The Importance of Audit Partner-Client Matches in Explaining Audit Quality and Fees

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Abstract

Audit partners are not assigned to their clients randomly. We investigate the economic importance of these partner-client matches in explaining audit quality and audit fees. Using a three way mixed-effect model to quantify the effect of these matches, we find that they explain a sizeable amount of the variation in audit quality and fees. Match effects explain substantially more variation in audit quality than individual partner effects do when considering typical measures, such as restatements and discretionary accruals. Match effects are also complements rather than substitutes to client and partner effects. Further analyses suggest that early audit partner rotations are more likely when the match on audit quality is worse, consistent with both client and auditor incentives to have higher audit quality. We also find some evidence that capital markets value matches that result in greater quality audits. Overall, our results highlight the importance of audit partner-client match effects in explaining audit quality and audit fees.

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1. Introduction

This paper focuses on understanding and quantifying the importance of audit partner-client matching for audit pricing and quality. While recent empirical research extensively focuses on the role and characteristics of individual audit partners (e.g., Gul et al. 2013; Lennox and Wu 2018), much less is known in the archival literature about audit partner client matches. Lennox and Wu (2018, p24) note that *"there is almost no evidence relating to the partner client matching process."*[1] However, certain audit partners are likely better at auditing particular types of clients, for example, when a partner's skills, technical, and industry expertise map better with clients' accounting, internal processes, and industry. Audit partners also likely conduct better audits under specific client environments and cultures. For example, a conservative audit partner might be more effective at constraining earnings management at an aggressive client relative to a less conservative partner, but might thrive more when matched with a conservative client (Lennox and Wu 2018). Consistent with these ideas, the qualitative literature also highlights the importance of audit partner-client matches. Besides stressing the value of audit partners having the proper skills for specific client circumstances, this literature highlights the importance of "chemistry" and "rapport" between audit partners and their clients, emphasizing the importance of cultural fit and working

[1] A limited number of studies focus on specific partner – client matching characteristics, such as common social connections (Guan et al. 2016), partner industry specialization (Goodwin and Wu 2014; Aobdia et al. 2021), the similarity of certain demographic level variables, including gender or ethnicity (Lee et al. 2019; Pham et al. 2022; Krishnan et al. 2023), and personality similarity (Aobdia et al. 2024). While these studies often find some effects of the matching of particular attributes with audit quality, they do not quantify the overall importance of the partner – client match for audit quality nor compare it with individual partner effects, which is the purpose of our study.

well with the client (e.g., Dodgson et al. 2020, Maksymov et al. 2024, Christensen et al. 2024).[2]

Motivated by these studies, we empirically investigate the importance of audit partner-client matches in explaining audit quality and fees. *Ex ante*, while the qualitative literature highlights the importance of audit partner-client relationships, audit firms also have standardized processes, large audit teams, and extensive quality control systems to provide audits of uniform quality, particularly for the Big 4 firms in the United States (e.g., Aobdia 2020). For example, Laurion et al. (2017), Gipper et al. (2021), and Aobdia et al. (2024a) do not find evidence that audit partner tenure with a given client influences audit quality, which suggests that audit firms carefully assign their audit partners to specific clients and actively manage audit partner rotations to avoid disruptions to the audit process. Thus, quantifying how much audit partner-client matches influence audit quality is ultimately an empirical question. In this paper, we aim to investigate the following questions: How much do partner-client matches explain audit fees and audit quality? How do these matches compare with time invariant audit partner effects, an extensive focus of the literature? Are the resulting match effects explained by a limited number of immediately observable audit partner and client characteristics, such as partner industry specialization? What specific attributes of partner-client matches are valued by clients and audit firms? And do capital markets understand the importance of partner-client matches? The answers to these questions provide new insights into the importance of audit partner-client matches and can guide researchers

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[2] Dodgson et al. (2020, p100) interview an audit partner who mentions that "everybody's got their own unique style [or] approach to things, and some people tend to work well together. We call that 'chemistry'," highlighting that different audit partner – client combinations can lead to different types of relationships and different audit quality outcomes. Maksymov et al. (2024) further highlight the importance of partners' professional rapport with their clients to resolve material issues identified during the audit, and Christensen et al. (2024) find that clients want audit partners who are available, flexible, reasonable, and good communicators.

about which first-order research questions to explore in the future regarding audit partners.

Empirically measuring the match quality between audit partners and clients can be challenging because (1) most client-audit partner match-specific heterogeneities are not readily observable, and (2) we lack satisfactory measurements of audit partner and client characteristics. In this paper, we apply recent methodological advances in the labor economics and executive compensation literature following Woodcock (2015), Jackson (2013), Lazear et al. (2015), and Ma et al. (2024).[3] We employ a three-way mixed model to quantify these match effects. The model initially quantifies in a first stage the combined importance of time invariant audit partner, client, and the audit partner-client match specific characteristics in the form of fixed effects for unique partner-client pairs (also known as "spell fixed effects"), controlling for time-varying observable client characteristics. Doing so allows us to remove the remaining effect of the time-varying characteristics. In the second stage, we decompose the "spell fixed effects" plus the first stage residual into time invariant audit partner and client random effects, and audit partner–client match random effects, and quantify the importance of each in explaining audit quality and fees. Our empirical setting is uniquely suitable for employing this approach, which relies on audit partners switching away from clients, because audit partners are mandated to rotate every 5 years following the Sarbanes Oxley Act of 2002 (SOX).

We employ this model on a company-year dataset spanning 2016 to 2023. We obtain the identity of audit partners from the Public Company Accounting Oversight Board (PCAOB), which

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[3] Using this method, Woodcock (2015) quantifies firm-worker match effects for worker wages. Jackson (2013) focuses on teachers and school matches, Lazear et al. (2015) on employees-manager matches, and Ma et al. (2024) on quantifying firm-manager match effects in executive compensation.

mandated public disclosure on Form AP of the audit engagement partner in the United States beginning in the 2016 fiscal year. Since we separate client, partner, and match effects by observing audit outcomes when matching different partners with different clients, we purposely focus on the partners of Big 4 firms and their clients, which allows us to consider a reasonably homogeneous set of partners and clients, for which the match between audit firm and client is less important.[4] We complement these data with client and stock return information obtained from Compustat and CRSP, and obtain information on audit fees, restatements, going concern opinions, and other audit characteristics from Audit Analytics. Doing so allows us to construct a connectedness sample that contains all partners who have ever worked for a client that has hired at least one partner who previously worked for other clients, allowing us to estimate individual and match effects.

Following prior literature that highlights that audit quality encompasses several dimensions (DeFond and Zhang 2014; Aobdia 2019a), we focus on several proxies for audit quality, which include discretionary accruals, misstatements in the fiscal-year-end financial statements that are subsequently restated, clients reporting small profits, and the propensity to issue going concern opinions. We also consider audit fees, which capture several dimensions, including audit hours, but also client risk, the client demand for auditing services, and the relative bargaining power between the auditor and the client (Simunic 1980; Hay et al. 2006; DeFond and Zhang 2014).

We find that audit partner-client matches explain a substantial amount of variation in audit

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[4] Clients typically do not see any major difference among the Big 4 audit firms and focus more on their lead audit partners (Beasley et al. 2009; Fiolleau et al. 2013; Aobdia et al. 2021). Thus, we focus on the match between client and audit partner instead of the match between client and Big 4 firm. In addition, the identification of client-audit firm match effects relies on observing audit outcomes when matching different Big 4 auditors with different clients. Currently, public companies are required to rotate engagement partners every five years; there is no requirement to rotate audit firms. As a result, very few clients match with more than one Big-4 auditor in our sample period (8% of client firms), leading to biased estimation.

quality and audit fees. Match effects explain 16.8% of the variation for fiscal-year-end client misstatements. The match effect also explains 10.5% of the variation in going concern opinions and 4.2% in discretionary accruals. These amounts are sizeable in comparison with the variation explained by (measurable) client characteristics, but, more importantly, much larger than individual partner effects that explain only up to 1.1% of the total variation in audit quality. The match effects also explain 2.4% of the variation in audit fees, which is more than double the individual partner effects at 1.0%. While 2.4% might appear small compared with the role of observable client characteristics, which explain 72.2% of the variation in audit fees, this was to be expected given that client size explains about 70% of audit fees (e.g., DeFond and Zhang 2014). Overall, our results suggest that audit partner-client match effects are a first order determinant in explaining audit quality, much larger than audit partner effects. This highlights the need for future literature to examine how particular audit partner characteristics have different effects for different types of clients, rather than just focusing on the overall average effect of such characteristics.

We also examine the correlations among client, audit partner, and match effects for each audit fee or quality measure considered. On the one hand, audit firms might assign more conservative audit partners to more aggressive clients to maintain uniform audit quality across the firm.[5] On the other hand, signaling theories (e.g., Titman and Trueman 1986) suggest that more conservative audit partners may match with more conservative clients to signal greater financial reporting quality to the capital markets. We find, for each measure considered, positive correlations between client, audit partner, and match effects, with all correlations above 0.29.

[5] Keeping audit quality constant is an assumption made in several audit production and fee models and consistent with the role of quality control systems within audit firms (O'Keefe et al. 1994; Hay et al. 2006; Aobdia 2020).

These results are consistent not only with potential signaling taking place, but also with complementarities, rather than substitution, in styles between audit client and audit partner financial reporting preferences. Thus, these results speak directly to theories that show that matching is assortative when types are complement (e.g., Becker 1973; Shimer and Smith 2000).

Next, we focus on particular characteristics that could influence the match effects. We consider audit partner industry specialization, which has been shown to influence audit fees and quality (Zerni 2012; Goodwin and Wu 2014; Aobdia et al. 2021). We also consider the number of audit partners working in an audit office, as greater partner availability might generate matches that are more preferred by clients and audit firms; non-audit fees, as they can signal a greater ability of the audit partner to sell services to the client; partner gender and busyness based on their number of clients; and material weaknesses which measure client risk. We find that audit partner industry specialization positively explains match effects measured using audit fees but is not associated with other types of matches. This result is consistent with prior literature (e.g., Zerni 2012; Goodwin and Wu 2014; and Aobdia et al. 2021) and provides comfort about the accuracy of our empirical approach. Non-audit fees and client material weaknesses also explain match effects measured using audit fees. Otherwise, we find limited evidence that these characteristics are associated with partner-client match effects. Importantly, the explanatory power of the regressions is low, with R-squared between 0.1% and 2.1%. Overall, our results are consistent with match effects capturing unobservable or difficult to measure characteristics of the partner-client relationship, which is consistent with the qualitative literature and the literature on the determinants of executive and audit partner fixed effects.[6] Our results also offer an opportunity for future research to better understand the determinants of audit partner–client match effects.

Next, we investigate which match attributes are valued by audit firms and clients. SOX mandated audit partners to rotate public clients every five years, but in practice, early rotations occur often (e.g., Aobdia and Petacchi 2019; Gipper et al. 2021). This provides an opportunity to explore how match effects influence early rotations, which reveal clients' and audit firms' preferences. Our overall evidence is consistent with clients and audit firms on average valuing audit quality. For example, early rotations are significantly more likely when the match results in a greater probability of misstatements, greater discretionary accruals, and a greater likelihood to report small profits. We also find evidence that audit partners are more likely to experience an early rotation when the match leads to abnormally high audit fees, which is consistent with clients caring about competitive audit fees (e.g., Christensen et al. 2024).

