MULTI-OFFICE AUDIT PARTNERS AND AUDIT IMPLICATIONS

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ABSTRACT

As the leader of an audit team, the audit partner can have a significant impact on the outcomes of an audit engagement. One hitherto unexplored aspect of partner assignments to audits is cases where they handle clients in multiple audit offices. I examine factors associated with the assignment of audit partners to multiple offices (henceforth multi-office partners or MOPs) and the implications of such assignments for audit quality. I document that audit firms assign partners to multiple offices to match partner expertise to client needs and to manage resource constraints in audit offices. Specifically, partners specializing in the financial sector, who report more skills on LinkedIn profiles, and have more professional experience, are more likely to be MOPs. Audit offices with fewer partner resources are more likely to share partners among the network of offices to mitigate resource constraints. In the audit quality analyses, I find that MOPs are, on average, associated with an increased likelihood of restatements, suggesting the negative impact of audit office resource constraints dominates the positive influence of partner expertise on audit quality. The negative effect of MOPs on audit quality exists for both local and non-local clients and is concentrated in MOPs who (1) are not industry specialists, (2) face greater information friction as the distance between different audit offices increases, and (3) have limited knowledge-sharing opportunities from audit offices.

To my parents and other family members

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CHAPTER 1

INTRODUCTION

Audit quality has always been of interest to regulators, practitioners, and researchers (DeFond and Zhang 2014; Knechel, Krishnan, Pevzner, Shefchik, and Velury 2013; PCAOB 2022). A large literature has examined the factors associated with audit quality at the audit firm and audit office levels and documents that certain attributes, such as auditor industry specialization and audit office size, are associated with higher audit quality (e.g., Francis and Yu 2009; Reichelt and Wang 2010).

More recently, the focus has been on human capital factors (e.g., audit partners and other employees that comprise the audit team) and their impact on the quality of audits (Lee, Naiker, and Stewart 2022; Francis 2023). Prior studies show that, as the leader of the audit team, the audit partner can have a significant impact on the audit quality of an audit engagement (Lennox and Wu 2018). While these studies examine a number of partner characteristics, one unexplored phenomenon is that some audit partners manage audits in multiple audit offices.

This study examines two research questions: (1) Why are some audit partners (henceforth multi-office partners or MOPs) assigned to clients at more than one audit office? (2) How do multi-office partners affect audit quality for the engagements to which they are assigned?[1] My research questions are important for two reasons. First, the client-partner matching process can impact audit partner quality (Aobdia 2019; Lee, Nagy, and Zimmerman 2019; Francis, Golshan, and Hallman 2022). Audit failures impose

[1] Using Form AP data, I identified that about 11% of the audit partners are multi-office partners.

significant costs on investors and auditors, such as stock price declines and audit client turnover (Chaney and Philipich 2002; Weber, Willenborg, and Zhang 2008). Violations related to audit evidence are the most frequently cited violations in PCAOB enforcement orders (Krishnan, Li, Mehta, and Park 2024). Managing clients and audit teams across multiple offices may impair multi-office partners' ability to adequately obtain and evaluate audit evidence. Understanding the multi-office partner assignment process and its audit quality implications is not only essential for an audit firm to maintain its reputation but also important for investors, creditors, regulators, and other stakeholders.

Second, there has been a human capital supply shortage in the accounting industry (AICPA 2019; AICPA 2021; Ellis 2022). A recent survey raises concern about partner turnover because about 25% of them are close to or past retirement age (The CPA Journal 2023). As the problem is likely to persist, audit offices need to more efficiently and effectively utilize partner resources to deliver high-quality audits. Multi-office partners may be a solution to alleviate the resource constraints faced by some offices by promoting interoffice collaborations. Recent studies show that interoffice interactions improve audit quality through knowledge sharing, resource sharing, and monitoring (Seavey, Imhof, and Westfall 2018; Beck, Gunn, and Hallman 2019). These studies use geographic proximity to proxy for interoffice connectedness. Multi-office partners directly interact with teams in multiple offices and can break geographical boundaries and improve audit quality for multiple offices. My study should be of interest to audit firms in adjusting their strategy in allocating and monitoring resources.

I expect partner expertise and experience, as well as audit office resource constraints, to play important roles in multi-office partner assignments. On one hand, audit firms consider partner industry specialization, accounting knowledge, and skills in relationship management skills when selecting partners for clients (Bell, Causholli, Knechel 2015; Dodgson, Agoglia, Bennett, and Cohen 2020). These factors should create a demand for multi-office partners with the appropriate expertise and experience. On the other hand, when local audit offices face resource constraints, they need to seek partners from other geographic locations to serve their local clients.

Using partner data available from Form AP filings and LinkedIn, as well as audit office data from Audit Analytics for the years 2016-2019, I find evidence consistent with my expectations.[2] First, I find that partners who specialize in the financial sector are more likely to be multi-office partners. This is possibly because their knowledge of auditing financial companies is not easily substitutable by experience in auditing companies in other industries. In addition, multi-office partners are more likely to be experienced but not the most senior partners because they have more experience than junior partners and stronger career motivation compared to the most senior partners.

