitan Statistical Area (*MSAPOP*). Next, we sequentially drop observations for each of the 35 states in which partners in our sample reside to ensure no single state is driving our results. The results hold without exception in all 35 instances for each of the model specifications.

Non-audit services

A natural question stemming from our analysis so far is whether risk-tolerant partners elicit any benefit for themselves or their firms from providing lower effort and quality on their audit engagements. The descriptive statistics in Table 3 suggest that partners with prior infractions serve approximately the same number of public clients as partners without infractions. Regrettably, data constraints prevent us from examining these partners' private clienteles to gauge whether risk-tolerant partners leverage the time saved on these public clients to attract and service more private clients. However, we are able to evaluate whether risk-tolerant partners supply more non-audit services to their public clients.[26] The dependent variable in these tests is the natural logarithm of one plus total non-audit fees collected from an audit client (*LN_NONAUDFEES*). The multivariate regression results in Table 7 indicate that partners with off-the-job infractions are associated with significantly higher levels of non-audit services relative

[26] Knechel et al. (2013a) document that partner compensation reflects both their technical and marketing performance, implying that risk-tolerant partners may focus on attracting non-audit fees at the expense of audit quality.

partners without such infractions ($p < 0.05$). We report similar evidence when we apply PSM or entropy balancing. These results reinforce the narrative underlying our primary findings that certain partners are more likely to engage in risky behavior to not only retain their audit clients, but also pursue alternative sources of benefit through the sale of greater non-audit services. Additionally, this evidence provides insight on why audit firms tolerate these partners; i.e., although they conduct lower-quality audits, partners known to exhibit risky behaviors also appear to attract more consulting revenue from these clients.

Cross-sectional analyses

In a final series of tests, we consider whether the importance of partners' risk tolerance varies systematically across certain audit firm and audit office characteristics known to shape audit quality according to prior research. This cross-sectional analysis provides insights beyond the average effects shown in our earlier regressions. In Table 8, we report subsample tests using seemingly unrelated estimation.[27] We rely on a split-sample design given the considerable differences in clienteles across types of audit firms and offices (DeFond et al. 2018; Gipper et al. 2021; Lawrence et al. 2011; Lennox and Pittman 2010b; Minutti-Meza 2013). This approach also facilitates evaluating not only whether there is a difference across subsamples, but also whether partners with prior infractions exhibit a significant relation with audit quality *within* a given subsample (holding within-group client characteristics more constant).

In Panel A of Table 8, we partition the sample by the size of the audit firm. Largely reflecting their size, Big 4 firms benefit from economies of scale that afford them more resources, standardized audit procedures, and superior quality control systems for monitoring performance

[27] Constructive for testing cross-model hypotheses, seemingly unrelated estimation allows the two regression models (e.g., Big 4 and non-Big 4) to have correlated error terms (Hayes et al. 2012; He et al. 2016; Chou et al 2021). Further, we exclude *ABSDA* from Table 8 since, consistent with our main results, the coefficient on *INFRACTION* is insignificant in all subsamples.

(Simunic 1980). They also experience fewer threats to independence since each client of a Big 4 firm is relatively less important than each client of smaller firms (DeAngelo 1981). Additionally, extant research implies that Big 4 firms are more eager to avoid costly litigation and protect their valuable reputations (Cooper and Robson 2006; El Ghoul et al. 2016). Finally, the Big 4 routinely assign larger teams to audit engagements, potentially diluting the role that partner-level risk tolerance plays (Gul et al. 2013). In fact, recent research documents that Big 4 firms constrain the importance of certain partner traits to audit quality (Chou et al. 2021; Kallunki et al. 2019).[28] It follows that the link between risk-tolerant partners and audit quality will be magnified in non-Big 4 audit firms. Our results imply that, except for audit fees, the association between partner infractions and audit quality is concentrated—and often statistically stronger—in non-Big 4 firms. The evidence for reported material weaknesses and asymmetric timely loss recognition shows that we only observe negative and significant coefficients for *INFRACTION* and *INFRACTION*RET*NEG*, respectively, in the non-Big 4 subsample. In contrast, the findings for the propensity to misstate, audit fees, and audit report timing differ in that *INFRACTION* is statistically significant in both subsamples, albeit only marginally in the Big 4 subsample. Altogether, this evidence lends some support to the intuition that the Big 4 better constrain more risk-tolerant partners from undermining audit quality.

Next, we re-estimate the regressions after splitting the sample according to audit office characteristics that may mitigate the influence of risk tolerant partners. In Panel B, we report the results for offices with and without local industry expertise based on the *CITY_EXPERT* variable (Reichelt and Wang 2010). We find that *INFRACTION* is only significant at conventional levels

[28] In discussions with partners and human resource representatives at U.S. audit firms, we observed considerably more formalized monitoring of this type of partner behavior by the larger firms. Specifically, new partners at Big 4 firms must undergo an extensive background check as part of the new partner promotion process. In contrast, smaller firms tend to rely on more informal peer-to-peer monitoring; for example, one non-Big 4 partner noted: "we are a close group and know each other pretty well…we don't go looking for issues but expect major ones to bubble up so that we would find out about them that way."

for partners located in offices without industry expertise in the propensity to misstate and likelihood of reporting a material weakness regressions; tests of coefficient equality reveal perceptible differences in both cases. Although *INFRACTION* is significant in both subsamples for audit report timing, the impact is stronger for non-expert offices. Similar to Panel A, we also find that audit fees are significantly lower for both expert and non-expert offices in the presence of a risk-tolerant partner. However, we do not find any evidence consistent with our conjecture in the timely loss recognition model. Collectively, these results generally imply that the importance of risk tolerant partners to audit quality rises when we isolate non-expect offices.