We finally investigate whether capital markets value audit partner-client matches, but note that this analysis is more exploratory in nature due to the limited time-series available to us (8 years at most). Following prior literature, we focus on earnings response coefficients and market responses at times of audit partner rotations (e.g., Teoh and Wong 1993; Aobdia et al. 2015; Gipper et al. 2020). We find some evidence that earnings response coefficients are greater when audit quality is perceived to be greater by equity markets, specifically when the match effects on audit fees is greater and the match on restatements or small profits is lower. We also find some evidence

[6] The literature on executive and audit partner fixed effects finds that immediately observable characteristics have limited explanatory power on such estimated fixed effects (e.g., Dyreng et al. 2010; Graham et al. 2012; Gul et al. 2013).

of negative (positive) market reaction at times of announcement of a partner change, when the departing partner had a high match in terms of audit fees (small profits). This result is consistent with equity markets expecting the incoming match not to be as good as (be better than) the prior match on average from an audit quality standpoint.

Overall, our evidence is consistent with audit partner-client matches explaining a substantial amount of audit quality in the United States, much more than the effects of individual audit partner characteristics. Thus, future literature will need to focus more on the determinants and consequences of these matches rather than on individual audit partner characteristics per se. Our study answers the call by Lennox and Wu (2018, p29) to *"better understand the partner-client matching process."* In particular, our results suggest that not only more conservative partners tend to match with more conservative clients, but that complementarities also exist when such matches occur. Thus, future research that focuses on individual audit partner characteristics will need to better incorporate the roles of matches before deriving conclusions about the importance of specific audit partner characteristics on audit quality.

We also contribute to a small but growing literature that focuses on audit partner-client matches (Goodwin and Wu 2014; Guan et al. 2016; Lee et al. 2019; Aobdia et al. 2021; Baugh et al. 2022; Pham et al. 2022; Krishnan et al. 2023; Aobdia et al. 2024b), and to the literature that focuses on audit partners in general. While the audit partner literature highlights the importance of individual audit partners characteristics in explaining audit quality outside of the United States (e.g., Gul et al. 2013), the evidence in the United States has been much more nuanced, with several studies finding limited evidence that audit partners influence audit quality (e.g., Laurion et al. 2017; Doxey et al. 2021; Gipper et al. 2021; Aobdia et al. 2024a). Our study contributes to this debate by quantifying the importance of audit partner matches relative to individual partner effects. Our results provide some evidence consistent with individual audit partner characteristics overall having limited influence on audit quality in the United States, but also with significant heterogeneity in the quality of audits provided by a given audit firm, depending on the quality of the audit partner-client match. Thus, our findings highlight the importance of audit partners in the United States, but future research will need to focus more on how particular audit partner characteristics have an effect on audit quality, depending on the context of their match with clients. Our results also suggest that examining the determinants of audit partner – client match effects may be a fruitful area for future research.

2. Background Information, Prior Literature, and Research Questions

2.1 The auditor client matching process

The qualitative literature highlights the importance of audit partner – client matches, particularly for clients of Big 4 auditors. While audit committee members tend to view the Big 4 firms as similar to each other in terms of technical skills and resources (e.g., Beasley et al. 2009; Fiolleau et al. 2013), they place great importance on their choice of audit partner.[7] Accordingly, audit firms carefully manage audit partner assignments and rotations. Dodgson et al. (2020) highlight that audit firms begin discussions with clients about upcoming audit partner rotations as early as 12 to 18 months prior to the rotation. Audit firms propose between one to three candidates to their clients, depending on the circumstances (Dodgson et al. 2020). These audit partners are

[7] For example, two audit committee members in Beasley et al. (2009, p103) report that *"I am not sure how much difference there is between firms, but there can be big differences between partners,"* and *"the audit committee is dealing with a commodity, when talking about the Big 4. The variation among the partners within the firms is more important than the variation across the firms."*

not necessarily chosen from the closest audit office, and many choose not to relocate once they are assigned to the client (e.g., Fiolleau et al. 2013; Francis et al. 2022). Dodgson et al. (2020) highlight that audit firms strive to assign audit partners who can have productive relationships with clients. While doing so can help improve audit quality, given that successful cooperation between clients and auditors is crucial for high-quality audits (Knechel et al. 2020), a risk is that audit firms cater too much to client preferences and the chosen audit partner becomes less effective at challenging client accounting choices when required. This can happen given that the qualitative literature finds that clients want audit partners who have autonomy from their national offices, and are also flexible and reasonable (Fiolleau et al. 2013; Christensen et al. 2024). Such flexibility can be problematic in instances when clients attempt to manage earnings. At the same time, this flexibility can also help improve audit quality when it is needed for clients to better incorporate their private information into their accounting estimates.[8] Thus, the same "autonomous, flexible and reasonable" audit partner can have a different influence on audit quality depending on particular client circumstances, which highlights the importance of audit partner – client matches.

2.2 Prior literature and Research questions

Despite the potential importance of audit partner – client matches in explaining audit quality, Lennox and Wu (2018) note that *"there is almost no evidence relating to the partner client matching process."* Studies include Guan et al. (2016) and He et al. (2017), who find in the Chinese setting that common social ties between auditors and their clients are negatively associated with

[8] This argument maps with the definition of audit quality by DeFond and Zhang (2014) as *"greater assurance that the financial statements faithfully reflect the firm's underlying economics, conditioned on its financial reporting system and innate characteristics."*

audit quality, and Baugh et al. (2022), who find that audit partners' attractiveness influence their selections for audit committees with less expertise. Other studies, such as Pham et al. (2022) and Aobdia et al. (2024b) find evidence that cultural proximity and similar personality help improve audit quality, while Lee et al. (2019) and Krishnan et al. (2023) find that female partners and partners from ethnic minorities are more likely to match with clients with more diversity at the top. Finally, studies on audit partner industry specialization find that industry specialist partners are associated with greater audit fees, and also with higher audit quality for riskier clients who require more difficult audits (Zerni 2012; Goodwin and Wu 2014; Aobdia et al. 2021).

While these studies focus on specific attributes of audit partners and their clients, there is no research to date quantifying the importance of audit partner – client matches and comparing this quantification with the effect of individual audit partner characteristics. However, doing so is important to help researchers understand where to focus their efforts moving forward. We note that the importance of audit partner – client matches is ultimately an empirical question. On the one hand, the qualitative literature and the aforementioned empirical literature highlight the importance of partner – client matches. This is consistent with PCAOB standard AS 1201 that makes lead partners ultimately responsible for their audits, and with arguments in theories of organizational hierarchies suggesting that the most important tasks are the responsibility of the highest level of hierarchy (Garicano 2000; Rajan and Zingales 2001; Garicano and Rossi-Hansberg 2006, Aobdia et al. 2024a). On the other hand, audits in the U.S. are comprised of large teams, and audit partner hours comprise a small proportion of total audit hours (e.g., Aobdia 2018; Aobdia et al. 2024a). Furthermore, audit firms have extensive quality control systems to ensure quality audits, including detailed methodologies, national offices, and consultation protocols (e.g., Aobdia 2020). As mentioned above, audit firms also carefully assign audit partners to their clients, perhaps with the aim of limiting variation in audit quality at times of audit partner rotations to give clients a consistent service. Thus, we first aim to quantify the importance of audit partner – client matches in explaining audit quality and fees. Next, we compare this importance with the importance of time invariant audit partner effects, to better understand where future research should focus moving forward, and assess the correlations among client, audit partner, and match effects. We also explore whether the partner – client match effects are explained by a limited set of observable characteristics, similarly to the literature that focuses on executive and audit partner fixed effects but generally finds limited evidence that specific characteristics substantially explain these effects (Dyreng et al. 2010; Graham et al. 2012; Gul et al. 2013).

We also aim to explain which characteristics of the match are valued by clients and audit firms in the context of early partner rotations. SOX mandates audit partners to rotate from their audit clients every 5 years, but early rotations are common (e.g., Aobdia and Petacchi 2019; Gipper et al. 2021); these can reveal clients' and audit firms' average preferences in terms of match characteristics. So far, little is known about this topic, except for survey evidence from Christensen et al. (2024) who highlight that early rotations are influenced by a lack of timeliness in communication and accessibility of the audit partner, as well as a lack of willingness to make decisions without consulting the national office. Finally, following a stream of literature that finds that capital markets positively react to audit quality (e.g., Teoh and Wong 1993; Aobdia et al. 2015; Gipper et al. 2020), we aim to assess whether equity markets react more at times of earnings announcement to the unexpected component of earnings when the match on audit quality is higher, consistent with earnings numbers having more credibility due to higher audit quality. We also focus on whether equity markets react at times of announcement of a new audit partner on the engagement when the prior match on audit quality was more extreme, and thus, an average expectation of change can be made. While equity markets may not use our exact empirical method to infer the quality of the match, better matches from an audit quality standpoint should be reflected in greater financial reporting quality or observable attributes of the audit, such as audit fees and the propensity to issue going concern opinions, and these should be observable.

3. Empirical Methodology of Identifying Match Effects in Audit Outcomes

In this section, we describe the empirical methodology of identifying match effects in audit outcomes. Specifically, we employ the three-way mixed effect developed in labor economics to quantify *time-invariant* match effects in audit outcomes (Woodcock 2015; Jackson 2013). We use the following regression model:

$$Audit\ Outcome_{ijt} = \mu_0 + \beta_1 Size_{jt} + \beta_2 Foreign\ Income_{jt} + \beta_3\ December\ Year\ End_{jt} + \beta_4\ Altman\ Z\ Score_{jt} + \beta_5 Business\ Segments_{jt} + \beta_6 Geographic\ Segments_{jt} + \beta_7 CFO_{jt} + \beta_8\ Std(CFO)_{jt} + \beta_8 BTM_{jt} + \beta_9 Sales\ Growth_{jt} + \beta_{10}\ Leverage_{jt} + \beta_{11}\ Litigation_{jt} + \beta_{12}\ Material\ Weakness_{jt} + \beta_{13}\ Integrated\ Audit_{jt} + Year\ Fixed\ Effects + \theta_i + \psi_j + \phi_{ij} + \varepsilon_{ijt} \quad (1)$$

where *i* indexes partners, *j* indexes clients, and *t* indexes years. θ_i is a time-invariant portable partner effect, which captures unobservable partner expertise and personality traits transferable across clients; ψ_j is a time-invariant client effect, which captures unobservable firm-specific characteristics or financial reporting policies; and ϕ_{ij} is a time-invariant match effect, which captures the match-specific heterogeneity between partner *i* and client *j*.

The dependent variables focus on audit fees and specific measures of audit quality. *Audit Fees* is the natural logarithm of audit fees. This variable captures several dimensions, including audit effort and audit risk, the specific client demand for audit quality, and relative bargaining power between client and auditor.[9] We also consider several measures of audit quality following DeFond and Zhang (2014) and Aobdia (2019a). First, *Abs(Disc. Accruals)* is the absolute value of discretionary accruals computed using the Jones model.[10] Second, *Restatement* is an indicator variable equal to one if the fiscal-year-end financial statements are subsequently restated. Third, *Small Profit* is an indicator equal to one if the company's return on assets is between 0% and 3%. Fourth, *Going Concern* is an indicator equal to one if the auditor issues a going concern opinion. These measures capture different dimensions of audit quality and have several advantages and drawbacks. For example, while restatements capture egregious issues where the client's financial statements were misstated and the auditor failed to catch the misstatement, they also occur infrequently, particularly during our sample period. In contrast, discretionary accruals aim to capture more gradual issues with audit quality. They have much more variation, but their measurement is noisy. Going concern opinions typically proxy for auditor independence.