Second, I find that smaller offices and offices with limited partner resources, proxied by partner to client ratio, are more likely to use multi-office partners to mitigate the resource constraint. In addition, audit offices without specialization in clients' industries are positively associated with multi-office partners because they lack in-house expertise and need to find resources from other offices. Taken together, my findings suggest that the multi-office partner phenomenon is an audit firm's solution to manage

[2] Partner demographic data is primarily from LinkedIn. In cases where a partner does not have a LinkedIn profile, I alternatively use online sources, such as audit firm website, FEC.gov, cpaverify.org, and others.

partner resource constraints. Furthermore, the multi-office partner assignments reflect good practice, ensuring that partner expertise meets audit clients' needs.

Next, I examine how the two reasons for assigning multi-office partners can jointly impact the audit quality of their engagements. On the one hand, audit partners' industry specialization and experience are associated with better audit quality (Chin and Chi 2009; Bell et al. 2015; Chi, Myers, Omer, and Xie 2017). On the other hand, greater human resource constraints impair audit quality (Bills et al. 2016). Therefore, the direction of the association between the use of MOPs and audit quality is an open question. To examine this question, I use financial restatements to proxy for audit quality because, as DeFond and Zhang (2014) note, they indicate that the auditor "issued an unqualified opinion on materially misstated financial statements." I find a positive association between multi-office partners and restatements, suggesting these partners provide lower quality audits. My results hold when I employ an entropy-balanced sample based on observable audit partner, office, and client characteristics.

In cross-sectional analyses, I examine whether the results vary based on partners' workload, expertise, and other audit office factors. Partners with a larger client base receive high compensation and have a stronger incentive to provide high-quality audits to avoid greater losses in the event of audit failures (DeAngelo 1981; Knechel, Niemi, and Zerni 2013). However, I do not find systematic evidence that multi-office partners with a heavier workload provide better quality audits than those with a lighter workload. Second, I examine whether partner expertise, measured by industry specialization, affects the negative relation between multi-office partners and audit quality. I find that multi-office partners with specialized industry knowledge from auditing clients in the same industry provide consistent audit quality as single-office partners.

Third, prior studies show that a longer distance between clients and auditors creates information friction and impairs audit quality (Choi et al. 2012; Francis et al. 2022).[3] Accordingly, I test whether my results are concentrated in multi-office partners who work in multiple offices that are farther away from each other. Consistent with the literature, as the distance between audit offices increases for multi-office partners, the audit quality suffers to a greater extent. Furthermore, I find that impaired audit quality exists for both local and non-local clients of multi-office partners.

Fourth, I examine whether audit office strategy influences the audit quality of multi-office partners. Offices that focus more on NAS shift resources away from audits which could then reduce audit quality (Beardsley et al. 2021; Mowchan 2023).[4] I do not find evidence that the audit quality of multi-office partner quality suffers when they are in audit offices with a greater NAS focus compared to those with a lesser NAS focus. Lastly, I test whether knowledge transfer from audit offices to multi-office partners impacts my results. I find that multi-office partners with greater knowledge-sharing

[3] Information friction is the efficiency loss in effective communication and impacts work performance (Bhattacharya and Chakraborty 2005). In the audit setting, information friction can occur between audit partner and the audit team, and audit partner/team and the client.

[4] Multiple office partners are supervised by offices with potentially diverse leadership culture and strategies. Although many non-audit services were banned by the Sarbanes Oxley Act of 2002, audit firms generate significant revenues from permissible non-audit services provided to their audit clients (Carcello, Neal, Reid, and Shipman 2019). Some audit offices place greater emphasis on non-audit service (NAS). Mowchan (2023) finds that audit office increases NAS and have lower audit quality following the appointment of advisory partner as the office managing partner. Beardsley, Imdieke, and Omer (2021) also find that audit quality is lower in high NAS offices.

opportunities, proxied by a combination of a larger office, industry-specialized office, and higher quality office, provide better audit quality than those with fewer knowledge-sharing opportunities.

My study contributes to the literature that examines the human capital at audit firms and its impact on audit quality (Bell, Causholli, and Knechel 2015; Bills, Swanquist, and Whited 2016; Francis et al. 2022; Hanlon, Yeung, and Zuo 2022; Lee et al. 2022). I show that audit partner resources are shared across audit offices in response to local office resource constraints and the need for specialized partners. However, resource sharing across offices may impair audit quality, especially when multi-office partners are not industry specialists, work in audit offices that are farther away from each other or have limited knowledge-sharing opportunities from audit offices. The results should be of interest to audit firms to weigh benefits and costs when allocating partner resources.

The findings also extend research on how audit inputs, both partner and audit office, impact audit quality (Francis 2011, DeFond and Zhang 2014; Lennox and Wu 2018). Prior literature has shown that partner innate characteristics and the client-partner matching process impact audit quality. I present evidence that the assignment of audit partners to multiple offices, a hitherto unexplored phenomenon, is associated with lower quality audits for all clients in their portfolios. Partner industry expertise and knowledge sharing from operating in multiple audit offices can mitigate this negative impact. However, the negative association is stronger as the distance between audit offices increases.

CHAPTER 2

MULTI-OFFICE PARTNER ASSIGNMENT

2.1 Background and Literature Review

Audit partners are a key input into the audit process and ultimately impact audit quality (Francis 2013; DeFond and Zhang 2014; Lennox and Wu 2018). The engagement partner is responsible for the overall performance of an audit (PCAOB 2022 AS 2101.03). As part of this process, engagement partners approve the audit plan for testing procedures, supervise team members and are the principal resource when the audit teams encounter any issues (Danos, Eichenseher, and Holt 1989; PCAOB 2022 AS 2101.05). In the event of audit failures, they can be personally held accountable by the regulators (Kedia, Khan, and Rajgopal 2018; Cunningham, Li, Stein, and Wright 2019; Dharmasiri, Phang, Prasad, and Webster 2022). An extensive literature shows partner characteristics, specifically tenure, experience, age, education, and expertise, impact audit quality (Lennox and Wu 2018). In a non-U.S. setting (Taiwan), there is also evidence of partner identity being priced by the capital market (Aobdia et al. 2015).