In Panel C, we examine potentially differential effects based on the proximity of the partner's engagement office to the audit firm's national office. Amin et al. (2021) document that national offices provide superior support, monitoring, and advising to physically closer offices, engendering higher audit quality. We follow Amin et al. (2021) by narrowing our focus to the top 12 audit firms in the U.S. and identify each firm's national office location. Afterward, we bisect the sample into close versus distant engagement offices based on the median value of their distance from the national office. We find that the impact of partners with prior infractions is stronger for the more distant offices in three of the five comparisons (the exceptions relate to material weakness reporting and audit reporting timing). Altogether, the evidence in Panels B and C generally supports that high-quality offices and offices subject to stricter internal monitoring better constrain risk-tolerant partners from compromising audit quality.

Finally, in Panel D, we report the results from undertaking a split-sample analysis according to whether the partner's engagement office is in the same city as one of the 12 SEC offices (including its headquarters in Washington D.C.). DeFond et al. (2018) show that greater awareness of SEC enforcement disciplines audit offices. It follows that audit offices in the same city as an SEC office will focus more intently on monitoring risk-tolerant partners given the threat of external oversight. Lending support to the underlying narrative on the importance of partners' risk tolerance, we find that the negative audit quality impact of partners with an infraction is concentrated in offices without a local SEC presence for the propensity to misstate, audit fees, audit report timing, and timely loss recognition regressions. However, in pairwise comparisons, we fail to observe a significant difference between the coefficients on *INFRACTION* in these subsamples. Besides that the analyses in Table 8 provide interesting insights in their own right, these findings also complement our earlier results with supportive cross-sectional evidence that would be difficult to attribute to a competing explanation.

5. Conclusion

We examine whether an audit engagement partner's tolerance for risk shapes audit quality in the U.S. Our analysis contributes to recent research documenting an association between audit quality and individual partner effects, with little variation explained by observable demographic traits (Cameran et al. 2020; Gul et al. 2013). Grounded in extensive prior research in economics and criminology (Dohmen et al. 2011; Ehrlich 1973; Gottfredson and Hirschi 1990), we gauge partner-level risk tolerance with their legal infractions before evaluating its role in audit quality. Analyzing the impact of partners' risk tolerance on audit quality distils to a joint test of: whether their risk profiles affect their performance, and whether variation in risk tolerance manifests in audit outcomes despite the presence of various constraining forces in the U.S.

We document that partners with prior infractions conduct lower quality audits evident in a greater propensity to misstate, fewer reported material weaknesses, less timely loss recognition, lower audit fees, and shorter audit report delays. In contrast, we fail to find evidence that partners with off-the-job legal infractions have a perceptible impact on discretionary accruals, suggesting that the importance of partner-level risk tolerance runs through more egregious threats to accounting transparency rather than less severe forms of within-GAAP earnings management.

Besides that these partners are more likely to engage in risky behavior to retain clients, we also report evidence that risk-tolerant partners pursue alternative sources of benefit by supplying more non-audit services to their public company audit clients. Additionally, consistent with expectations, we generally find that the association between partner infractions and audit quality is concentrated in non-Big 4 audit firms, non-expert offices, offices farther from the firm's national office, and offices more distant from the SEC. In contrast to recent research implying that observable lead partner characteristics hardly matter to audit quality in the U.S. (e.g., Aobdia et al. 2021; Gipper et al. 2021; Lee et al. 2019), our results collectively imply that audit quality is sensitive to partners' risk tolerance. Accordingly, we respond to specific calls for evidence on this issue (Cameran et al. 2020; Lennox and Wu 2018).

Our analysis is subject to several caveats. First, since we cannot directly observe partner's risk tolerance during engagements, we construct a measure from the existence of prior legal infractions. In a major upside, gauging partner style with off-the-job behavior improves identification of partner type relative to prior research that resorts to measuring style with on-the-job behavior (Aobdia et al. 2015; Knechel et al. 2015). We also verify that our results are robust to alternative measures of risk tolerance that capture more severe or more recent infractions. Although this design choice is based on extensive research in criminology and psychology, it remains plausible that our measure captures characteristics of the audit partner other than their risk tolerance. Despite that we control for several observable partner characteristics in the regressions (e.g., gender, age, expertise, education, location, number of clients), we cannot dismiss the possibility that our measure represents a partner trait other than risk tolerance.

Second, we cannot fully dispel the threat to reliable inference stemming from selection bias and correlated omitted variables. Extant archival audit research struggles with identifying whether differences in audit and financial reporting quality reflect client versus auditor characteristics (e.g., Lawrence et al. 2011; Lennox and Pittman 2010b). We confront this concern by controlling for observable differences across partners that could be correlated with the presence of legal infractions, controlling for characteristics representing executives' risk appetites and client risk, applying PSM and entropy balancing techniques, and implementing a falsification test that exploits mandatory partner rotation. However, given our inability to identify proper exclusion restrictions (Lennox et al. 2012), we are unable to fully address potential selection bias stemming from the non-random assignment of partners to clients (Kinney 2015; Lennox and Wu 2018). Lennox et al. (2012: 590) stress that "…it may not be feasible to implement a convincing selection model in some research settings and, in this case, our advice is that studies acknowledge this limitation and provide a caveat that the reported results could be affected by selection bias." Accordingly, we do not ascribe causality to our evidence.

Finally, we restrict our sample drawn from the first year of Form AP disclosures to partners with at least two clients since most audits in a given year are handled by partners with multiple clients; requiring a minimum of two clients per partner alleviate concerns that our evidence spuriously stems from a single client; and this facilitates balancing the benefits of assembling a large sample against the high costs of data collection. Although this approach is consistent with prior work focusing on partners with multiple public clients (Cameran et al. 2020; Gul et al. 2013), we caution that it may undermine the generalizability of our findings to the full population of partners.