We also include a set of variables to control for observable client characteristics that determine the audit outcomes (Francis et al., 2005; Francis and Yu, 2009; and Reichelt and Wang, 2010). Following Aobdia (2018 and 2019a), we add the following variables to control for company size, foreign operations and overall business complexity, risk, growth, and whether the audit is an integrated audit of financial statements and internal control: *Size*, *Foreign Income, December Year End*, *Altman Z Score*, *Business Segments*, *Geographic Segments*, *CFO*, *Std(CFO)*, *BTM*, *Sales*

[9] Under a model where the market for audits is competitive and audit quality is held constant for a given firm, audit fees only capture the extent of audit effort and client risk (e.g., Simunic 1980, Hay et al. 2006). We relax these assumptions and consider that audit fees could include client demand attributes, such as a greater need for audit quality, as well as differences in bargaining power between client and audit partner (e.g., DeFond and Zhang 2014). Such differences likely exist because audits exhibit credence good attributes (e.g., Causholli and Knechel 2012).

[10] We do not adjust for performance because Aobdia and Petacchi (2023) find a stronger association between non-adjusted discretionary accruals and a measure of audit quality from PCAOB inspection findings.

Growth, *Leverage, Litigation*, *Material Weakness*, and *Integrated Audit*. Detailed variable definitions are provided in Appendix 1. We additionally include year fixed effects to capture differences in audit outcomes across years. Lastly, we cluster standard errors at the client level to correct them for within-client correlation.

Following Abowd, Kramarz, and Margolis (1999; AKM), we construct a connectedness sample that contains all the partners who have ever worked for a client that has matched with at least one mover partner, i.e., a partner who previously worked for other clients in our sample period. Note that this sample contains both mover and non-mover partners. The group connectedness is a necessary and sufficient condition to separate client, partner, and match effects, which is similar to the identification conditions of separating firm and person effects in AKM (1999) (see Woodcock 2015).

The idea of identifying match effects in Equation (1) is straightforward. By observing audit outcomes for multiple partners who switch across clients, researchers can separate match effects from partner and client effects. Consider the extreme scenario with two partners and two clients. Both partners C and D are matched with clients A and B. Suppose that for client A the audit outcomes are better than client B by α. Additionally, partner C improves audit outcomes by β_1, whereas partner D worsens outcomes by β_2 at client A relative to client B. When partner C switches from client B to client A, the resulting audit outcome at client A is $\alpha + \beta_1$ better than that at firm B. In contrast, when partner D switches from client B to client A, the resulting audit outcome is $\alpha - \beta_2$ worse. Although there is a client effect (i.e., α) when matching with both partners, the difference in audit outcomes associated with switches is the basis for identifying match effects.

More generally, we can identify client effects based on the common component of audit outcomes among different partners matched with the client, partner effects based on the common component of audit outcomes when a partner matches with different clients, and match effects based on covariation in audit outcomes within the partner-client match that is not explained by partner and client effects. Specifically, we estimate Equation (1) using a "hybrid" mixed-effects model, which takes a two-step estimation approach (Woodcock 2015; Jackson 2013; Lazear et al. 2015). In the first step, we calculate the within-match estimator of β in Equation (1), equivalent to the estimator from the "spell fixed effects" approach in Graham et al. (2012):

$$y_{ijt}=x'_{ijt}\beta+\mu_t+v_{ij}+\varepsilon_{ijt} \tag{2.1}$$

where v_{ij}, the "spell," is an indicator variable for each unique combination of partner *i* and client *j*. x_{ijt} denotes the intercept term and observable characteristics in Equation (1), and μ_t is year-fixed effects. In the second step, we decompose the component of audit outcomes that cannot be explained by the observable client characteristics (i.e., the client-by-partner effect v_{ij} and the idiosyncratic error term ε_{ijt}) into firm, manager, match effects, and an error term.

$$y_{ijt}- x'_{ijt}\hat{\beta} -\hat{\mu}_t =\theta_i+\psi_j+\phi_{ij}+e_{ijt} \tag{2.2}$$

where $\theta_i \sim N[0, \sigma^2_\theta]$, $\psi_j \sim N[0, \sigma^2_\psi]$, $\phi_{ij} \sim N[0, \sigma^2_\phi]$, and $e \sim N[0, \sigma^2_e]$.[11]

The random-effects model estimates the variances of partner, client, and match effects ($\hat{\sigma}^2_\theta$, $\hat{\sigma}^2_\psi$, and $\hat{\sigma}^2_\phi$) using a Restricted Maximum Likelihood approach (REML).[12] This approach identifies the variances of manager, firm, and match effects that make the observed data points (y_{ijt}-$x'_{ijt}\hat{\beta}$-$\hat{\mu}_t$)

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[11] To assess the sensitivity of our estimation to the normality assumption, we conduct a simulation reported in Appendix 2 where client, partner, match effects, and errors are randomly drawn from a uniform distribution for *audit fees* and *Abs(Disc. Accruals)*, and *Restatement*, *Small Profit*, and *Going Concern* are randomly drawn from a Poisson distribution. We find that the difference between estimated match effects from the three-way mixed effects model and actual match effects is insignificant. The simulation results suggest that the deviation from the normality assumption does not significantly bias the estimated effects. These findings are consistent with those of Jiang (1996) that the estimation of random effects by a REML approach is consistent when normality does not hold.

[12] Bates et al. (2015) discuss the iterative algorithm for REML to maximize the likelihood function in detail.

"most likely." The variances of partner, client, and match effects, $\hat{\sigma}^2_\theta$, $\hat{\sigma}^2_\psi$, and $\hat{\sigma}^2_\phi$, are largely estimated from mover partners.

Lastly, the mixed-effects model uses the estimated variances of partner, client, and match random effects ($\hat{\sigma}^2_\theta$, $\hat{\sigma}^2_\psi$, and $\hat{\sigma}^2_\phi$), and then generates the best linear unbiased predictors (BLUPs) of these effects based on the size of estimated variances and the number of observations on each partner, client, and match. The larger the estimated variance of an effect relative to the variances of other effects, the more unexplained audit outcomes is allocated to that effect.[13] Moreover, when we have more observations on a particular client (partner, match), this particular client (partner, match) effect can be more precisely estimated. Essentially, the mixed-effects model creates BLUPs of client, partner, and match effects using the standard Bayesian approach.[14]

4. Data and Sample

4.1 Sample

Our sample period begins in 2016 and ends in 2023. Public audit partner disclosures on PCAOB form AP allow us to track through time engagement partners participating in audits of U.S. public companies from 2016 and construct a connectedness sample that contains all partners who have ever worked for a client that has hired at least one partner who previously worked for other clients. Since the separation of client, partner, and match effects relies on observing audit outcomes when matching different partners with different clients, we focus on the partners of Big 4 firms and their clients, which allows us to consider reasonably homogeneous partners and clients.

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[13] All else equal, a greater proportion of unexplained audit fees or audit quality is attributed to an effect if that effect has a larger variance because values far from zero (prior mean) are more likely.

[14] We note that the condition $\phi_{ij} \sim N[0, \sigma^2_\phi]$ in equation (2.2) requires match effects to have zero mean in the entire sample. That is, a negative match effect indicates a negative deviation from the mean of the entire sample, suggesting that the match is lower than an average client-partner pair in the sample.

We obtain financial accounting data from Compustat, and audit related information, (i.e., audit fees, restatements, and going concern opinions) from Audit Analytics. We also obtain stock return information from CRSP. We remove observations with missing control variables in Equation (1). The resulting sample contains 13,809 client-partner-year observations, but is slightly smaller, at 12,398 observations, when using discretionary accruals as the dependent variable because we estimate those in industry-years with more than ten observations. The sample is also smaller, with 5,502 observations, when considering going concern opinions because we restrict the sample to distressed companies, defined as having negative earnings or operating cash flows during the fiscal year, following prior literature (Reynolds and Francis 2000; DeFond et al. 2002).

4.2 Partner Mobility

Since we separate client, partner, and match effects by observing audit outcomes when matching different partners with different clients, we report the mobility structure of the sample in Table 1. The sample contains 2,053 partners and 2,599 clients. Panel A shows that about 70% of partners have matched with at least two clients during our sample period. Panel B shows that 47.63% of clients hired two partners during the sample period. 24.12% of them hired three partners, and 2.27% of them hired four partners, suggesting that a client matches with multiple partners.

[Insert Table 1 about here]

4.3 Summary Statistics

Table 2 reports summary statistics for the sample. The average audit fee is $2.374 million. In our sample, the mean (median) absolute value of discretionary accruals is 0.12 (0.06). 6% of client firm years had misstated fiscal year ends that resulted in subsequent restatements, and 8% of distressed client firm-years received a going concern opinion. An average client has assets of $2.1 billion, and cash flows from operations at 3% of beginning assets. 89% of client-years have integrated audits of financial statements and internal control which is intuitive given that the Big 4 audit larger clients, 78% a December fiscal year end, and 40% operate in industries with greater litigation risk.

[Insert Table 2 about here]

5. Match Effects in Audit Outcomes

We begin our empirical analyses by demonstrating the importance of match effects in explaining audit outcomes. Table 3 reports the OLS regression results of Equation (2.1). Across all columns, we control for partner-client spells, which absorb a large variation in some of the explanatory variables. Despite this, we still find a positive (negative) association between *Size* and *Audit Fees* (*Going Concern*), consistent with prior literature (e.g., Hay et al. 2006; Li 2009).

[Insert Table 3 about here]

To assess the existence of match effects, we report in the last row of columns (1)-(5) a REML likelihood ratio test (REMLRTs) based on the log-likelihoods of specifications with and without match effects.[15] The likelihood ratio test rejects the null hypothesis of no match effects ($p<0.00001$).

Next, following Graham et al. (2012) and Ma, Pan, and Wang (2024), we decompose the variance of audit outcomes based on Equation (3) below to compute the proportion of variation explained by each component, which measures the relative economic importance of match effects.

$$1= var(y_{ijt})/var(y_{ijt}) = cov(y_{ijt}, \hat{y}_{ijt})/var(y_{ijt}) + cov(y_{ijt}, e_{ijt})/var(y_{ijt})$$

[15] We compare the log likelihood of the null model (Equation (1) without match effects) to that of the alternative model (Equation (1)) using test statistic: x^2=-2(log likelihood(null model)-log likelihood(alternative model)) . Abowd, Kramarz, and Woodcock (2006) discuss the likelihood ratio test in details.

$$= \text{cov}(y_{ijt}, x_{ijt}\hat{\beta}+\hat{\mu}_t+\hat{\theta}_i+\hat{\psi}_j+\hat{\varphi}_{ij})/\text{var}(y_{ijt}) + \text{cov}(y_{ijt}, e_{ijt})/\text{var}(y_{ijt})$$

$$= \text{cov}(y_{ijt}, x_{ijt}\hat{\beta})/\text{var}(y_{ijt}) + \text{cov}(y_{ijt}, \hat{\mu}_t)/\text{var}(y_{ijt}) + \text{cov}(y_{ijt}, \hat{\theta}_i)/\text{var}(y_{ijt}) + \text{cov}(y_{ijt}, \hat{\psi}_j)/\text{var}(y_{ijt})$$

$$+ \text{cov}(y_{ijt}, \hat{\varphi}_{ij})/\text{var}(y_{ijt}) + \text{cov}(y_{ijt}, e_{ijt})/\text{var}(y_{ijt}) \quad (3)$$

where y_{ijt} is one of the audit outcomes; x_{ijt} is time-variant observable client characteristics; $\hat{\mu}_t$ captures estimated year effects; $\hat{\theta}_i$ captures estimated partner effects; $\hat{\psi}_j$ captures estimated client effects; $\hat{\phi}_{ij}$ captures estimated match effects, and e_{ijt} is the residual. The proportion explained by each component equals the covariance of the component and y_{ijt}, scaled by the variance of y_{ijt}.