Recognizing the crucial role audit partners play in audits, some studies examine the matching between partners and clients (Bell et al. 2015; Lee et al. 2019; Francis et al. 2022). These studies do not consider the role of audit offices in the process and do not examine the complexities of auditing clients from multiple offices. Effectively, because the multi-office partners audit clients at more than one audit office, they are shared human capital resources across offices and overseen by different office leaders. Local office resource constraints may motivate audit offices to look for nonlocal partners from the audit firm's national talent pool. Since there is no literature on how multi-office assignments are determined, I argue that audit firms evaluate client characteristics to select partners with the matching expertise/experience while also accommodating local office resource constraints in the assignment process.

2.1.1 Partner Expertise and Experience

Partner expertise and experience plays an important role in MOP assignment. First, partners are generally matched with clients based on industry (Bell et al. 2015; Francis et al. 2022). Bell et al. (2015), using propriety data from a U.S. Big 4 firm, find that in 87.9% of partner-client pairs, the partner's designated industry specialization matches the client's line of business. Francis et al. (2022) document that industry specialist partners may be assigned to distant clients because of their expertise. Moreover, auditing standards also emphasize the importance of obtaining an understanding of the industry including the competitive and regulatory environment as part of auditors' risk assessment process (PCAOB 2022 AS 2110). Therefore, partners with exceptional industry expertise may be highly desirable to clients and are responsible for audits based in multiple offices.

Besides industry expertise, partners' technical accounting knowledge and skills in relationship management also impact partner-client assignment (Dodgson et al. 2020). Partners with greater experience in auditing and superior abilities in managing client relationships may be able to handle clients in multiple locations, thus becoming multi-office partners.

2.1.2 Audit Office Resource Constraints

Finding audit partners from local offices is often more desirable as geographical distance creates information friction and reduces bonding opportunities between partners, clients, and audit teams (Choi et al. 2012; Francis et al. 2022). However, local offices may face resource constraints, which forces them to expand the partner search to other geographical locations. First, audit offices may share partner resources if some offices do not have enough partners, creating the demand for partners from other offices (i.e., the multi-office partner phenomenon). Bills et al. (2016) find that offices with greater human resource constraints arising from significant growth are associated with lower quality. More importantly, they provide some evidence that the negative association is mitigated by the Big 4 firms. Thus, they argue that the Big 4 firms can better allocate resources among a larger network of office locations and reduce the negative impact from rapid office growth. Taken together, multi-office partners are likely to be more needed in smaller offices, offices with significant growth, and offices that do not have sufficient partners available to conduct audits. The multi-office partner phenomenon is also likely to be more prevalent in Big 4 firms, possibly as part of Big 4's strategy to better allocate partners across offices and address resource constraints in certain offices.

Second, an audit office may lack industry specialization for a client and need to borrow an expert from a different office. Extant literature shows that industry specialist offices charge a fee premium, achieve economies of scale, and provide better audit quality (Balsam, Krishnan, and Yang 2003; Reichelt and Wang 2010; Fung, Gul, and Krishnan 2012). Non-specialist audit offices may not have sufficient in-house expertise to conduct audits and therefore require the use of multi-office partners.

Lastly, Beardsley et al. (2021) and Mowchan (2023) find that some audit offices have a greater emphasis on NAS as an office growth strategy. Mowchan (2023) documents an increase in NAS work following the appointment of an advisory partner as the office managing partner. Devoting more resources to non-audit services (NAS) can put a strain on the audit team. NAS-focused offices can shift the resources away from the core audit work and request additional partner resources from other office locations.

2.1.3 Other Factors

Ultimately, the partner-client assignment is a joint decision process by the client and audit firm/partner. There are additional factors that may be taken into consideration, including partner gender, capacity, independence, client importance, risk, and complexity. First, a female partner may be more hesitant to take on non-local clients due to greater family responsibilities. Second, audit firms and partners need to consider whether they have sufficient capacity to handle an additional audit and whether an audit can be sufficiently staffed when accepting clients (Christensen, Newton, and Wilkins 2021). Lennox and Wu (2018) argue that partner workload is an equilibrium, in which more capable partners may handle larger workloads. Multi-office partners may be selected to work in different offices because of their greater abilities to manage a larger workload. However, partners may also refuse to take on additional clients in other offices if they have high workload pressure (Christensen et al. 2021).

Third, both auditor and client need to evaluate partner independence. The SEC has expressed the concern that non-audit services (NAS) may impair auditor independence (POB 2000). Some studies find that auditor provision of NAS results in lower audit quality because NAS is negatively associated with earnings response coefficients and bond rating (Brandon, Crabtree, and Maher 2004; Krishnan, Sami, and Zhang 2005) and positively associated with ex ante cost of equity capital (Khurana and Raman 2006). Due to concerns about auditor independence, the client may be reluctant to choose a muti-office partner with a higher percentage of NAS in the portfolio. However, prior literature finds that auditor-provided tax service (a recurring NAS) improves internal control quality and audit quality from information spillover (Robinson 2008; De Simone, Ege, and Stomberg 2015). Therefore, tax related NAS may not be a concern for choosing a multi-office partner.