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APPENDIX
Variable Definitions

Dependent Variables:

FSCORE	the predicted probability of accounting misstatements from model 2 in Table 7, Panel A of Dechow et al. (2011), scaled by the unconditional probability of having accounting misstatements. Values greater than (less than) one indicate a higher (lower) probability of misstatement/ manipulation than the unconditional expectation. We use model 2 in Dechow et al. (2011) since this model incorporates important non-financial metrics and off-balance sheet variables that are key misstatement indicators (Brazel et al. 2009; Ge 2007). However, our core evidence is nearly identical if we replace *FSCORE* with a measure based on model 1 in Dechow et al. (2011).
ABSDA	the absolute value of discretionary accruals based on the modified Jones model using a cross-sectional regression for each two-digit SIC industry and year with at least 10 observations. Specifically, we estimate the following model and then difference each company's residual with the residual from a company with the closest *ROA* in the same two-digit SIC industry and year: $TA_{it}/A_{it-1} = \beta_1(1/A_{it-1}) + \beta_2((\Delta S_{it} - \Delta AR_{it})/A_{it-1}) + \beta_3(PPE_{it}/A_{it-1}) + u_{it}$ where *TA* equals total accruals using the indirect cash flow method (i.e., income before extraordinary items minus operating cash flow from continuing operations); *A* equals total assets; ΔS equals the change in total sales from the prior year; ΔAR equals the change in accounts receivable from the prior year; *PPE* equals net property, plant, and equipment; and *i* and *t* are company and year indicators, respectively.
MW	1 if the company or the auditor disclosed a material weakness under SOX 404a/404b in year *t*, and 0 otherwise.
LN_AUDFEES	the natural logarithm of audit fees in year *t*.
DELAY	the number of days that the audit report is issued ahead of the client firm's SEC filing deadline.
EARN	earnings before extraordinary items (IB) in year *t* divided by the market value of equity (PRCC_F*CSHO) in year *t*-1.
LN_NONAUDFEES	the natural logarithm of 1 plus total non-audit fees in year *t*.

Test Variables:

INFRACTION	1 if the criminal background check reported at least one infraction for the audit engagement partner, and 0 otherwise.
SEVERE_INFRACTION	1 if the criminal background check reported at least one infraction, other than parking and less severe traffic violations (other than speeding tickets) for the audit engagement partner, and 0 otherwise.

RECENT_INFRACTION	1 if the audit engagement partner has at least one legal infraction in the criminal background check that is less than or equal to seven years old, and 0 otherwise.
NUM_INFRACTION	the natural logarithm of 1 plus the number of infractions in the criminal background check for the audit engagement partner.
<u>Audit Partner Control Variables:</u>	
NUM_CLIENTS	the number of public clients in our sample for each audit engagement partner in year *t*.
PTR_AGE	the audit engagement partner's age calculated as of the date of the financial statements in year *t*.
PTR_EDUCATION	1 if the audit engagement partner (each examined separately): (1) majored in accounting in their undergraduate studies, (2) holds a graduate degree, or (3) holds an accounting degree from one of the top accounting programs. We follow Sunder et al. (2017) by defining the top accounting programs as the 12 schools listed as the "Best Undergraduate Accounting Programs" in the most recent *U.S. News and World Report* rankings.
PTR_EXPERT	1 if the audit engagement partner has the largest market share based on audit fees in a given two-digit SIC industry-city-year—where city is defined as a Metropolitan Statistical Area (MSA)—and the partner has more than 10% market share greater than their closest competitor, and 0 otherwise.
PTR_FEMALE	1 if the audit engagement partner is a female, and 0 otherwise.
PTR_NONLOCAL	1 if the audit engagement partner's home office is greater than 100 kilometers from the client's headquarters following Francis et al. (2020). We obtain the partner's home address in the background check reports so we can accurately determine the partner's home office.
<u>Other Auditor Control Variables:</u>	
AUDITOR_CHG	1 if the one if the company changes auditors in year *t*, and 0 otherwise.
BIG4	1 if the auditor is a Big 4 firm, and 0 otherwise.
CITY_EXPERT	1 if the auditor has the largest market share based on audit fees in a given two-digit SIC industry-city-year—where city is defined as a Metropolitan Statistical Area (MSA)—and the auditor has more than 10% market share greater than their closest competitor, and 0 otherwise.
<u>Client Control Variables:</u>	
ACQUISITION	sum of acquisitions (ACQ) for year *t*-1 and year *t* scaled by total assets (AT) in year *t*-1.
ARC	accounting reporting complexity from Hoitash and Hoitash (2018) as measured by the count of unique XBRL tags per financial statement disclosure in year *t*.

BUSY	1 when fiscal year *t* ends in the month of December, and 0 otherwise.
CAPEX	capital expenditures (CAPX) scaled by total assets (AT) in year *t*.
CEO_AGE (CFO_AGE)	the age of the CEO (CFO) in year *t* according to data retrieved from ExecuComp or hand-collected from SEC filings.
CEO_FEMALE (CFO_FEMALE)	1 if the CEO (CFO) is a woman according to data retrieved from ExecuComp or hand-collected from SEC filings, and 0 otherwise.
CEO_PILOT (CFO_PILOT)	1 if the CEO (CFO) has a pilot license according to the database maintained by the Federal Aviation Administration (FAA), and 0 otherwise.
FOREIGN_INC	absolute value of pretax income from foreign operations (PIFO) divided by the absolute value of pretax income (PI).
GROWTH	sales growth from year *t*-1 to year *t*, scaled by sales in year *t*-1 (SALE).
LEVERAGE	total debt (DLC + DLTT) divided by total assets (AT) in year *t*.
LOSS	1 if earnings before extraordinary items (IB) in year *t* are less than zero, and 0 otherwise.
MB	market value of assets (AT + (PRCC_F*CSHO) – CEQ) divided by book value of assets (AT) in year *t*.
MSAPOP	population for a given Metropolitan Statistical Area (MSA) based on the 2010 census, as well as the estimated population for 2017.
NEG	1 if *RET* is negative in year *t*, and 0 otherwise.
OCF	cash flow from operations (OANCF) in year *t* divided by total assets (AT) in year *t*-1.
PERC_EXTEND	ratio of extended XBRL tags to total tags in year *t* from Hoitash and Hoitash (2018). Extended tags are created by companies when firms determine that the available taxonomy tags cannot accurately capture their company-specific economic transactions.
R&D	research and development (XRD) expenditures scaled by total assets (AT) in year *t*.
RET	annual buy and hold return estimated for the fiscal year *t*. Return data is obtained from CRSP (and supplemented with Compustat return data if missing from CRSP).
SEGMENTS	natural logarithm of the number of business segments in year *t* as obtained from the Compustat Segments file.
SIZE	natural logarithm of total assets (AT) in year *t*.
VOLATILITY	standard deviation of operating cash flows (OANCF/AT) over the past four years (*t*-3 to *t*).