[Insert Table 4 about here]

Table 4 reports the results. Column (1) shows that client, partner, and match effects explain 20.6%, 1.0%, and 2.4% of the variation in audit fees, whereas observable client characteristics explain 72.2%. The last result is not surprising, given that client size is well known to explain a large proportion of audit fees, approximately 70% (Hay et al. 2006; DeFond and Zhang 2014). Interestingly, match effects are larger than partner effects in this specification. Column (1) also shows that the standard deviation of match effects is 0.08. Column (2) demonstrates that match random effects explain 4.2% of the variation in *Abs(Disc. Accruals)*, which is sizable in comparison with observable client characteristics and time invariant effects which collectively explain 24.4% of the variation in discretionary accruals. In contrast, partner effects do not seem to matter much in explaining accruals. We also note that the residuals explain a large variation, almost 71%, which is consistent with discretionary accruals being measured with significant error. In column (3), the three-way mixed-effects model estimation results indicate that client, partner, and match effects explain 11%, 1%, and 17% of the variation in *Restatement*, respectively. Similar to column (2), the residual explains almost 70% of the variation, which is consistent with a lack of explanatory power of typical models in the restatement literature. In column (4), we find that match random effects explain 4.6% of the variation in *Small Profit*, and client and partner effects explain 15.7% and 1.1% of the variation, respectively. Column (5) demonstrates that client, partner, and match random effects explain 10.3%, 0.3%, and 10.5% of the variation in *Going Concern*, respectively. Collectively, these results suggest that match effects explain a sizable amount of audit quality, and the match effects are more important economically than the partner effects.[16]

In addition, we use summary statistics in Table 4 to demonstrate the economic impact of match effects. If match effects in *Audit Fees* increase by one standard deviation (0.08), the natural logarithm of audit fees increases from its average of 14.68 to 14.76 (=14.68+0.08), corresponding to an increase of $0.198 million in audit fees (=$2.572 million – $2.374 million). A one standard deviation increase in match effects in *Abs(Disc. Accruals)* represents a 8.3% (0.01/0.12) increase in *Abs(Disc. Accruals)* from the mean. Last, if match effects in *Restatement*, *Small Profit*, and *Going Concern* increase by one standard deviation, the probability of *Restatement*, *Small Profit*, and *Going Concern* increases by 6, 3, and 4 percentage points, respectively. Thus, match effects appear to have a significant economic impact on audit outcomes. Overall, the results presented thus far suggest that time-invariant client-partner match heterogeneity explains a sizeable proportion of the variation in audit outcomes. Importantly, partner match effects are generally much larger than audit partner effects, highlighting the need for future research to focus more on the determinants of these match effects rather than specific audit partner characteristics alone.

[16] To evaluate the performance of the mixed-effects model in capturing true effects, we conduct a simulation presented in Appendix 3. In the simulation, client, partner, match effects, and errors are randomly drawn from a N(0,1) distribution. The results show insignificant differences between the estimated match effects from the three-way mixed-effects model and the true match effects, supporting that the three-way mixed-effects model is well performing when the numbers of partners, clients, and matches are sufficiently large (Jiang 1996, 1998).

We also report for each measure of audit fee or audit quality considered the correlations among client, partner, and match effects. All correlations are positive and above 0.29, with the highest correlation at 0.67 when considering going concern opinions. These results are consistent with two ideas. First, the positive correlations between client and audit partner effects suggest that more conservative clients match with more conservative audit partners. This is consistent with signaling theories such as Titman and Trueman (1986). Second, the positive correlations between client and match effects and partner and match effects suggest that complementarities, rather than substitution effects, exist between client and audit partner styles. In other words, the results suggest that financial reporting quality is even more accurate when a conservative audit partner is matched with a conservative client.[17] These results are consistent with theories that show that matching is assortative when types are complement (e.g., Becker 1973; Shimer and Smith 2000).

6. Understanding Audit Outcome Match Effects

6.1 The Relation between Audit Outcome Match Effects and Client-partner heterogeneity

We next focus on immediately observable characteristics that could influence the partner-client match effects we estimated in the prior section. As a first step, we assess whether the audit outcome match effects estimated capture partner-client match-specific *heterogeneity* documented

[17] We note that positive correlations between audit partner and match effects, and client and match effects, are also consistent with more conservative clients and auditors seeking to enter more conservative matches, under the assumption that the quality of the match can be determined even before the client and audit partner match, i.e., that matches are search goods. While this is possible, especially when the client and audit partner know each other before forming a match, the literature on matches such as Jovanovic (1979) assumes that matches are an experience good, i.e., a good where the quality can only be inferred after both parties have entered the match. There is some evidence in the qualitative audit literature that audit partner – client matches have some attributes of experience goods. For example, Dodgson et al. (2020) highlight that audit firms use client satisfaction surveys and relationship partners, particularly during the first year following a partner rotation, to ensure that clients are satisfied. If clients are not satisfied, audit firms are willing to rotate the engagement partner early. Nevertheless, we cannot rule out that audit partner – client matches also have search good attributes. If so, the results are nevertheless consistent with signaling models where more conservative clients and audit partners aim to enter into more conservative matches.

in prior studies. First, we examine the complementarity arising from matching the client industry with audit partner specialization (Aobdia, Siddiqui, Vinelli, 2021). A better match due to complementarities between client industry and partner specialization may be partially reflected in improved audit fees and quality. This would lead to higher match-specific audit fees and better match-specific reporting outcomes, as measured by absolute discretionary accruals, and probability of restatement, small profits, and going concerns. We identify an audit partner as specialized in the industry from which he/she collects the most audit fees, defined using the Fama and French 48 industry groups. The variable *Industry Specialization* equals one if an industry specialist partner matches with a client in the same industry. Second, we examine whether the availability of audit partners in a given audit office affects the match between partners and clients. Offices with more partners might be able to provide a match that fits better with client needs, potentially explaining the audit office effect documented in prior literature if clients value higher quality audits (Francis and Yu 2009). We consider *Office #Partners*, the number of partners at the office level, measured one year before a partner matches with a client.

Third, we examine the extent to which audit outcome match effects are explained by the ability of the audit partner to cross-sell non audit services to the focal client. An extensive line of research focuses on whether the provision of non audit services negatively affect audit quality and finds inconclusive results (see for example DeFond et al. 2002; DeFond and Zhang 2014). Further, a greater ability to sell resulting from a particular match might also have an influence on audit fees, as the provision of non-audit fees could reflect a better auditor bargaining power or ability to sell (e.g., Aobdia 2019b). We measure partner-client relations using non-audit fees averaged over the partner-client pair, *Non-Audit Fees*. We also explore the relation between audit outcome match effects and the expected riskiness and complexity of the audit assignment, as measured by material weaknesses in internal control over financial reporting. We expect that riskier clients are more difficult to audit, which, in turn, is associated with higher match-specific audit fees and worse match-specific reporting outcomes. We also consider partner gender (*Partner Female*) and busyness based on the partner's number of clients (*Partner # Clients*) as additional variables.

Given that the estimated audit outcome match effects are time-invariant, we measure client and partner characteristics, including *Office #Partners* and *Material Weakness*, the year before a partner matches with a client. The variables *Industry Specialization*, *Non-Audit Fees*, and *Partner #Clients* are averaged over the partner-client pair. We estimate the following cross-sectional regressions:

$$Match(Audit\ Quality)_{ij} = \beta_0 + \beta_1 Industry\ Specialization_j + \beta_2\ Office\ \#Partners_j + \beta_3\ Non\text{-}Audit\ Fees_{ij} + \beta_4\ Material\ Weakness_i + \beta_5\ Partner\ Female_j + \beta_4\ Partner\ \#Clients_j + \varepsilon_{ij} \quad (4)$$

[Insert Table 5 about here]

Table 5, column (1) shows the regression results for audit fee match effects. We find that audit fee match effects are positively and significantly associated with partners' industry expertise, supporting the idea in the empirical and qualitative literature that matching client industry with partner expertise improves audit fees and quality (e.g., Fiolleau et al. 2013; Lennox and Wu 2018; Dodgson et al. 2020; Aobdia et al. 2021; Christensen et al. 2024). In addition, we find the coefficient on *Non-Audit Fees* is positive and significant. This finding is consistent with particular client-partner matches allowing the audit partner to sell more audit and non-audit services to the focal client. We do not find evidence to suggest that audit offices with more audit partners choose a match that is a better fit in terms of audit fee generation with a particular client. The results are also insignificant on partner gender and busyness. Last, we find a positive and significant coefficient on *Material Weakness*, suggesting a higher match effect in audit fees when clients are riskier and more difficult to audit. Overall, the findings support that match effects measured using audit fees capture multiple dimensions of client-partner match heterogeneity, including match-specific audit quality, the ability of an audit partner to sell audit and non audit services to the focal client, and the complexity of audit assignments.

The results are generally insignificant for all measures of audit quality, except for non audit fees that are weakly positively associated with some matches on audit quality, and partner busyness, where the results differ depending on the measure of audit quality considered. More importantly, in each of the analyses reported in Table 5, the explanatory power of the model to explain audit quality match effects is low, suggesting that observed partner, client, and match-specific attributes do not explain much variation of audit outcome match effects. This result is consistent with prior literature on partner effects that finds limited influence of partner characteristics on the estimated fixed effects (e.g., Gul et al. 2013). We note, though, that two reasons can jointly contribute to the low R-squared. First, estimated match effects are primarily intended to quantify the *unobservable* partner-client heterogeneity in audit quality. The *observable* variables *Industry Specialization*, *Office #Partners*, *Litigation*, *and Material Weakness* only explain a small proportion of the variation in match effects. The rest of the variation might be attributable to matching arising from harder-to-measure audit partner and client characteristics, including audit partner-client chemistry and personality fit (e.g., Dodgson et al. 2020; Maksymov et al. 2024; Aobdia et al. 2024b), but also other dimensions previously unexplored in the archival literature, such as alignment in attitudes about conservative or aggressive reporting. Focusing on such areas can provide a fruitful area for future research, especially given the importance of partner-client match effects in explaining variation in audit fees and quality, as reported in Table 4.

Second, we note that audit outcome match effects are estimated random effects, which can contain measurement error. Also, the independent variables, *Industry Specialization*, *Office #Partners*, *Non-Audit Fees*, *Litigation*, and *Material Weakness*, may be noisy measures of underlying partner and client characteristics. Measurement errors in both the dependent and independent variables may further decrease the R-squared of the model.

6.2 Audit Quality Match Effects and Partner Turnover

Next, we use audit partner turnover as a setting to further demonstrate the importance of audit partner-client match and understand the attributes of partner-client matches that are valued by both clients and auditors. SOX mandates audit partners to rotate off their public clients every five years. Since we are interested in understanding whether audit partner-client matches explain turnover, we focus on early rotations, i.e., rotations that occur before the fifth year end of the mandatory rotation period. However, a data issue that arises is that the PCAOB form-AP filings do not disclose in which year of the mandatory rotation cycle the partner is. Thus, we need to eliminate the initial partner-client observations until a new partner comes on the engagement, where we can precisely identify that the partner was in the first year of the mandatory rotation period. We also eliminate all observations where a mandatory rotation occurs the following fiscal year (i.e., the 5th year of the partner – client cycle), and estimate the following probit regression:

$$Probit(Partner\ Turnover_{ijt}) = \mu_0 + \beta_1\ Match(Audit\ Outcome)_{ij} + Controls + Year\ FEs + \varepsilon_{ijt} \quad (5)$$

where *i* indexes partners, *j* clients, and *t* years. $Partner\ Turnover_{ijt}$ equals one if a client's current partner differs from the partner in the following year and zero otherwise. The variable *Match(Audit Outcome)* represents the match effects of one of the following audit outcomes: *Audit Fees, Abs(Disc. Accruals), Restatement, Small Profit,* and *Going Concern*. β_1 measures the sensitivity of turnover to the match.