Lastly, I consider how client importance, risk, complexity, and audit committee characteristics might affect MOP assignment. Specifically, Francis et al. (2022) show that the effect of partner characteristics on client assignment varies based on client importance and complexity. These two client factors are likely to impact multi-office partner assignment as well. More prestigious clients have more bargaining power and may require undivided attention from the partners and are less likely to choose multi-office partners. More complex clients may require partners with specific skills that are not available from the local partner pool. Besides client importance and complexity, client risk is likely to affect multi-office partner and client matching as well. Multi-office partners may be more hesitant to take on risky clients while managing work in different offices. In addition, audit committee characteristics can also affect the assignment of multi-office partners. Audit committees are responsible for selecting and overseeing audit firms. Downes, Draeger, and Sadler (2022) document that larger audit committees are more likely to disclose their involvement in the partner selection process.

2.2 Empirical Model

To understand how multi-office partners are matched to audit clients, I estimate the following logistic regression model.[5] I include year and industry fixed effects and calculate robust standard error clustered by clients. I define all variables in Appendix A and describe them briefly below.

$$MOP_{it} = \beta_0 + \beta_1 Partner\_Expertise_{it} + \beta_2 Resource\_Constraints_{it} + \beta_3 Controls_{it} + Fixed\ Effects + e_{it} \quad (1)$$

My dependent variable is a dummy variable coded 1 for a multi-office partner, and 0 otherwise. For each calendar year, I count the unique number of audit offices where the audit partners issue the audit reports, based on the auditor city and auditor state fields from Audit Analytics. I use the metropolitan statistical area (MSA) definition of a city following Francis, Reichelt, and Wang (2005). If the audit partners are associated with more than one MSA, I classify them as a multi-office-partner (MOP).[6] If the audit partners only audit clients in one MSA, I refer to them as single-office-partners (SOP).

I include several partner expertise and experience measures. My first expertise measure is industry specialization, captured by PARTFIN and PARTNONFIN with positive predicted signs. PARTFIN (PARTNONFIN) equals one if the partner audits clients only in one industry in my sample period and the industry belongs to the financial (non-financial) sector. Partners who audit clients in the same industry will develop more

[5] Because linear probability models may reduce the bias from estimating nonlinear models with fixed effects (Wooldridge 2002), I also re-estimate equation (1) with the linear probability model, and the results (untabulated) are qualitatively the same.
[6] For example, in 2017, one engagement partner conducted three audits from three different MSAs: Albany (New York), Memphis (Tennessee), and Miami (Florida). This partner is an MOP.

in-depth knowledge about the industry. I separate the financial sector from the other sectors because firms in the financial sector have different capital structures from firms in other sectors.[7] Furthermore, Bell et al. (2015) find that specialized knowledge benefits audits in the financial sector. They interpret that partner specialization benefits the most in industries with complex transactions. I use the SEC office for industry classification because the groupings match more closely to how accounting firms classify industries.[8] My second expertise measure captures the partners' general skills following Francis et al. (2022). PARTSKILL equals 1 if the number of skills reported on partners' LinkedIn profile is in the top quartile, and I expect a positive coefficient.

To construct partner experience measures, I also follow Francis et al. (2022). I include variables based on partners' online profile. I expect partner experience to be positively associated with the assignment of MOP. I use audit partner's number of years

[7] I also consider combining utilities with the financial sector as both industries are highly regulated and require partner expertise in working with regulators. In untabulated analyses, I find that partners specializing in regulated sectors are more likely to be MOPs, while those in other sectors are less likely. The results suggest that experience working with regulators is highly desirable and not substitutable.

[8] I compare accounting firm industry classification with classifications used by academia, such as Fama and French and SEC industry office classifications (e.g., Ege, Glenn, Robinson 2019; Francis et al. 2022). I find SEC office industry classification more closely matches accounting firms' classification. For example, PwC lists the following six industries: consumer markets, energy, utilities, and resources, financial services, health industries, industrial products, technology, media, and communication (https://www.pwc.com/us/en/industries.html). The other three Big 4 auditors also provide similar industry classifications on their websites. The SEC currently has 10 offices under the Division of Corporate Finance: Office of Industrial Applications and Services, Office of Energy & Transportation, Office of Real Estate & Construction, Office of Manufacturing, Office of Life Sciences, Office of Technology, Office of Trade & Service, Office of Finance, Office of Structured Finance, and Office of Crypto Assets. I group the last three finance-related offices into one. Clients in the Office of Real Estate & Construction and Office of Finance are in the financial sector with most of the SIC codes from 6000-6999.

professional experience to differentiate junior partners from more experienced and the most senior ones. PARTEXP (PARTSR) equals 1 if the audit partner's number of years professional experience is between 25^{th} and 75^{th} percentile (above 75^{th} percentile). Lastly, I include three indicator variables to capture whether partners discuss being in a leadership position at their firm, including managing partners (PARTMP), human capital related positions (PARTHR), and other leadership positions (PARTOL).