TABLE 1
Sample selection

Observations in PCAOB Form AP data [a]	7,524
Less: Observations with a fiscal year-end on 10/31/2016 or prior [b]	(185)
Less: Second year of Form AP data for a specific client firm	(938)
Less: Observations with AT < $1 million and without necessary data for variables	(2,805)
Less: Observations in financial industries (two-digit SIC codes between 60-69)	(963)
Total available client firm observations in the first year of Form AP	2,633
Total number of available audit partners in the first year of Form AP	1,739
Less: Observations for partners with only one public client in the sample	(1,132)
Total observations for partners with more than one public client to collect background check data	1,501
Plus: Extend observations with fiscal year-ends through 10/31/2020 for the same partners	3,015
Total client firm-year observations in final sample	**4,516**
Total number of audit partners in final sample	**649**

[a] The original PCAOB Form AP data (https://pcaobus.org/Pages/AuditorSearch.aspx) was downloaded on March 12, 2018. We limited this dataset to only include Issuer clients from the U.S. with original filings (not duplicates or dual-dated) and non-missing CIKs.

[b] We exclude stale filings with fiscal year-ends on or before October 31, 2016 to avoid including Form AP observations related to restatements or other issues requiring significant delays in the audit. Data was retrieved on March 12, 2018 for the first Form AP filing issued for a given client with the audit report issued on or after January 31, 2017; therefore, 10-K filings related to fiscal year-ends on or before October 31, 2016 would have issuance dates extending beyond 90 days, which is the SEC deadline for the smallest, non-accelerated filers.

TABLE 2
Details of legal infractions

Panel A: Types of infractions committed by audit partners

Infraction Description	Count
Speeding tickets	101
Reckless, red light, and safety related traffic tickets	22
Driving under the influence (DUI) tickets	8
Drugs, assault, and evading arrest tickets	4
Parking and other traffic tickets [a]	84
Sport and leisure tickets [b]	4
Total infractions	**223**

Panel B: Number of infractions committed by audit partners

	Partners	%	Infractions
Number of partners with 0 infractions	538	82.9%	0
Number of partners with 1 infractions	52	8.0%	52
Number of partners with 2 infractions	31	4.8%	62
Number of partners with 3 infractions	16	2.5%	48
Number of partners with 4 infractions	7	1.1%	28
Number of partners with 5 infractions	2	0.3%	10
Number of partners with 6 infractions	2	0.3%	12
Number of partners with 11 infractions	1	0.1%	11
Total	**649**	**100%**	**223**

[a] Other traffic tickets include less severe traffic infractions than speeding, such as an expired vehicle registration or license.

[b] Sport and leisure tickets include infractions related to activities such as fishing, water sports, and fire management while camping.

TABLE 3
Audit partner characteristics

Panel A: Descriptive statistics for all audit partners (N = 649)

Variable	Mean	Median	Std. Dev.
PTR_FEMALE	0.143	0.000	0.351
PTR_AGE	49.109	48.478	6.212
PTR_EXPERT	0.134	0.000	0.232
PTR_NONLOCAL	0.312	0.000	0.339
BIG4	0.686	1.000	0.465
NUM_CLIENTS	2.266	2.000	0.739
INFRACTION_COUNT	0.344	0.000	0.961

Panel B: Comparison of audit partners by the existence of infractions

Variable	*INFRACTION=0* Mean	*INFRACTION=1* Mean	Test of Mean Diff. (p-value)	
PTR_FEMALE	0.147	0.126	0.571	
PTR_AGE	49.030	49.492	0.476	
PTR_EXPERT	0.116	0.222	0.000	***
PTR_NONLOCAL	0.301	0.365	0.070	*
BIG4	0.701	0.613	0.069	*
NUM_CLIENTS	2.293	2.137	0.043	**
INFRACTION_COUNT	0.000	2.009	0.000	***
N	538	111		

Panel A presents descriptive statistics of all audit partners in our sample. Since *AGE*, *PTR_EXPERT*, *PTR_NONLOCAL*, and *NUM_CLIENTS* varies by year for each partner, these descriptives represent the average for each partner in the sample for purposes of reporting partner-level statistics. Panel B presents the mean difference by risk tolerance of the audit partner, where *INFRACTION* represents instances in which the audit partner has at least one infraction in his/her criminal background check. Variable definitions are provided in the Appendix.