[Insert Table 6 about here]

Table 6 reports results from the probit regression of early partner rotations on the match effects. In column (1), the coefficient on *Match(Audit Fees)* is positive and significant, suggesting that clients will switch audit partners when audit fees are too high. Next, we find that the coefficients on *Match(Abs(Disc. Accruals))*, *Match(Restatement),* and *Match(Small Profit)* are positive and significant, which is consistent with audit firms and their clients having preferences on average for matches that bring better audit quality measured using discretionary accruals, restatements, and small profits. Overall, these results are consistent with the idea that clients and audit firms are concerned about poor match-specific audit quality. Thus, partners will be rotated early if their match with clients are perceived to decrease audit quality. Finally, we do not find evidence to suggest that partner-client going concern matches are associated with early turnover.

Overall, our results are consistent with clients and audit firms valuing greater audit quality. Further, the results on misstatements are consistent with audit standards which highlight that the auditor responsibility is to *"obtain reasonable assurance about whether the financial statements are free of material misstatement"* (PCAOB AS 1001).

6.3 Audit Quality Match Effects and Cumulative Abnormal Returns Around Annual Earnings Announcements

Prior literature finds evidence of capital market consequences of audit partner quality (e.g., Aobdia et al. 2015). Similarly, we assess whether investors value particular client partner matches. We note that the reasonably limited time-series available to us (8 years at most) make these analyses more exploratory in nature. Following Teoh and Wong (1993), Aobdia et al. (2015), and Gipper et al. (2020), we measure investors' assessments of the quality of audited financial reports based on how strongly they respond to a given amount of earnings news. Ceteris paribus, the market response to earnings news should increase if investors believe the partners produce high quality audits and reported numbers are more credible. We measure earnings response coefficients (ERCs) based on the association between abnormal returns over the window [-1,1] relative to the annual earnings announcement dates and unexpected earnings news. Unexpected earnings are measured based on analyst forecasts scaled by price as of the end of the fiscal year. To allow the market participants to learn the match quality of client-partner by observing the audit outcomes, we restrict the sample to the last year of each client-partner pair. We estimate the following Equation:

$$CAR[-1,1]_{ijt} = \mu_0 + \beta_1 \, High\ Match(Audit\ Outcome)_{ij} + \beta_2 Unexpected\ Earnings_{it} + \beta_3 \, Unexpected\ Earnings_{it} \times High\ Match(Audit\ Outcome)_{ij} + \beta_4 Controls_{it} + \beta_5 \, Unexpected\ Earnings_{it} \times Controls_{it} + Year\text{-}Month\ Fixed\ Effects + \varepsilon_{ij} \quad (6)$$

[Insert Table 7 about here]

where *i* indexes partners, *j* clients, and *t* years. *CAR[-1,1]* is the cumulative abnormal return over trading days [-1, 1] relative to earnings announcements. Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The variable *High Match(Audit Outcome)* equals one if the client-partner match effect is in the top tercile and zero otherwise. We measure audit outcomes with *Audit Fees*, *Abs(Disc. Accruals)*, *Restatement*, *Small Profit*, and *Going Concern*.

In Table 7 column (1), we find a positive coefficient on *Unexpected Earnings* × *High Match(Audit Fees)* (0.004, t-stat=2.72), suggesting a higher earnings response coefficient (ERC) when a client-partner pair has high audit fee match effects. The results support the idea that high audit fees are perceived as a signal for high-quality audits (Ball et al. 2012, Aobdia 2019a). In column (3), we find a negative coefficient on *Unexpected Earnings × High Match(Restatement)* (-0.003, t-stat=-2.44), suggesting a lower ERC when a client-partner pair has high restatement match effects. We also find some evidence that ERCs are lower when the match on small profits is higher. Overall, the results provide some evidence that the estimated match effects reflect match-specific audit quality and that capital markets incorporate the value of the match.

6.4 Audit Quality Match Effects and Cumulative Abnormal Returns to the Announcements of New Engagement Partners

Finally, we examine investor reactions to audit partner switches around the filings of Form-AP. Following Doxey, Lawson, Lopez, and Swanquist (2021), we collect Form AP filings from the PCAOB's AuditorSearch database and focus on the timing of their release.[18] For each client, we compare the names of engagement partners from the last year to the current, and identify an engagement partner rotation if the engagement partner listed in the Form AP has changed from the prior year to the current year. We remove all client-years in year 5 of partner-client pairs, i.e., when audit partners are mandated to rotate, as these turnovers are typically well anticipated and any stock market reactions may occur well before the Form AP filing. We estimate a regression model of market reactions to the announcement of a new engagement partner, i.e., filing Form-AP, on the variable indicating the departing partner has a high match effect, defined as the effect being in the top tercile in the sample. The underlying idea is that even though equity markets cannot know yet the value of the match between the incoming partner and the client, the new match is likely to be similar or lower in magnitude than the predecessor match. Thus, equity markets can form a

[18] Audit firms must file Form AP within 35 days following the date of the audit report. More detailed information on Form AP is available at https://pcaobus.org/Pages/form-ap-reporting-certain-audit-participants.aspx

prediction about the future match becoming worse or better on average. We consider the following regression:

$$CAR[-1,1]_{ijt} = \mu_0 + \beta_1\ High\ Match(Audit\ Outcome)_{ij} + \beta_2 Controls_{it} + Year\text{-}Month\ Fixed\ Effects + \varepsilon_{ij} \tag{7}$$

[Insert Table 8 about here]

where *i* indexes partners, *j* clients, and *t* years. *CAR[-1,1]* is the cumulative abnormal return over trading days [-1, 1] relative to the filing dates of Form-AP. Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of companies matched on size and the book-to-market ratio. The variable *High Match(Audit Outcome)* equals one if the departing partner has a match effect in the top tercile, and zero otherwise. Table 8 column (1) reports the results for audit fee match effects. We find a negative coefficient on *High Match(Audit Fees)* (-0.006, t-stat=-1.96), suggesting a negative market reaction when the departing partner has a high audit fee match effect. These results support the idea that equity investors perceive the audit fee match effect to capture audit quality, similar to the ERC results. In column (4), we find a positive coefficient on *High Match(Small Profit)* (0.006, t-stat=1.73), suggesting that the market reacts positively to the filing of Form-AP when the departing partner is perceived as providing low audit quality for the firm, as captured by a greater small profit match effect. Overall, the findings support the idea that investors perceive audit fees and small profits as signals of match-specific audit quality provided by an engagement partner.

6.5 Robustness Check: Estimating Match Effects Using a Rolling Window

The match effects used in Tables 6–8 are estimated using the connected sample from 2016 to 2023. The advantage of this approach is that it preserves all partners and clients within the connectedness sample. This is important because Jiang (1996, 1998) shows that a sufficiently large number of firms, managers, and matches are essential for the mixed-effects model to generate consistent estimates of random effects. However, a potential disadvantage is that this procedure may be susceptible to look-ahead bias, since investors in any given year during the sample period would not have access to future audit fees or other audit outcomes to infer partner-client match effects. To address this concern, we re-estimate Models (5)–(7) using match effects derived from a rolling window approach. Specifically, for each year, the match effect for a given partner-client pair is estimated using data from 2016 up to that year. We report the coverage of connected samples for the periods 2016-2017, 2016-2018, 2016-2019, 2016-2020, 2016-2021, and 2016-2022 in Table 9 Panel A.

[Insert Table 9 about here]

The earlier samples (2016–2017, 2016–2018, and 2016–2019) include a small number of partners and clients due to limited partner mobility over shorter periods. For example, the 2016–2019 sample covers only 4.2% of the unique partners and 6.2% of the unique clients in the full 2016–2023 sample. In contrast, the 2016–2020 sample captures 36.8% of the unique partners and 43.1% of the unique clients in the 2016–2023 sample. Thus, we estimate match effects for the periods 2016–2020, 2016–2021, 2016–2022, and 2016–2023, and re-estimate Models (5)–(7) using data from 2020 to 2023. The estimation results are presented in Panels B-D of Table 9.

Panel B of Table 9 presents results from the probit regression of early partner turnover on match effects. We find that the coefficients on *Match(Abs(Disc. Accruals))* (t-stat=1.84) and *Match(Small Profit)* (t-stat=2.02) are positive and significant, suggesting that partners are more likely to be rotated early when the matches are perceived to be of lower quality as measured by discretionary accruals and small profits. In contrast, we find no evidence that match effects based on audit fees, restatements, or going concern opinions are significantly associated with early partner turnover.

In Table 9 Panel C, we report empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the annual earnings announcements. As shown in column (3), the coefficient on *Unexpected Earnings* × *High Match(Restatement)* is significantly negative (t-stat=-4.28), suggesting a lower ERC when a client-partner pair exhibits high restatement match effects. In column (4), we also find that ERCs are lower when the match on small profits is higher (t-stat=-1.68).

Panel D of Panel 9 reports empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the announcement of a new engagement partner. In column (4), the coefficient on *High Match(Small Profit)* is positive and significant (t-stat=1.76). The evidence suggests that the market reacts favorably to filing Form-AP when the departing partner is perceived as providing low audit quality for the client, as measured by a greater small profit match effect.

Overall, these results are consistent with those reported in Tables 6-8, albeit weaker for some. Nevertheless, it is important to note that these results should be interpreted with caution for two reasons. First, since Models (5)–(7) are re-estimated using data from 2020 to 2023, the number of observations, and thus the statistical power, is substantially reduced compared to the estimations presented in Tables 6–8. Second, the connected samples for the periods 2016–2020, 2016–2021, and 2016–2022 include significantly fewer clients and partners than the full 2016–2023 sample, which may lead to biased match effect estimates, particularly for the earlier periods. Finally, both clients and capital markets, have access to additional information that is likely to be correlated to the matches estimated in Tables 6-8, especially for clients in Table 6.

7. Conclusion

We empirically investigate the importance of audit partner-client matches in explaining audit quality and audit fees, and compare their predictive power with audit partner individual effects. We apply recent methodological advances in the labor economics and executive compensation literature and employ a three-way mixed model to quantify the match effects. We find evidence suggesting that audit partner-client matches are a first order determinant in explaining audit quality, much larger than audit partner effects. Audit partner, client, and match effects are also positively correlated with each other, consistent with signaling models and with complementarities resulting from similar styles between audit partners and their clients. Importantly, we find limited evidence that immediately observable characteristics such as audit partner industry specialization explain the match effects, consistent with match effects mostly capturing unobservable characteristics of the partner-client relationship, and leaving an opportunity for future literature to study additional determinants of audit partner – client match effects. We also find that audit firms and clients value matches that result in greater audit quality. Finally, we find some evidence consistent with equity markets positively valuing audit partner-client matches that are perceived to be of greater audit quality.