For audit office resource constraints, I use partner to client ratio by industry because Bell et al. (2015) show clients generally are matched with partners with specialization in clients' industries. Specifically, I compute the ratio of the total number of SOPs to the total number of audit clients in the client's industry in an audit office (SOPRATIO) and predict a negative sign on SOPRATIO. Following Bills et al. (2016), I use audit office fee growth to identify offices that face larger human resource constraints (OFFGR) and predict a positive sign. OFFGR equals 1 if the audit office is in the top decile of fee growth. In addition, I use office size to capture office resources. Office size is based on the natural log of total audit fees charged to all audit clients within an auditor office in year t (OFFSIZE) following Choi et al. (2012). I include a Big 4 indicator (BIG4) as Bills et al. (2016) show that the Big 4 firms respond to human resource constraints differently from non-Big 4 firms. Based on the discussion in the previous section, I expect a positive sign on BIG4 and negative sign on OFFSIZE. I use OFFSPEC to capture office industry specialization and predict a negative sign. OFFSPEC is measured following Reichelt and Wang (2010). If the audit office (MSA) has an audit fee market share in a two-digit SIC code industry of 50% or more for a given city-year, then the office is a specialist. I use the percentage of audit office non-tax NAS fees to total fees, OFFNAS, to proxy for audit office's NAS focus. Consistent with the partner NAS measure, I exclude tax-related fees from total NAS fees.

The final set of factors I include in equation (1) are additional partner and client characteristics (Francis et al. 2022). I included partner gender identification. PARTMALE equals 1 if the partner is male with a negative predicted sign. Following Francis et al. (2022), two variables capture partner workload and are expected to be positively associated with MOP. PARTWORK is the natural log of the number of unique clients in a partner's portfolio in a given year. PARTFEE is the natural log of audit fees received from all clients in a partner's portfolio in a given year. The last partner variable I include for partner factor is PARTNAS with a negative predicted sign. PARTNAS is measured by the percentage of audit partner non-tax NAS fees to total fees. I exclude tax-related services from total NAS fees following Mowchan (2023) and based on the reasons discussed above. Client importance is proxied by whether the firm is an S&P 500 company (S&P500) following Asthana and Kalelkar (2014) and I predict a negative sign on S&P500. Complexity measures include an integrated audit indicator (ICFR) and sales growth (SALEGR), both with positive predicted signs.[9] The proxies for client risk have negative predicted signs and include leverage (LEV) and whether a firm is in a high litigation industry (LITIG) based on Francis, Philbrick, and Schipper (1994). I include audit committee size (ACSIZE) and whether the audit committee has a higher percentage of designated financial expert (ACEXP) (DeFond, Hann, and Xu 2005). If the percentage of designated financial experts in an audit committee belongs to the highest quartile of its

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[9] The correlation between TA and SP500 is 0.42. When I re-estimate equation (1) with TA added to the model, and the results (untabulated) are qualitatively the same.

distribution, I designate the audit committee as having accounting expertise (ACEXP). I winsorize all continuous variables at the 1st and 99th percentiles to minimize the potential influence of outliers.

2.3 Data and Sample Selection

Table 1 outlines the sample selection. PCAOB Rule 3211 requires disclosure of the names of engagement partners in Form AP for audit reports issued on or after January 31, 2017. Accordingly, my sample period begins in 2016 due to Form AP availability. My sample period ends in 2019 to allow sufficient time for the discovery and disclosure of restatements and to avoid possible confounding effects of Covid-19. I require all 22,249 U.S. firm-year observations to have a U.S.-based auditor and a valid SIC code. I exclude 2,188 observations with missing audit fees and NAS in Audit Analytics. I then exclude 88 special purpose acquisition companies (SPACs) because they do not have actual business operations and are formed solely to raise money through an initial public offering (IPO) to buy another company. Next, I exclude 596 observations without MSA codes. The final sample for multi-office partners (henceforth MOP) comprises 19,377 client-years. I further exclude 5,309 observations with missing Compustat variables and audit offices with less than five clients. Lastly, I remove 2,646 observations with missing BoardEx variables. The final sample for multi-office partner assignment includes 11,422 client-years and 3,035 unique partners. For these unique partners, I manually searched their online profiles (including LinkedIn, audit firm website, FEC.gov, cpaverify.org, etc.) from the winter of 2023 to the spring of 2024. I used these online sources to collect partner demographic information, such as gender, local office location, skills, and number of years of professional experience.

Table 1. Sample Selection

	Clients-years	Unique clients	Partner-years	Unique partners
US-based observations in the Form AP with valid SIC code from 2016 to 2019	22,249	7,194	10,911	3,922
Less: observations with missing Audit fees and NAS	(2,188)	(643)	(432)	(108)
Analytics information				
Less: SPAC companies	(88)	(69)	(11)	(5)
Less: observations without MSA codes	(596)	(135)	(204)	(56)
Sample to calculate multi-office-partner (MOP)	19,377	6,347	10,264	3,753
Less: observations with missing Compustat information and audit offices with less than 5 clients	(5,309)	(1,771)	(1,362)	(428)
Less: observations with missing BoardEx information	(2,646)	(751)	(1,039)	(290)
Final sample for MOP	11,422	3,825	7,863	3,035
Less: observations with additional missing control	(339)	(105)	(148)	(34)
Final sample for audit quality	11,083	3,720	7,716	3,001

Table 1 reports sample selection for chapters II and III

2.4 Descriptive Statistics

Table 2, Panel A presents the count and percentage of partners that issue audit reports from one or more offices. The percentage of MOPs is consistent from year to year. Across the sample period, about 89% of audit partners are SOPs and 11% of audit partners are MOPs. The majority (91%) of the MOPs audit clients in two MSAs and 8% and 1% audit clients in three and four MSAs, respectively (untabulated).