TABLE 4
Client firm descriptive statistics

	Full Sample			INFRACTION=0			INFRACTION=1			
Variable	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	
FSCORE	4,385	0.998	0.742	3,695	0.990	0.744	690	1.041	0.728	*
ABSDA	4,516	0.131	0.170	3,820	0.132	0.172	696	0.124	0.156	
MW	4,516	0.105	0.306	3,820	0.108	0.311	696	0.085	0.279	*
LN_AUDFEES	4,516	13.973	1.221	3,820	14.007	1.212	696	13.788	1.250	***
DELAY	4,516	-6.481	11.067	3,820	-6.230	10.988	696	-7.859	11.403	***
BIG4	4,516	0.670	0.470	3,820	0.683	0.465	696	0.596	0.491	***
CITY_EXPERT	4,516	0.430	0.495	3,820	0.413	0.492	696	0.523	0.500	***
AUDITOR_CHG	4,516	0.043	0.202	3,820	0.041	0.199	696	0.050	0.219	
BUSY	4,516	0.776	0.417	3,820	0.772	0.419	696	0.796	0.403	
CEO_PILOT	4,516	0.082	0.275	3,820	0.081	0.273	696	0.091	0.287	
CEO_FEMALE	4,516	0.056	0.231	3,820	0.048	0.215	696	0.101	0.301	
CEO_AGE	4,516	56.616	7.856	3,820	56.657	7.793	696	56.395	8.192	***
CFO_PILOT	4,516	0.076	0.264	3,820	0.070	0.255	696	0.108	0.310	***
CFO_FEMALE	4,516	0.122	0.327	3,820	0.124	0.330	696	0.106	0.308	
CFO_AGE	4,516	52.455	7.529	3,820	52.392	7.522	696	52.802	7.562	
SIZE	4,516	6.417	2.193	3,820	6.452	2.194	696	6.228	2.185	**
LOSS	4,516	0.445	0.497	3,820	0.454	0.498	696	0.399	0.490	***
LEVERAGE	4,516	0.299	0.289	3,820	0.303	0.289	696	0.277	0.289	**
MB	4,516	2.400	1.979	3,820	2.421	2.018	696	2.285	1.746	*
OCF	4,516	-0.001	0.267	3,820	-0.005	0.272	696	0.019	0.235	**
VOLATILITY	4,516	0.097	0.174	3,820	0.100	0.181	696	0.077	0.127	***
ARC	4,516	5.748	0.379	3,820	5.754	0.378	696	5.711	0.383	***
PERC_EXTEND	4,516	0.130	0.067	3,820	0.131	0.067	696	0.123	0.066	***
GROWTH	4,516	0.191	0.858	3,820	0.204	0.903	696	0.118	0.539	**
SEGMENTS	4,516	0.617	0.693	3,820	0.619	0.693	696	0.610	0.694	
FOREIGN_INC	4,516	0.367	0.902	3,820	0.372	0.915	696	0.341	0.830	
EARN	4,464	-0.111	0.425	3,776	-0.118	0.433	688	-0.075	0.378	***
RET	4,464	0.101	0.567	3,776	0.101	0.577	688	0.105	0.512	
NEG	4,464	0.462	0.499	3,776	0.466	0.499	688	0.436	0.496	**

This table presents descriptive statistics on client characteristics in the full sample of firm-year observations as well as separate subsamples by the existence of audit partner infractions. *INFRACTION* represents instances in which the audit partner has at least one infraction in his/her criminal background check. Variable definitions are provided in the Appendix. ***, **, * represent significance at the 0.01, 0.05, and 0.10 levels, respectively, for two-sample t-tests of the difference in mean values.

TABLE 5
Audit partner infractions and audit quality

Panel A: Regression results for propensity to misstate, accruals, MWs, audit fees, and audit report timing

Dependent Variable:	Model (1): *FSCORE*		Model (2): *ABSDA*		Model (3): *MW*		Model (4): *LN_AUDFEES*		*Model (5): DELAY*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
INFRACTION	**0.088****	**0.038**	**0.000**	**0.006**	**-0.401****	**0.189**	**-0.076*****	**0.029**	**-1.753*****	**0.662**
PTR_FEMALE	-0.061	0.041	-0.005	0.007	-0.010	0.213	0.033	0.030	0.260	0.573
PTR_AGE	0.003	0.002	0.000	0.000	0.011	0.009	0.000	0.002	0.034	0.039
PTR_EXPERT	-0.005	0.039	0.004	0.007	0.600***	0.227	0.115***	0.032	0.289	0.650
PTR_NONLOCAL	-0.007	0.030	0.001	0.005	0.608***	0.130	-0.104***	0.022	1.967***	0.494
NUM_CLIENTS	0.009	0.013	0.004	0.002	0.030	0.051	-0.021**	0.009	0.133	0.229
BIG4	-0.133***	0.041	-0.010	0.006	-0.235	0.177	0.429***	0.033	-0.990	0.672
CITY_EXPERT	-0.028	0.032	0.008	0.005	-0.254	0.169	0.010	0.024	-0.390	0.464
AUDITOR_CHG	-0.106**	0.054	-0.008	0.013	0.697***	0.191	0.035	0.039	3.817***	1.120
BUSY	-0.044	0.034	0.005	0.006	-0.183	0.162	0.024	0.026	0.558	0.553
CEO_PILOT	0.018	0.051	-0.001	0.008	0.207	0.240	-0.073**	0.033	0.156	0.647
CEO_FEMALE	-0.141***	0.049	-0.007	0.010	0.217	0.280	0.021	0.043	0.344	1.002
CEO_AGE	-0.001	0.002	0.000	0.000	-0.010	0.008	-0.002	0.001	-0.003	0.029
CFO_PILOT	0.069	0.051	0.000	0.008	0.258	0.240	0.058*	0.035	0.849	0.755
CFO_FEMALE	-0.091**	0.039	0.015**	0.007	-0.090	0.178	0.019	0.030	0.110	0.677
CFO_AGE	-0.001	0.002	0.000	0.000	0.014*	0.008	0.003**	0.001	0.052*	0.030
SIZE	0.012	0.013	-0.010***	0.002	-0.499***	0.062	0.365***	0.010	-0.683***	0.209
LOSS	-0.145***	0.029	0.044***	0.006	0.441***	0.141	0.138***	0.022	0.662	0.485
LEVERAGE	0.103**	0.051	0.028**	0.012	0.533***	0.184	-0.065*	0.037	2.100**	0.916
MB	-0.023***	0.007	0.008***	0.002	-0.080**	0.035	0.039***	0.005	0.118	0.135
OCF	-0.131	0.093	-0.045**	0.020	0.516**	0.258	-0.213***	0.047	-0.044	1.129
VOLATILITY	0.244	0.163	0.128***	0.000	0.050	0.349	0.097	0.063	0.267	1.659
ARC	0.379***	0.061	0.000	0.000	1.465***	0.281	0.792***	0.042	4.601***	1.035
PERC_EXTEND	-0.683***	0.248	0.113***	0.043	1.890	1.191	-1.234***	0.179	8.765**	3.623
GROWTH	0.229***	0.032	0.008*	0.004	0.157***	0.050	-0.019**	0.009	0.067	0.208