Our evidence suggests that audit partner-client matches explain a substantial amount of audit quality in the United States, much more than individual audit partner effects. Thus, future literature might want to focus more on understanding the determinants and consequences of these matches, rather than focusing on individual audit partner characteristics. Our study answers the call by Lennox and Wu (2018, p29) to *"better understand the partner-client matching process."*

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Appendix 1. Variable Definitions

Variables	Definitions
Dependent variables	
Audit Fees	Natural logarithm of audit fees (source = Audit Analytics)
Abs(Disc. Accruals)	Absolute value of residual of discretionary accruals computed using the Jones model. Discretionary accruals are residuals from industry-year regressions of total accruals (ACC) on one over beginning assets, gross property, plant, and equipment (PP&E), and change in revenues (ΔREV). ACC, PP&E, and ΔREV are deflated by beginning assets. Total accruals are defined as income before extraordinary items minus cash flow from operations, excluding extraordinary items and discontinued operations. We require a minimum of ten observations in an industry-year.
Restatement	Indicator variable if the fiscal-year-end financial statements are subsequently restated (source = Audit Analytics)
Small Profit	Indicator variable if the company's returns on assets, defined as income before extraordinary items deflated by average beginning and ending assets is between 0% and 3%
Going Concern	Indicator variable if the auditor issues a going concern opinion for the fiscal-year-end
CAR[-1,1]	CAR[-1,1] is the cumulative abnormal return over trading days [-1, 1] around earnings announcement (day 0). Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The benchmark portfolios are constructed using Fama and French's (1992) method. All firms with CRSP share codes 10 and 11 are classified into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.
Explanatory variables	
Size	Natural logarithm of company assets
Foreign Income	Absolute value of pretax income from foreign operations (PIFO) divided by the absolute value of pretax income (PI)
December Year End	Indicator variable when the fiscal year ends in December
Altman Z Score	Altman Z score of the company, computed as 1.2*((act-lct)/at)+1.4*re/at+3.3*oiadp/at+0.6*(csho*prcc_f)/lt+sale/at
Business Segments	Number of business segments
Geographic Segments	Number of geographic segments
CFO	Client's cash flows from operations deflated by beginning assets
Std(CFO)	Standard deviation of the client's cash flows from operations deflated by beginning assets, computed over t-3 to t
BTM	Shareholder's equity (book value) deflated by fiscal year end market capitalization
Sales Growth	Year-on-year sales growth of the client firm
Leverage	Total debt divided by debt plus stockholder's equity

Litigation	Indicator variable if the client is in a high litigation industry (SIC code between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, or 5200 and 5961)
Material Weakness	Indicator variable equal to one if the auditor identifies a material weakness in internal controls over financial reporting as of the fiscal-year-end
Integrated Audit	Indicator variable equals one if the audit is an integrated audit of internal control over financial reporting and financial statements
Industry Specialization	Indicator variable equals one if a client and a partner are in the same Fama-French 48 industry. We assign a partner to the industry from which the partner collects the most audit fees in the year before a partner matches with a client.
Office #Partners	Number of partners at the office level, measured in the year before a partner matches with a client.
Partner Female	Indicator variable equals one if the engagement partner is female.
Partner #Clients	Number of clients at the partner level, averaged over the partner-client pair
Non-Audit Fees	Non-audit fee averaged over the partner-client pair, measured in $millions.
Unexpected Earnings	Unexpected earnings based on analyst forecasts scaled by price as of the end of the fiscal quarter.
ROA	Income before extraordinary items, divided by the average total assets.
Analyst Coverage	Natural logarithm of the number of analysts that provide earnings forecasts within 90 days before clients' earnings announcements.
Analyst Dispersion	The standard deviation of analyst quarterly EPS forecasts.

Appendix 2. Simulation Assessing the Impact of Normality Assumption

As described in Section 2, we estimate partner, client, and match effects by assuming that these effects follow a normal distribution. To evaluate the robustness of our mixed-effects model estimation to violations of the normality assumption**,** we perform a simulation with randomly generated match effects. To preserve the connectedness and mobility, we use the same sample as in the paper to conduct the simulation, which follows the procedure below:

Step 1: Randomly draw partner, client, match effects, and errors from uniform distribution for audit fees and *Abs(Disc. Accruals)*, and from Poisson distribution for *Restatement*, *Small Profit*, and *Going Concern*.
Step 2: Generate audit fees and quality by adding the randomly drawn partner, client, match effects, and errors.
Step 3: Estimate partner, client, and match effects using a three-way mixed-effects model.
Step 4: Compute the proportion of audit fees and quality explained by match effects estimated from Step 3.
Step 5: Repeat Steps 1 to 4 for 1,000 iterations.

For each iteration, we compare the proportion of audit fees and quality explained by the estimated effects (Step 3) with the randomly generated actual effects (Step 1). The results from the 1000 iterations are reported below:

	Audit Fees	*Abs(Disc. Accruals)*	*Restatement*	*Small Profit*	*Going Concern*
	(1)	(2)	(3)	(4)	(5)
The distribution assumed for the data generating process	Uniform	Uniform	Poisson	Poisson	Poisson
% of the variance of audit fees and quality attributable to the estimated value of match mixed effects − % of the variance of audit fees and quality attributable to the actual value of match mixed effects	0.02%	0.04%	0.16%	-0.03%	0.04%
t-statistics	0.41	0.88	1.60	-0.48	0.45

As shown in the table, we observe no significant difference between estimated and actual match effects when we use the three-way mixed-effects model that includes match effects. The simulation results suggest that the deviation from the normality assumption does not significantly bias the match effects estimated from a three-way mixed-effects model.

Appendix 3. Simulation Assessing the Performance of the Mixed-Effects Model

To help evaluate the performance of the mixed-effects model in capturing the true effects, we repeated the simulation described in Appendix 2 with a modification to Step 1: for each firm-manager-year observation, we randomly drew partner, client, match effects, and errors from a N(0,1) distribution. The results from the 1000 iterations are reported below:

	Audit Fees	*Abs(Disc. Accruals)*	*Restatement*	*Small Profit*	*Going Concern*
	(1)	(2)	(3)	(4)	(5)
The distribution assumed for the data generating process	Normal	Normal	Normal	Normal	Normal
% of the variance of audit fees and quality attributable to the estimated value of match mixed effects − % of the variance of audit fees and quality attributable to the actual value of match mixed effects	0.0%	-0.01%	-0.05%	0.05%	-0.04%
t-statistics	0.01	-0.26	-1.23	1.19	-0.48

As reported in the table, the differences between estimated and actual effects are insignificant. This evidence supports the notion that the three-way mixed-effects model performs well, generating consistent estimates of random effects when the numbers of partners, clients, and matches are sufficiently large (Jiang 1996, 1998).

Table 1. Structure of the Connectedness Sample

This table provides information about the structure of the connectedness sample. The sample period starts in 2016 and ends in 2023. In the connectedness sample, all the partners have audited clients that have used at least one mover partner. The connectedness sample includes 2,053 partners and 2,599 clients.

Panel A: Number of clients for which partners have audited

Number of clients for which a partner has matched	Number of partners	Percentage	Cumulative percentage
1	617	30.05%	30.05%
2	561	27.33%	57.38%
3	384	18.70%	76.08%
4	259	12.62%	88.70%
5	127	6.19%	94.89%
6	105	5.11%	100.00%
Total number of partners	2,053		

Panel B: Number of partners who have matched with the same client

Number of partners which have matched the same client	Number of clients	Percentage	Cumulative percentage
1	669	25.74%	25.74%
2	1238	47.63%	73.37%
3	627	24.12%	97.50%
4	59	2.27%	99.77%
5	6	0.23%	100.00%
Total number of clients	2,599		

Table 2. Summary Statistics

This table provides summary statistics of the main variables in the connectedness sample. The sample period starts in 2016 and ends in 2023. The definitions for the variables are available in Appendix 1.

Variable	N	Mean	Std	10%	25%	Median	75%	90%
Audit Fees	13,809	14.68	0.93	13.53	14.06	14.64	15.28	15.91
Abs(Disc. Accruals)	12,398	0.12	0.18	0.01	0.03	0.06	0.14	0.28
Restatement	13,809	0.06	0.25	0.00	0.00	0.00	0.00	0.00
Small Profit	13,809	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Going Concern	5,502	0.08	0.26	0.00	0.00	0.00	0.00	0.00
Size	13,809	7.63	1.80	5.33	6.41	7.61	8.82	9.99
Foreign Income	13,809	0.34	0.60	0.00	0.00	0.06	0.47	0.99
December Year End	13,809	0.78	0.42	0.00	1.00	1.00	1.00	1.00
Altman Z Score	13,809	3.50	8.54	-0.14	1.21	2.61	4.44	8.48
Business Segments	13,809	2.89	1.53	1.00	2.00	2.00	4.00	5.00
Geographic Segments	13,809	3.38	2.09	1.00	2.00	3.00	5.00	7.00
CFO	13,809	0.03	0.27	-0.20	0.02	0.08	0.13	0.20
Std(CFO)	13,809	0.11	0.43	0.01	0.02	0.04	0.08	0.18
BTM	13,809	0.39	0.88	0.03	0.15	0.32	0.59	0.98
Sales Growth	13,809	0.21	0.89	-0.18	-0.02	0.07	0.21	0.48
Leverage	13,809	0.45	0.44	0.02	0.19	0.42	0.62	0.86
Litigation	13,809	0.40	0.49	0.00	0.00	0.00	1.00	1.00
Material Weakness	13,809	0.04	0.20	0.00	0.00	0.00	0.00	0.00
Integrated Audit	13,809	0.89	0.31	0.00	1.00	1.00	1.00	1.00

Table 3. Determinants of the Measures of Audit Fees and Quality

Table 3 reports the OLS regression results for the determinants of audit fees and quality, using the connectedness sample.

$$Measures\ of\ Audit\ Fees\ and\ Quality_{ijt} = \mu_0 + \beta_1 Size_{jt} + \beta_2 Foreign\ Income_{jt} + \beta_3\ December\ Year\ End_{jt} + \beta_4\ Altman\ Z\ Score_{jt} + \beta_5 Business\ Segments_{jt} + \beta_6 Geographic\ Segments_{jt} + \beta_7 CFO_{jt} + \beta_8\ Std(CFO)_{jt} + \beta_8 BTM_{jt} + \beta_9 Sales\ Growth_{jt} + \beta_{10}\ Leverage_{jt} + \beta_{11}\ Litigation_{jt} + \beta_{12}\ Material\ Weakness_{jt} + \beta_{13}\ Integrated\ Audit_{jt} + Year\ Fixed\ Effects + v_{ij} + \varepsilon_{ijt}$$

The variable v_{ij} denotes client-partner spells. The sample period starts in 2016 and ends in 2023. The definitions for all the variables are available in Appendix 1. The standard errors are clustered by client firms. We report t-statistics in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively. In the last row, we report the likelihood ratio test based on the log-likelihoods of specifications with and without match effects.

	Audit Fees	*Abs(Disc. Accruals)*	*Restatement*	*Small Profit*	*Going Concern*
	(1)	(2)	(3)	(4)	(5)
Size	0.284***	0.030*	0.015	0.038**	-0.080***
	(16.74)	(1.88)	(1.00)	(2.27)	(-3.50)
Foreign Income	0.010*	-0.006	-0.002	0.137***	-0.012
	(1.76)	(-1.33)	(-0.32)	(9.15)	(-1.49)
December Year End	-0.051	0.006	-0.068	0.196	-0.274
	(-0.60)	(0.28)	(-0.77)	(1.57)	(-0.76)
Altman Z Score	-0.003***	0.001	0.000	-0.001**	-0.002**
	(-3.30)	(0.39)	(0.63)	(-2.34)	(-2.06)
Business Segments	-0.006	0.001	-0.002	0.004	0.015
	(-0.90)	(0.21)	(-0.23)	(0.37)	(1.18)
Geographic Segments	0.007	-0.005	-0.008	-0.013	0.011
	(0.72)	(-0.71)	(-0.88)	(-1.05)	(0.59)
CFO	-0.116***	-0.073	0.009	-0.015	-0.030
	(-3.48)	(-1.51)	(0.82)	(-1.33)	(-0.89)
Std(CFO)	-0.030**	0.003	-0.005	-0.011*	0.015
	(-1.97)	(0.12)	(-0.91)	(-1.77)	(0.55)
BTM	-0.007	-0.004	-0.006	0.003	-0.028**
	(-1.15)	(-0.73)	(-0.69)	(0.51)	(-2.06)
Sales Growth	0.007	0.027***	-0.003	0.000	-0.002
	(1.19)	(4.49)	(-1.63)	(0.02)	(-0.25)
Leverage	0.025*	-0.010	-0.015	-0.025*	0.020
	(1.65)	(-0.53)	(-1.36)	(-1.96)	(0.65)
Litigation	-0.130	-0.027	0.004	0.017	-0.04