Table 2, Panel B reports the demographic information of MOPs and SOPs. The univariate analysis shows that MOPs are more likely to be male (PARTMALE), have more years of professional experience and discuss being in a managing partner (PARTMP) or serve other leadership roles at their firm while SOPs are more likely to serve human capital leadership roles. MOPs and SOPs report similar numbers of skills on their LinkedIn profile. Since there is no statistical difference in the percentages of MOPs and SOPs with LinkedIn profiles, skills reporting, and discussions of leadership roles within their firms, it is unlikely that the self-selection of sharing information on LinkedIn would introduce biases in partner measures based on their online profiles.

Table 2, Panel C presents the univariate comparison of the mean values of partner characteristics variables between MOPs and SOPs. The univariate analysis shows that MOPs are more likely to be specialists in the financial sector (PARTFIN) and less likely to be specialists in non-financial sectors (PARTNONFIN). MOPs tend to have a higher workload in terms of the number of clients (PARTWORK) and total audit fees earned (PARTFEE). There is no statistical difference in the extent of NAS in partners' portfolios (PARTNAS) between MOPs and SOPs. Overall, I find that MOPs are systematically different from SOPs in terms of workload and industry specialization.

Table 2, Panel D presents the percentage of MOPs and SOPs by industry. More complex industries may have a higher demand for specialized MOP partners and can benefit more from using MOPs (Owhoso, Messier, and Lynch 2002; Moroney 2007). I find that the percentage of MOPs relative to SOPs varies across industries. Financial industry and real estate and construction industry have the highest percentage of MOPs relative to SPOs. In contrast, life science industry and industrial applications and services industry have the lowest MOP to SOP ratio. These findings are generally consistent with the expectation that there are more MOPs in complex industry to meet the demand for specialized knowledge.

Table 2. Multi-Office Partner Descriptives

Panel A: MOP Frequency by Year

	No. (%) of Partners by No. of MSAs			
Year	1 MSA	2 MSAs	3 MSAs	4 MSAs
2016	2,145 (91%)	197 (8%)	18 (1%)	0 (0%)
2017	2,337 (89%)	256 (10%)	27 (1%)	1 (0%)
2018	2,331 (88%)	281 (11%)	23 (1%)	0 (0%)
2019	2,358 (89%)	265 (10%)	22 (1%)	3 (0%)

Panel B: MOP vs SOP Demographic

Variables	MOP Mean	SOP Mean	Difference in Means	p-value for t test
Missing LinkedIn	0.10	0.10	0.00	0.78
Missing Skills	0.31	0.29	0.02	0.33
Number of Skills	18.47	17.88	0.58	0.30
Leadership Position	0.34	0.35	-0.02	0.48
Managing Partner	0.14	0.11	0.03	0.04**
Human Capital Leader	0.00	0.02	-0.01	0.02**
Other Leadership Role	0.20	0.23	-0.03	0.10*
Gender Male	0.86	0.81	0.04	0.02**
Experience Begin Year	1993	1994	-0.55	0.08*
Observations	579	2,456		

Table 2. (Continued)

Panel C: MOP vs SOP Descriptives

Variables	MOP Mean	SOP Mean	Difference in Means	p-value for t test
PARTFIN	0.24	0.21	0.03	0.00***
PARTNONFIN	0.14	0.31	-0.17	0.00***
PARTWORK	2.46	1.63	0.83	0.00***
PARTFEE	4,958,101	3,886,897	1,071,203	0.00***
PARTNAS	0.07	0.07	0.00	0.29
Observations	1,024	6,839		

Panel D: MOP and SOP Distribution by Industry

	MOP		SOP	
Industry	N	%	N	%
Industrial Applications and Services	175	14%	1,097	86%
Energy & Transportation	258	19%	1,092	81%
Finance	419	21%	1,537	79%
Life Sciences	86	8%	950	92%
Manufacturing	275	16%	1,404	84%
Real Estate & Construction	269	22%	927	78%
Technology	220	15%	1,239	85%
Trade & Services	271	18%	1,203	82%
Total	1,973		9,449	

Table 2 reports multi-office partner descriptives. Panel A reports the frequency and percentage of audit partners who issue audit reports from x number of unique MSAs in each calendar year using “Sample to calculate multi-office-partner (MOP).” Panel B reports the demographic information for the MOP vs SOP sample at partner level using “Final Sample for MOP.” Panel C reports the descriptives of partner variables for the MOP vs SOP sample at partner-year level using “Final Sample for MOP.” Panel D reports MOP and SOP distribution by industry using “Final Sample for MOP.” The % represents the number of client-years in a given industry audited by MOP (SOP) over the total number of client-years in a given industry.

Table 3 presents descriptive statistics for the variables used in Equation (1). Table 3 indicates that MOPs audit about 17.3 percent (1,973/11,422) of client-years in the sample. The t-tests of means confirm that partner expertise and experience measures differ between multi-office partner (MOP) and single-office partner client years. Specifically, MOPs are more likely to specialize in the financial sector (PARTFIN) and are less likely to specialize in the non-financial sector (PARTNONFIN). They are also more likely to be experienced partners (PARTEXP) but not the most senior ones (PARTSR). A higher percentage of MOPs hold leadership positions as managing partners (PARTMP), though they are less likely to take on other forms of leadership roles (PARTHR and PARTOL). Furthermore, all audit office resource constraint measures, except for OFFNAS, differ between multi-office partner and single-office partner client years.