SEGMENTS	0.051**	0.023	0.001	0.003	-0.041	0.115	0.046***	0.018	-0.223	0.372
FOREIGN_INC	-0.002	0.012	-0.004***	0.002	0.125**	0.052	0.064***	0.009	0.255	0.168
Intercept	-1.514***	0.366	0.092	0.062	-9.152***	1.598	6.441***	0.247	-37.581***	6.138
Model	OLS		OLS		Logit		OLS		OLS	
N	4,385		4,516		4,516		4,516		4,516	
Adj./Pseudo R2	0.183		0.214		0.176		0.867		0.055	

Panel A presents the regression results for the association between audit partners with "off-the-job" infractions and indicators of audit quality. The first measure of audit quality is the *FSCORE* based on model 2 in Dechow et al. (2011). The second measure is *ABSDA*, which is the absolute value of performance-matched discretionary accruals from a cross-sectional modified Jones model. The third measure is *MW*, which is an indicator variable that captures the likelihood of identifying and reporting material weaknesses in internal controls. The fourth measure is *LN_AUDFEES*, which is the natural logarithm of fees charged for performing the audit services in an attempt to capture audit effort. The fifth measure is *DELAY*, which is the number of days that the audit report is issued prior to the client firm's SEC filing deadline. For brevity, coefficients on industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients for *INFRACTION* is based on a one-tailed test given the directional prediction in our hypothesis, while the significance of coefficients on the control variables is based on a two-tailed test. The Appendix provides detailed variable definitions.

TABLE 5 (*continued*)
Audit partner infractions and audit quality

Panel B: Regression results for asymmetric timely loss recognition

Dependent Variable:	Model (6): *EARN*	
	Coeff.	S.E.
RET	-0.142	0.100
NEG	0.164*	0.097
RET × *NEG*	1.624***	0.313
INFRACTION	0.002	0.030
INFRACTION × *RET*	0.066	0.053
INFRACTION × *NEG*	-0.051	0.049
INFRACTION* × *RET* × *NEG	**-0.364****	0.191
SIZE	0.039***	0.007
SIZE × *RET*	0.013	0.013
SIZE × *NEG*	-0.012	0.012
SIZE × *RET* × *NEG*	-0.096**	0.042
MB	0.005	0.008
MB × *RET*	0.011	0.014
MB × *NEG*	-0.023**	0.011
MB × *RET* × '*NEG*	-0.196***	0.032
LEVERAGE	-0.161	0.099
LEVERAGE × *RET*	-0.133	0.109
LEVERAGE × *NEG*	0.143	0.121
LEVERAGE × *RET* × *NEG*	0.684***	0.248
Intercept	-0.333***	0.068
Model	OLS	
N	4,464	
Adjusted R2	0.267	

Panel B presents the regression results for audit quality measured by the Basu (1997) model for asymmetric timely loss recognition. *SIZE*, *MB*, and *LEVERAGE* are the same as previously defined except they represent the lagged variables at the end of year t-1. For brevity, coefficients on industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficient of interest (*INFRACTION* × *RET* × *NEG*) is based on a one-tailed test given the directional prediction in our hypothesis, while the significance of coefficients on the control variables is based on a two-tailed test. The Appendix provides detailed variable definitions.

TABLE 6
Propensity score matching and entropy balancing analyses

Panel A: Descriptive statistics for the PSM sample

	INFRACTION=1	*INFRACTION*=0	*Difference*
Variables	**Mean**	**Mean**	**p-value**
PTR_FEMALE	0.136	0.136	1.000
PTR_AGE	48.894	48.753	0.685
PTR_EXPERT	0.223	0.220	0.896
PTR_NONLOCAL	0.365	0.371	0.823
NUM_CLIENTS	2.295	2.295	1.000
BIG4	0.603	0.584	0.474
CITY_EXPERT	0.519	0.497	0.417
AUDITOR_CHG	0.048	0.053	0.711
BUSY	0.796	0.804	0.735
CEO_PILOT	0.089	0.087	0.849
CEO_FEMALE	0.091	0.092	0.925
CEO_AGE	56.317	56.457	0.749
CFO_PILOT	0.109	0.101	0.659
CFO_FEMALE	0.108	0.114	0.731
CFO_AGE	52.868	52.991	0.766
SIZE	6.252	6.291	0.748
LOSS	0.396	0.409	0.620
LEVERAGE	0.278	0.280	0.887
MB	2.283	2.275	0.934
OCF	0.020	0.017	0.849
VOLATILITY	0.077	0.079	0.876
ARC	5.714	5.729	0.503
PERC_EXTEND	0.122	0.122	0.834
GROWTH	0.114	0.172	0.144
SEGMENTS	0.619	0.621	0.945
FOREIGN_INC	0.347	0.346	0.982
N	682	682	

This table presents descriptive statistics for the propensity-score matched (PSM) samples. We predict the propensity of a client firm having an audit partner with at least one infraction using a logistic regression where the dependent variable is *INFRACTION* and the independent variables are the control variables from the respective regression in Table 5, including industry and year fixed effects. We modify the matching model depending on the control variables for each model in Table 5; the descriptive statistics presented above show the details for the *FSCORE* matched sample as an example. The resulting 1-to-1 matched sample refers to the sample in which each observation with *INFRACTION* = 1 is matched to an observation with *INFRACTION* = 0 by propensity score, within common support, without replacement, using a caliper distance of 0.03. The Appendix provides detailed variable definitions.