	(-1.36)	(-0.75)	(0.06)	(0.25)	(-0.42)
Material Weakness	0.170***	-0.003	-0.045	-0.010	0.025
	(8.35)	(-0.28)	(-1.35)	(-0.39)	(0.89)
Integrated Audit	-0.005	-0.055***	-0.008	0.023	-0.040*
	(-0.24)	(-2.84)	(-0.49)	(1.42)	(-1.82)
H_0: No match effects	425.71	17.31	212.32	19.587	45.866
(p-value)	(0.000) ***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Year Effects	Yes	Yes	Yes	Yes	Yes
Client Effects	Yes	Yes	Yes	Yes	Yes
Partner effects	Yes	Yes	Yes	Yes	Yes
Match Effects	Yes	Yes	Yes	Yes	Yes
Observations	13,809	12,398	13,809	13,809	5,502
R-squared	0.979	0.581	0.593	0.566	0.759

Table 4. Relative Importance of Different Components in Determining Audit Fees and Quality

Table 4 reports the summary statistics of observable and unobservable components that determine audit fees and quality, using the estimation results of Table 3. The decomposition is based on the following Equation:

$$1=\frac{Var\left(y_{ijt}\right)}{Var\left(y_{ijt}\right)}=\frac{Cov\left(y_{ijt},\hat{y}_{ijt}\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\ \left(y_{ijt},e_{ijt}\right)}{Var\left(y_{ijt}\right)}=\frac{Cov\left(y_{ijt},X_{ij}\hat{\beta}+W_{jt}\hat{\gamma}+\hat{\mu}_t+\hat{\theta}_i+\hat{\psi}_j+\hat{\varphi}_{ij}\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\ \left(y_{ijt},e_{ijt}\right)}{Var\left(y_{ijt}\right)}$$
$$=\frac{Cov\left(y_{ijt},X_{it}\hat{\beta}\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},W_{jt}\hat{\gamma}\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},\hat{\mu}_t\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},\hat{\theta}_i\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},\hat{\psi}_j\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},\hat{\varphi}_{ij}\right)}{Var\left(y_{ijt}\right)}+\frac{Cov\left(y_{ijt},e_{ijt}\right)}{Var\left(y_{ijt}\right)}$$

The observable time-variant characteristics component includes $Size_{jt}$, $Foreign\ Income_{jt}$, $December\ Year\ End_{jt}$, $Altman\ Z\ Score\ _{jt}$, $Business\ Segments_{jt}$, $Geographic\ Segments_{jt}$, CFO_{jt}, $Std(CFO)_{jt}$, BTM_{jt}, $Sales\ Growth_{jt}$, $Leverage_{jt}$, $Litigation_{jt}$, $Material\ Weakness_{jt}$, $Integrated\ Audit_{jt}$. The percentage of the variance of audit quality attributable to particular components equals the covariance between each component and audit quality scaled by the variance of audit quality. The bottom of the table also reports the correlations among client, partner, and match effects computed based on the corresponding measure of audit fee or audit quality in each column.

		Client, partner, and match mixed effects				
		Audit Fees	*Abs(Disc. Accruals)*	*Restatement*	*Small Profit*	*Going Concern*
		(1)	(2)	(3)	(4)	(5)
S.D.	Client Effects	0.38	0.05	0.05	0.10	0.05
	Partner effects	0.04	0.00	0.00	0.01	0.00
	Match effects	0.08	0.01	0.06	0.03	0.04
% of the variance of dependent variables attributable to particular components	Observable time-variant characteristics (xβ)	72.2%	7.9%	0.8%	7.7%	25.3%
	Client Effects	20.6%	16.5%	10.9%	15.7%	10.3%
	Partner effects	1.0%	0.0%	0.6%	1.1%	0.3%
	Match effects	2.4%	4.2%	16.8%	4.6%	10.5%
	Year effects	0.4%	0.5%	1.0%	0.1%	0.5%
	Residuals	3.5%	70.9%	69.8%	70.7%	53.2%
Correlations among client, partner, and match effects	Client and Partner	0.29	0.35	0.31	0.37	0.41
	Client and Match	0.31	0.58	0.58	0.58	0.67
	Partner and Match	0.48	0.56	0.52	0.57	0.53

Table 5. The Relation between Audit Fees and Quality Match Effects and Client-partner Complementarities

This table reports the relation between audit fees and quality match effects and determinants of client-partner complementarities. The sample period starts in 2016 and ends in 2023.

$$Match(Audit\ Fees\ and\ Quality)_{ij} = \beta_0 + \beta_1 Industry\ Specialization_j + \beta_2 Office\ \#Partners_j + \beta_3\ Non\text{-}Audit\ Fees_{ij} + \beta_4\ Litigation_i + \beta_5\ Material\ Weakness_i + \varepsilon_{ij}$$

Match(Audit Fees and Quality)$_{ij}$ denotes client-partner audit fees and quality match effects. We measure audit quality by *Abs(Disc. Accruals)*, *Restatement*, *Small Profit*, and *Going Concern*. The definitions of all the variables are available in Appendix 1. We report t-statistics in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively.

	Audit Fees	*Abs(Disc. Accruals)*	*Restatement*	*Small Profit*	*Going Concern*
	(1)	(2)	(3)	(4)	(5)
Industry Specialization	0.019***	0.000	-0.002	0.001	0.001
	(4.54)	(0.08)	(-0.68)	(0.77)	(0.31)
Office #Partners	0.001	-0.000	0.000	-0.000	-0.001
	(0.79)	(-1.18)	(0.36)	(-0.62)	(-0.82)
Non-Audit Fees	0.003***	-0.000	-0.000	-0.001**	0.001*
	(3.52)	(-1.03)	(-0.42)	(-2.40)	(1.83)
Material Weakness	0.036***	-0.000	-0.002	0.002	-0.000
	(5.24)	(-0.38)	(-0.47)	(0.85)	(-0.02)
Partner Female	-0.004	0.000	-0.000	0.002	0.001
	(-1.08)	(0.43)	(-0.12)	(1.51)	(0.37)
Partner #Clients	0.002	-0.001*	0.002	0.002**	0.005**
	(0.47)	(-1.69)	(1.02)	(2.09)	(2.17)
Observations	3,157	2,840	3,157	3,157	1,731
R-squared	0.021	0.002	0.001	0.005	0.004

Table 6. Audit Fees and Quality Match Effects and Partner Turnover

This table reports results from the probit regression of early partner turnover on audit fees and quality match effects and other control variables. The sample period is from 2016 to 2023. We eliminate the first partner that a client is matched with from the sample because we cannot determine which year of the mandatory rotation cycle the partner is in. The variable $Partner\ Turnover_{ijt}$ equals one if a client's current partner differs from the partner in the following year and zero otherwise.

$$Probit(Partner\ Turnover_{ijt}) = \mu_0 + \beta_1\ Match(Audit\ Fees\ and\ Quality)_{ij} + Controls + Year\ FEs + \varepsilon_{ijt}$$

$Match(Audit\ Fees\ and\ Quality)_{ij}$ denotes client-partner audit fees and quality match effects, and we neasure audit quality by *Abs(Disc. Accruals)*, *Restatement*, *Small Profit*, and *Going Concern*. The controls include $Size_{jt}$, $Foreign\ Income_{jt}$, $December\ Year\ End_{jt}$, $Altman\ Z\ Score\ _{jt}$, $Business\ Segments_{jt}$, $Geographic\ Segments_{jt}$, CFO_{jt}, $Std(CFO)_{jt}$, BTM_{jt}, $Sales\ Growth_{jt}$, $Leverage_{jt}$, $Litigation_{jt}$, $Material\ Weakness_{jt}$, $Integrated\ Audit_{jt}$.. We report the coefficient estimate and z-statistics (in parentheses), and F-statistics for the tests of the null that the sum of coefficients on *Match(Audit Fees and Quality)* and *Match(Audit Fees and Quality) × Neg Match(Audit Fees and Quality)* are zero. We cluster standard errors by clients. The definitions of all the variables are available in Appendix 1. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively.

	Probit (Partner Turnover = 1)				
	(1)	(2)	(3)	(4)	(5)
Match(Audit Fees)	0.654**				
	(2.20)				
Match(Abs(Disc. Accruals))		4.181**			
		(2.20)			
Match(Restatement)			1.226***		
			(3.75)		
Match(Small Profit)				1.574**	
				(2.10)	
Match(Going Concern)					-0.127
					(-0.18)
Size	-0.062***	-0.062***	-0.061***	-0.062***	-0.087***
	(-3.88)	(-3.60)	(-3.79)	(-3.86)	(-4.06)
Foreign Income	0.028	0.035	0.024	0.024	-0.024
	(0.73)	(0.88)	(0.62)	(0.63)	(-0.50)
December Year End	-0.008	0.001	-0.005	-0.007	-0.092
	(-0.15)	(0.01)	(-0.08)	(-0.13)	(-1.24)
Altman Z Score	-0.000	-0.000	-0.000	-0.000	-0.001
	(-0.04)	(-0.15)	(-0.06)	(-0.13)	(-0.18)
Business Segments	-0.023	-0.028*	-0.024	-0.023	-0.028
	(-1.46)	(-1.67)	(-1.54)	(-1.45)	(-1.24)

Geographic Segments	0.008	0.009	0.008	0.008	0.002
	(0.67)	(0.68)	(0.68)	(0.64)	(0.14)
CFO	-0.108	-0.069	-0.104	-0.102	-0.121
	(-1.02)	(-0.65)	(-0.99)	(-0.97)	(-1.06)
Std(CFO)	0.095***	0.080**	0.095***	0.095***	0.087***
	(3.14)	(2.47)	(3.10)	(3.11)	(3.00)
BTM	0.027	0.028	0.032	0.030	0.023
	(1.10)	(1.08)	(1.31)	(1.25)	(0.87)
Sales Growth	-0.015	-0.005	-0.014	-0.014	-0.016
	(-0.66)	(-0.21)	(-0.65)	(-0.62)	(-0.71)
Leverage	0.027	0.013	0.022	0.023	0.088
	(0.47)	(0.21)	(0.38)	(0.39)	(1.25)
Litigation	-0.119**	-0.094*	-0.119**	-0.119**	-0.196***
	(-2.35)	(-1.81)	(-2.36)	(-2.35)	(-3.08)
Material Weakness	0.509***	0.466***	0.502***	0.508***	0.398***
	(5.31)	(4.61)	(5.29)	(5.36)	(3.62)
Integrated Audit	-0.194***	-0.214***	-0.196***	-0.192***	-0.144*
	(-2.63)	(-2.79)	(-2.64)	(-2.60)	(-1.81)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	6,496	5,857	6,496	6,496	3,774
pseudo R-squared	0.031	0.029	0.033	0.031	0.034

Table 7. Audit Fees and Quality Match Effects and Cumulative Abnormal Returns Around Annual Earnings Announcements

This table reports empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the annual earnings announcements over the period from 2016 to 2023.

$$CAR[-1,1]_{ijt} = \mu_0 + \beta_1\ High\ Match(Audit\ Fees\ and\ Quality)_{ij} + \beta_2 Unexpected\ Earnings_{it} + \beta_3\ Unexpected\ Earnings_{it} \times High\ Match(Audit\ Fees\ and\ Quality)_{ij} + \beta_4 Controls_{it} + \beta_5\ Unexpected\ Earnings_{it} \times Controls_{it} + Year\text{-}Month\ Fixed\ Effects + \varepsilon_{ij}$$

The variable *High Match(Audit Fees and Quality)* equals one if the client-partner match effect is in the top tercile, and zero otherwise. The variable, *Unexpected Earnings*, is measured based on analyst forecasts. We control for *Size*, *ROA*, *Analyst Coverage*, *Analyst Dispersion*, and *Leverage*. We cluster standard errors by clients. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively.