Table 4 provides correlations among independent and test variables. The correlations among partner (Panel A), audit office (Panel B), and client (Panel C) characteristics are below 0.29 except for PARTEXP and PARTSR, which have a correlation of -0.49, and BIG4 and OFFSIZE, which have a correlation of 0.79. MOPs are positively associated with partner expertise and experience measures (PARTFIN and PARTEXP) and audit office resource constraints measures (SOPRATIO, OFFGR, OFFSIZE and OFFSPEC) with $p<0.01$.

Table 3. Descriptive Statistics for Multi-Office Partner Assignment Model

	MOP (N=1,973)					SOP (N=9,449)					
Variables	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Diff in Mean
Partner Expertise/Experience											
PARTFIN	0.255	0.436	0.000	0.000	1.000	0.187	0.390	0.000	0.000	0.000	0.068***
PARTNONFIN	0.128	0.334	0.000	0.000	0.000	0.262	0.439	0.000	0.000	1.000	-0.134***
PARTEXP	0.499	0.500	0.000	0.000	1.000	0.429	0.495	0.000	0.000	1.000	0.070***
PARTSR	0.254	0.436	0.000	0.000	1.000	0.246	0.431	0.000	0.000	0.000	0.008
PARTSKILL	0.493	0.500	0.000	0.000	1.000	0.469	0.499	0.000	0.000	1.000	0.024
PARTMP	0.137	0.344	0.000	0.000	0.000	0.111	0.314	0.000	0.000	0.000	0.026***
PARTHR	0.003	0.050	0.000	0.000	0.000	0.015	0.121	0.000	0.000	0.000	-0.012***
PARTOL	0.200	0.400	0.000	0.000	0.000	0.228	0.421	0.000	0.000	0.000	-0.028*
Audit Office Resource Constraints											
OFFSIZE	16.654	1.804	15.272	16.978	18.060	16.910	1.943	15.500	17.280	18.522	-0.256**
SOPRATIO	0.412	0.189	0.333	0.438	0.538	0.518	0.185	0.409	0.500	0.625	-0.106***
OFFGR	0.050	0.218	0.000	0.000	0.000	0.038	0.191	0.000	0.000	0.000	0.012**
OFFSPEC	0.310	0.463	0.000	0.000	1.000	0.278	0.448	0.000	0.000	1.000	0.032***
OFFNAS	0.083	0.060	0.041	0.075	0.109	0.082	0.057	0.041	0.073	0.107	0.001
Other Variables											
PARTMALE	0.865	0.342	1.000	1.000	1.000	0.833	0.373	1.000	1.000	1.000	0.032***
PARTWORK	0.934	0.370	0.693	0.693	1.099	0.549	0.558	0.000	0.693	1.099	0.385***
PARTFEE	15.035	1.005	14.395	15.128	15.779	14.519	1.247	13.748	14.622	15.383	0.516***
PARTNAS	0.069	0.075	0.013	0.046	0.095	0.066	0.084	0.003	0.035	0.096	0.003
BIG4	0.692	0.462	0.000	1.000	1.000	0.647	0.478	0.000	1.000	1.000	0.045***
S&P500	0.120	0.325	0.000	0.000	0.000	0.124	0.330	0.000	0.000	0.000	-0.004
ICFR	0.801	0.399	1.000	1.000	1.000	0.713	0.452	0.000	1.000	1.000	0.088***
LEV	0.298	0.351	0.080	0.251	0.423	0.328	0.602	0.060	0.238	0.439	-0.030***
SALEGR	0.175	0.605	-0.001	0.077	0.189	0.212	0.810	-0.018	0.073	0.205	-0.037
LITIG	0.200	0.400	0.000	0.000	0.000	0.293	0.455	0.000	0.000	1.000	-0.093***
ACSIZE	3.920	1.422	3.000	4.000	5.000	3.704	1.343	3.000	4.000	4.000	0.216***
ACEXP	0.260	0.438	0.000	0.000	1.000	0.262	0.440	0.000	0.000	1.000	-0.002

Table 3 reports descriptive statistics for the variables used in the multi-office partner assignment analyses. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Variable definitions are provided in Appendix A.

Table 4. Correlations for Multi-Office Partner Assignment Model

Panel A: Partner Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
MOP	1.00												
PARTFIN	0.07***	1.00											
PARTNONFIN	-0.11***	-0.26***	1.00										
PARTEXP	0.06***	-0.05***	0.00	1.00									
PARTSR	0.01	0.06***	-0.02***	-0.49***	1.00								
PARTSKILL	0.01	-0.03***	0.01	-0.02**	0.04***	1.00							
PARTMP	0.04***	-0.03***	-0.01	0.03***	0.04***	0.03***	1.00						
PARTHR	-0.03***	0.01	0.03***	0.03***	-0.01	0.01	-0.03***	1.00					
PARTOL	-0.02**	0.01	-0.03***	0.02**	0.04***	-0.04***	-0.19***	-0.06***	1.00				
PARTMALE	0.04***	-0.02***	-0.01*	-0.07***	0.13***	0.04***	0.00	-0.08***	0.02**	1.00			
PARTWORK	0.22***	-0.12***	-0.26***	0.00	-0.02**	0.03***	-0.01	-0.05***	-0.05***	0.06***	1.00		
PARTFEE	0.16***	-0.03***	0.09***	0.17***	0.01	-0.03***	0.03***	0.04***	0.04***	0.01	0.12***	1.00	
PARTNAS	0.01*	0.15***	-0.04***	-0.02***	0.06***	0.02**	0.01	-0.01	0.02**	0.02*	0.02***	0.03***	1.00