TABLE 6 (*continued*)
Propensity score matching and entropy balancing analyses

Panel B: Regression results using the PSM samples (1-to-1)

Dependent Variable:	(1): *FSCORE*		(2): *ABSDA*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
INFRACTION	0.132***	0.043	0.001	0.008	-0.532***	0.220	-0.084***	0.032	-2.075***	0.767		
INFRACTION × *RET* × *NEG*											-0.710***	0.243
Control Variables	Yes		Yes		Yes		Yes		Yes		Yes	
Model	OLS		OLS		Logit		OLS		OLS		OLS	
N	1,364		1,386		1,386		1,386		1,386		1,376	
Adj./Pseudo R2	0.233		0.227		0.201		0.877		0.045		0.299	

Panel B presents the results using the 1-to-1 matched samples where each observation with *INFRACTION* = 1 is matched to an observation with *INFRACTION* = 0 by propensity score, within common support, without replacement, using a caliper distance of 0.03. For brevity, coefficients on industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients is based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.

Panel C: Regression results using the entropy balancing samples

Dependent Variable:	(1): *FSCORE*		(2): *ABSDA*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
INFRACTION	0.084***	0.027	0.002	0.006	-0.459***	0.163	-0.078***	0.018	-1.835***	0.469		
INFRACTION × *RET* × *NEG*											-0.108***	0.048
Control Variables	Yes		Yes		Yes		Yes		Yes		Yes	
Model	OLS		OLS		Logit		OLS		OLS		OLS	
N	4,385		4,516		4,516		4,516		4,516		4,464	
Adj./Pseudo R2												
Maximum Weight	1.876		1.858		1.858		1.858		1.858		0.605	
Weight Ratio	0.029		0.034		0.034		0.034		0.034		0.000	

Panel C presents the results using entropy balancing samples after requiring covariate balance on the first, second, and third moments of the distributions of all covariates for the corresponding model. The maximum weight represents the largest weight assigned to a control observation for the respective entropy balancing regression. The weight ratio represents the number of control observations receiving above equal weight in the entropy-balancing regression divided by the number of observations appearing in a one-to-one match without replacement. For brevity, coefficients on industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients is based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.

TABLE 7
Audit partner infractions and non-audit fees

Dependent Variable:	*LN_NONAUDFEES*					
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
INFRACTION	**0.539****	**0.251**	**0.391***	**0.288**	**0.495*****	**0.176**
PTR_FEMALE	0.379	0.251	0.848**	0.370	0.668***	0.225
PTR_AGE	0.014	0.016	-0.012	0.025	0.007	0.015
PTR_EXPERT	0.319	0.259	0.243	0.368	0.101	0.237
PTR_NONLOCAL	-0.139	0.208	-0.158	0.321	-0.322*	0.196
NUM_CLIENTS	-0.077	0.084	-0.308*	0.162	-0.265**	0.119
BIG4	1.792***	0.314	1.050**	0.455	1.303***	0.284
CITY_EXPERT	0.065	0.209	0.165	0.345	0.239	0.208
AUDITOR_CHG	-0.915**	0.393	-0.616	0.623	-1.279**	0.547
BUSY	-0.121	0.229	0.215	0.398	0.323	0.242
CEO_PILOT	0.357	0.311	0.179	0.494	0.118	0.302
CEO_FEMALE	-0.205	0.422	-0.230	0.525	-0.437	0.352
CEO_AGE	0.027**	0.012	0.003	0.018	0.010	0.011
CFO_PILOT	-0.523	0.344	-1.030**	0.509	-0.941***	0.326
CFO_FEMALE	-0.055	0.258	-0.258	0.420	-0.171	0.279
CFO_AGE	0.003	0.013	0.010	0.020	0.005	0.012
SIZE	0.536***	0.086	0.474***	0.132	0.536***	0.083
LOSS	-0.135	0.191	-0.655*	0.350	-0.453*	0.239
LEVERAGE	-0.268	0.343	0.307	0.505	0.286	0.340
MB	0.049	0.053	0.078	0.085	0.025	0.063
OCF	-0.112	0.517	-0.681	1.003	0.400	0.610
VOLATILITY	1.181*	0.712	1.327	1.410	3.466***	0.905
ARC	1.839***	0.421	1.830***	0.655	1.355***	0.398
PERC_EXTEND	-2.532	1.718	-2.461	2.587	-2.449	1.688
GROWTH	-0.128	0.087	-0.399	0.279	-0.369*	0.203
SEGMENTS	0.110	0.147	0.262	0.231	0.239*	0.140
FOREIGN_INC	0.265***	0.062	0.275**	0.139	0.228***	0.083
Intercept	-8.854***	2.453	-5.775	3.896	-4.541	2.382
Sample	Full Sample		PSM Sample (1-to-1)		Entropy Balancing Sample	
Model	OLS		OLS		OLS	
N	4,516		1,386		4,516	
Adjusted R2	0.262		0.245		0.257	

This table presents the regression results for the association between audit partners with "off-the-job" infractions and non-audit fees. The dependent variable, *LN_NONAUDFEES*, is calculated as the natural logarithm of 1 plus total non-audit fees. For brevity, coefficients on industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficient for *INFRACTION* is based on a one-tailed test consistent with our main tests, while the significance of coefficients on the control variables is based on a two-tailed test. The Appendix provides detailed variable definitions.