	CAR[-1,1]				
	(1)	(2)	(3)	(4)	(5)
Unexpected Earnings	0.007*	0.007**	0.009**	0.008**	0.005
	(1.89)	(2.04)	(2.57)	(2.45)	(1.03)
High Match(Audit Fees)	-0.015*				
	(-1.89)				
Unexpected Earnings × High Match(Audit Fees)	0.004***				
	(2.72)				
High Match(Abs(Disc. Accruals))		0.000			
		(0.01)			
Unexpected Earnings × High Match(Abs(Disc. Accruals))		-0.001			
		(-0.78)			
High Match(Restatement)			0.016**		
			(2.16)		
Unexpected Earnings × High Match(Restatement)			-0.003**		
			(-2.44)		
High Match(Small Profit)				0.004	
				(0.52)	
Unexpected Earnings × High Match(Small Profit)				-0.002*	
				(-1.66)	
High Match(Going Concern)					-0.004
					(-0.32)
Unexpected Earnings × High Match(Going Concern)					0.001
					(0.36)
Size	-0.003	-0.004	-0.003	-0.004	-0.007
	(-1.00)	(-1.11)	(-1.00)	(-1.10)	(-1.47)
ROA	0.099	0.105	0.100	0.096	0.153*

	(1.36)	(1.36)	(1.36)	(1.30)	(1.71)
Analyst Coverage	0.010	0.010	0.010	0.010	0.015
	(1.33)	(1.29)	(1.34)	(1.41)	(1.51)
Analyst Dispersion	0.017	0.017	0.016	0.016	0.018
	(0.82)	(0.76)	(0.77)	(0.78)	(0.72)
Leverage	-0.006	-0.006	-0.005	-0.005	-0.011
	(-0.34)	(-0.30)	(-0.29)	(-0.30)	(-0.48)
Unexpected Earnings × Controls	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	4,105	3,723	4,105	4,105	2,122
R-squared	0.078	0.078	0.077	0.077	0.076

Table 8. Audit Fees and Quality Match Effects and Cumulative Abnormal Returns Around the Announcement of a New Engagement Partner

This table reports empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the announcement of a new engagement partner, i.e., the filing of Form-AP, from 2016 to 2023.

$$CAR[-1,1]_{ijt} = \mu_0 + \beta_1 \; High\ Match(Audit\ Fees\ and\ Quality)_{ij} + \beta_2 Controls_{it} + Year\text{-}Month\ Fixed\ Effects + \varepsilon_{ij}$$

The indicator variable *High Match(Audit Fees and Quality)*$_{ij}$ equals one if the departing partner has a match effect in the top tercile, and zero otherwise. We control for *Size*, *ROA*, *Analyst Coverage*, *Analyst Dispersion*, and *Leverage*. We cluster standard errors by clients. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively.

	CAR[-1,1]				
	(1)	(2)	(3)	(4)	(5)
High Match(Audit Fees)	-0.006**				
	(-1.96)				
High Match(Abs(Disc. Accruals))		0.005			
		(1.46)			
High Match(Restatement)			-0.000		
			(-0.02)		
High Match(Small Profit)				0.006*	
				(1.73)	
High Match(Going Concern)					0.010
					(1.36)
Size	-0.001	-0.002	-0.001	-0.001	-0.006**
	(-1.08)	(-1.26)	(-1.02)	(-1.19)	(-2.49)
ROA	0.041	0.044	0.039	0.045	0.085*
	(1.13)	(1.16)	(1.07)	(1.25)	(1.80)
Analyst Coverage	0.001	0.002	0.001	0.002	0.007
	(0.42)	(0.49)	(0.38)	(0.55)	(1.37)
Analyst Dispersion	0.017	0.020	0.017	0.018	0.020
	(1.40)	(1.59)	(1.41)	(1.45)	(1.51)
Leverage	-0.012	-0.009	-0.012	-0.011	-0.003
	(-1.26)	(-0.91)	(-1.24)	(-1.23)	(-0.18)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,848	1,643	1,848	1,848	879
R-squared	0.029	0.034	0.027	0.029	0.063

Table 9. Robustness Check: Estimating Match Effects Using a Rolling Window

This table presents the estimation results of Models (5)-(7) using match effects estimated using a rolling window. The match effect for a partner-client in a given year is estimated using a sample from 2016 up to that year. Panel A reports the sample coverage for the periods 2016-2017, 2016-2018, 2016-2019, 2016-2020, 2016-2021 and 2016-2022. Panel B presents results from the probit regression of early partner turnover on audit fees and quality match effects. Panel C reports empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the annual earnings announcements. Panel D reports empirical results on cumulative abnormal returns (CARs) over days [-1,1] around the announcement of a new engagement partner. We cluster standard errors by clients. ***, **, and * denote significance at the 1, 5, and 10 percent levels (two-tailed), respectively.

Panel A. Coverage of the Connectedness Sample

Sample Period	Number of Unique Partners	As % of the Number of Unique Partners in the 2016-2023 Sample	Number of Unique Clients	As % of the Number of Unique Clients in the 2016-2023 Sample
2016-2017	7	0.3%	16	0.6%
2016-2018	28	1.4%	58	2.2%
2016-2019	87	4.2%	161	6.2%
2016-2020	756	36.8%	1119	43.1%
2016-2021	1342	65.4%	1874	72.1%
2016-2022	1770	86.2%	2307	88.8%
2016-2023	2053		2599	

Panel B. Audit Fees and Quality Match Effects and Partner Turnover

	Probit (Partner Turnover = 1)				
	(1)	(2)	(3)	(4)	(5)
Match(Audit Fees)	0.364				
	(0.69)				
Match(Abs(Disc. Accruals))		4.561*			
		(1.84)			
Match(Restatement)			1.132		
			(1.62)		
Match(Small Profit)				4.120**	
				(2.02)	
Match(Going Concern)					-1.716
					(-1.54)
Size	0.004	0.011	0.004	0.003	0.008
	(0.16)	(0.41)	(0.17)	(0.10)	(0.24)
Foreign Income	0.007	0.006	0.005	-0.003	-0.042
	(0.12)	(0.11)	(0.09)	(-0.06)	(-0.59)
December Year End	-0.024	-0.041	-0.015	-0.029	-0.235**
	(-0.31)	(-0.52)	(-0.20)	(-0.38)	(-2.17)
Altman Z Score	-0.001	-0.001	-0.002	-0.002	-0.005
	(-0.30)	(-0.24)	(-0.32)	(-0.33)	(-0.79)
Business Segments	-0.015	-0.023	-0.017	-0.015	-0.033
	(-0.66)	(-0.95)	(-0.72)	(-0.63)	(-0.93)
Geographic Segments	-0.015	-0.014	-0.015	-0.014	-0.024
	(-0.88)	(-0.76)	(-0.88)	(-0.79)	(-0.94)
CFO	0.003	0.038	-0.002	-0.007	0.069
	(0.02)	(0.19)	(-0.01)	(-0.03)	(0.28)
Std(CFO)	0.155***	0.125***	0.157***	0.156***	0.140***
	(3.40)	(3.32)	(3.44)	(3.34)	(3.61)
BTM	0.048	0.047	0.047	0.044	0.028
	(1.03)	(0.95)	(1.00)	(0.96)	(0.61)
Sales Growth	0.004	0.016	0.005	0.006	-0.011
	(0.14)	(0.49)	(0.15)	(0.19)	(-0.31)
Leverage	-0.113	-0.122	-0.119	-0.116	-0.130
	(-1.23)	(-1.25)	(-1.28)	(-1.24)	(-1.28)
Litigation	0.010	0.034	0.005	0.014	-0.112
	(0.15)	(0.46)	(0.07)	(0.20)	(-1.17)
Material Weakness	0.739***	0.720***	0.721***	0.743***	0.706***
	(5.18)	(4.95)	(5.09)	(5.24)	(4.38)
Integrated Audit	-0.216*	-0.252*	-0.220*	-0.219*	-0.166
	(-1.69)	(-1.90)	(-1.72)	(-1.71)	(-1.23)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,197	2,908	3,197	3,197	1,611
pseudo R-squared	0.030	0.029	0.031	0.032	0.038

Panel C. Audit Fees and Quality Match Effects and Cumulative Abnormal Returns Around Annual Earnings Announcements

	CAR[-1,1]				
	(1)	(2)	(3)	(4)	(5)
Unexpected Earnings	0.001	0.001	0.002	0.002	-0.002
	(0.32)	(0.28)	(0.67)	(0.46)	(-0.50)
High Match(Audit Fees)	-0.006				
	(-0.70)				
Unexpected Earnings × High Match(Audit Fees)	0.001				
	(0.65)				
High Match(Abs(Disc. Accruals))		0.002			
		(0.29)			
Unexpected Earnings × High Match(Abs(Disc. Accruals))		-0.000			
		(-0.30)			
High Match(Restatement)			0.029***		
			(4.01)		
Unexpected Earnings × High Match(Restatement)			-0.005***		
			(-4.28)		
High Match(Small Profit)				0.012	
				(1.51)	
Unexpected Earnings × High Match(Small Profit)				-0.002*	
				(-1.68)	
High Match(Going Concern)					0.004
					(0.34)
Unexpected Earnings × High Match(Going Concern)					-0.003
					(-1.32)
Size	-0.001	-0.001	-0.002	-0.002	-0.005
	(-0.42)	(-0.28)	(-0.48)	(-0.58)	(-0.92)
ROA	0.095	0.110	0.096	0.098	0.156*
	(1.33)	(1.44)	(1.36)	(1.37)	(1.76)
Analyst Coverage	0.004	0.002	0.001	0.004	0.000
	(0.45)	(0.24)	(0.17)	(0.49)	(0.02)
Analyst Dispersion	0.008	0.006	0.008	0.009	0.013
	(0.57)	(0.40)	(0.56)	(0.58)	(0.70)
Leverage	-0.016	-0.009	-0.011	-0.015	-0.008
	(-0.89)	(-0.51)	(-0.63)	(-0.82)	(-0.37)
Unexpected Earnings × Controls	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2,210	2,011	2,210	2,210	1,258
R-squared	0.064	0.066	0.073	0.066	0.078

Panel D. Audit Fees and Quality Match Effects and Cumulative Abnormal Returns Around the Announcement of a New Engagement Partner

	CAR[-1,1]				
	(1)	(2)	(3)	(4)	(5)
High Match(Audit Fees)	-0.002				
	(-0.45)				
High Match(Abs(Disc. Accruals))		0.003			
		(0.51)			
High Match(Restatement)			-0.005		
			(-1.06)		
High Match(Small Profit)				0.008*	
				(1.76)	
High Match(Going Concern)					0.009
					(1.34)
Size	-0.000	-0.003	-0.000	-0.001	-0.005*
	(-0.13)	(-1.27)	(-0.26)	(-0.48)	(-1.88)
ROA	0.033	0.042	0.031	0.039	0.078
	(0.59)	(0.71)	(0.55)	(0.71)	(1.13)
Analyst Coverage	-0.002	0.002	-0.002	-0.001	0.006
	(-0.54)	(0.48)	(-0.43)	(-0.13)	(0.89)
Analyst Dispersion	0.019	0.020*	0.020	0.021*	0.021
	(1.57)	(1.67)	(1.64)	(1.72)	(1.56)
Leverage	0.006	0.012	0.004	0.006	0.016
	(0.45)	(0.93)	(0.32)	(0.48)	(0.99)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	373	335	373	373	232
R-squared	0.046	0.079	0.049	0.054	0.095