TABLE 8
Cross-sectional analyses

Panel A: Analysis of partners employed at Big 4 versus non-Big 4 firms

Dependent Variable:	(1): *FSCORE*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
INFRACTION	0.059*	0.145**	0.071	-0.737***	-0.080***	-0.070*	-0.957*	-3.080***		
	(0.042)	(0.073)	(0.249)	(0.263)	(0.023)	(0.048)	(0.663)	(1.314)		
INFRACTION × *RET* × *NEG*									-0.187	-0.464**
									(0.247)	(0.270)
Model	OLS		Logit		OLS		OLS		OLS	
Subsample	B4	NB4	B4	NB4	B4	NB4	B4	NB4	B4	NB4
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,953	1,432	3,025	1,491	3,025	1,491	3,025	1,491	3,009	1,455
Adj./Pseudo R2	0.226	0.144	0.097	0.176	0.745	0.781	0.035	0.086	0.254	0.258
$\chi 2$ Test of Coeff. Diff. between B4 and NB4	1.05		4.96 **		0.03		2.08 *		0.57	

This table presents the Big 4 (B4) versus non-Big 4 (NB4) subsample regression results for the association between audit partner infractions (*INFRACTION*) and audit quality. Note that we exclude model (2) for *ABSDA* since the results—consistent with the main findings—are insignificant in all subsamples. For brevity, coefficients on the control variables as well as industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients and chi-squared test are based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.

TABLE 8 (*continued*)
Cross-sectional analyses

Panel B: Analysis of partners employed at expert versus non-expert offices

Dependent Variable:	(1): *FSCORE*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
INFRACTION	0.001	0.165***	-0.036	-0.666***	-0.085**	-0.056*	-1.021*	-2.663***		
	(0.048)	(0.058)	(0.301)	(0.264)	(0.040)	(0.038)	(0.794)	(1.030)		
INFRACTION × *RET* × *NEG*									-0.427**	-0.245
									(0.232)	(0.241)
Model	OLS		Logit		OLS		OLS		OLS	
Subsample	Exp	NExp	Exp	NExp	Exp	NExp	Exp	NExp	Exp	NExp
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,891	2,494	1,942	2,574	1,942	2,574	1,942	2,574	1,938	2,558
Adj./Pseudo R2	0.190	0.192	0.196	0.186	0.816	0.842	0.833	0.855	0.238	0.287
χ2 Test of Coeff. Diff. between Exp and NExp	5.00 **		2.43 *		0.31		1.65 *		0.37	

This table presents the expert (Exp) versus non-expert (NExp) subsample regression results for the association between audit partner infractions (*INFRACTION*) and audit quality. Expert is defined at the local office level based on the variable *CITY_EXPERT*. Note that we exclude model (2) for *ABSDA* since the results—consistent with the main findings—are insignificant in all subsamples. For brevity, coefficients on the control variables as well as industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients and chi-squared test are based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.

TABLE 8 (*continued*)
Cross-sectional analyses

Panel C: Analysis of partners employed in offices closer to versus further away from the national office

Dependent Variable:	(1): *FSCORE*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
INFRACTION	0.004	0.130**	-0.361	-0.352	-0.004	-0.162***	-2.235**	-0.929		
	(0.055)	(0.057)	(0.342)	(0.311)	(0.045)	(0.041)	(1.014)	(0.829)		
INFRACTION × *RET* × *NEG*									-0.029	-0.662***
									(0.343)	(0.183)
Model	OLS		Logit		OLS		OLS		OLS	
Subsample	Close	Far	Close	Far	Close	Far	Close	Far	Close	Far
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,847	1,798	1,873	1,856	1,873	1,856	1,873	1,856	1,621	2,843
Adj./Pseudo R2	0.212	0.199	0.115	0.148	0.834	0.767	0.046	0.050	0.348	0.231
χ2 Test of Coeff. Diff. between Close and Far	2.54 *		0.00		6.81 ***		0.99		2.65 *	

This table presents the subsample results for audit offices that are closer (Close) versus further away (Far) from the audit firm's national office. Following Amin et al. (2021), we only include the top 12 audit firms in this analysis and identify the location for the national office of each firm. Close (Far) is defined at the local office level based on offices that are less (greater) than the median distance from the national office. Note that we exclude model (2) for *ABSDA* since the results—consistent with the main findings—are insignificant in all subsamples. For brevity, coefficients on the control variables as well as industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients and chi-squared test are based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.

TABLE 8 (*continued*)
Cross-sectional analyses

Panel D: Analysis of partners employed in offices that are in the same versus different city as an SEC office

Dependent Variable:	(1): *FSCORE*		(3): *MW*		(4): *LN_AUDFEES*		(5): *DELAY*		(6): *EARN*	
INFRACTION	0.053	0.097**	-0.728*	-0.217	-0.041	-0.079***	-1.761	-1.361**		
	(0.078)	(0.043)	(0.463)	(0.224)	(0.040)	(0.032)	(1.501)	(0.729)		
INFRACTION × RET × NEG									0.016	-0.471***
									(0.376)	(0.159)
Model	OLS		Logit		OLS		OLS		OLS	
Subsample	Same	Diff	Same	Diff	Same	Diff	Same	Diff	Same	Diff
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,595	2,790	1,639	2,877	1,639	2,877	1,639	2,877	1,621	2,843
Adj./Pseudo R2	0.192	0.184	0.171	0.200	0.816	0.842	0.060	0.060	0.348	0.231
$\chi 2$ Test of Coeff. Diff. between Same and Diff	0.25		0.99		0.33		0.06		1.44	

This table presents the subsample results for audit offices that are in the same (Same) versus different (Diff) city location from one of the 12 SEC offices following DeFond et al. (2018). Note that we exclude model (2) for *ABSDA* since the results—consistent with the main findings—are insignificant in all subsamples. For brevity, coefficients on the control variables as well as industry and year fixed effects are suppressed. Robust standard errors clustered by client firm are included in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. The significance of the coefficients and chi-squared test are based on a one-tailed test given the directional prediction in our hypothesis. The Appendix provides detailed variable definitions.