Panel B: Audit Office Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MOP	1.00						
OFFSIZE	-0.02***	1.00					
SOPRATIO	-0.19***	0.11***	1.00				
OFFGR	0.02***	-0.20***	-0.05***	1.00			
OFFSPEC	0.03***	0.20***	-0.02***	-0.04***	1.00		
OFFNAS	0.01	0.20***	0.04***	-0.05***	0.02***	1.00	
BIG4	0.05***	0.79***	0.12***	-0.17***	0.28***	0.17***	1.00

Table 4. (Continued)

Panel C: Client Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOP	1.00							
S&P500	0.00	1.00						
ICFR	0.09***	0.25***	1.00					
LEV	-0.04***	-0.04***	-0.17***	1.00				
SALEGR	-0.01*	-0.05***	-0.10***	-0.02**	1.00			
LITIG	-0.08***	-0.07***	-0.19***	0.02***	0.10***	1.00		
ACSIZE	0.07***	0.19***	0.27***	-0.06***	-0.11***	-0.22***	1.00	
ACEXP	-0.01	0.06***	-0.03***	0.13***	-0.03***	-0.07***	-0.02**	1.00

Table 4 reports pairwise correlations for the variables used in the multi-office partner assignment analyses. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Variable definitions are provided in Appendix.

2.5 Results

Table 5 reports the results examining the assignment of multi-office partners. The first set of variables is partner expertise and experience. Industry specialization in the financial sector (PARTFIN) is positively associated with MOP. This suggests that clients in the financial sector are matched with specialist MOPs because MOPs' knowledge is in high demand and not substitutable, consistent with my prediction. In contrast, industry specialization in non-financial sectors (PARTNONFIN) is negatively associated with MOP, which is inconsistent with my prediction. My interpretation is that if the industry is not overly complex or distinct from other industries, specialist MOPs are less likely to be used. For example, if there is no partner who has the expertise for a manufacturing client, the audit office can assign a partner with experience in industrial applications. In addition, I find that more experienced partners, PARTEXP, (but not the most senior ones, PARTSR) are more likely to be MOPs compared to junior partners. These results, along with the positive coefficient on PARTSKILL, support the notion that partners with more skills and experience are more likely to be MOPs to meet the needs of nonlocal clients for experts.

The second set of variables in Table 5 capture audit office resource constraints. The coefficients on audit office size (OFFSIZE), partner to client ratio (SOPRATIO), and audit office specialization (OFFSPEC) are negative and significant. Consistent with my prediction, these results indicate that clients in larger audit offices or with more partner or in-house resources available for the client industry are less likely to use MOPs. When audit offices experience human resource constraints, they would engage in interoffice collaboration through resource sharing from offices with greater resources to resource constrained offices.

When examining how other partner and client characteristics impact MOP assignments, I find that both workload measures, PARTWORK and PARTFEE are positively associated with MOP. The results imply that MOPs may be more capable or willing to handle a larger workload. Partners with higher NAS workload, thus more independence concern, (PARTNAS) are less likely to be MOPs. The coefficient on BIG4 is positive and significant, which is consistent with my prediction and prior literature that firms with a larger national network can better assign partners to offices with a greater need for human resource (Bills et al. 2016).[10] Furthermore, I find that more complex clients that require integrated audits (ICFR) are likely to match with MOPs, consistent with my prediction. It is possible that MOPs may have certain experience or expertise, like conducting internal control audits, that are valued by these clients. Lastly, the coefficients on S&P500 and LITIG are negative and significant. This result is consistent with my expectation that more prestigious clients expect undivided attention from partners and are therefore less likely to choose MOPs. Furthermore, offices may be

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[10] The positive coefficient on BIG4 and the negative coefficient on OFFSIZE may seem counterintuitive because Big 4 offices have more resources and tend to be larger on average than non-Big 4 offices. In untabulated analyses, I re-estimate equation (1) using the Big 4 (non-Big 4) subsamples and find the coefficients on OFFSIZE to be significant and negative in both subsamples. Therefore, the result that clients in larger offices are less likely to use MOPs is consistent across the two subsamples. I interpret the BIG4 results as a firm-wide strategy. Big 4 have national administrative offices that provide support for local offices (Francis and Yu 2009), which can include assigning and sharing partners across offices. This practice may not be as prevalent for non-Big 4 firms.

hesitant to assign riskier clients to MOPs or MOPs may be less willing to take on riskier clients because MOPs need to handle a larger workload in multiple offices.

Table 5. Multi-Office Partner Assignment

		MOP	
Variables	**Predicted Sign**	**Coefficient**	**t-statistic**
Partner Expertise/Experience			
PARTFIN	+	0.501***	(3.03)
PARTNONFIN	+	-0.244**	(-2.07)
PARTEXP	+	0.227***	(2.69)
PARTSR	+	0.034	(0.34)
PARTSKILL	+	0.126*	(1.70)
PARTMP	+	0.059	(0.48)
PARTHR	+	-1.423**	(-2.09)
PARTOL	+	-0.123	(-1.30)
Audit Office Resource Constraints			
OFFSIZE	−	-0.496***	(-12.40)
SOPRATIO	−	-2.266***	(-11.87)
OFFGR	+	0.126	(0.89)
OFFSPEC	−	-0.199**	(-2.38)
OFFNAS	+	1.003	(1.46)
Other Variables			`
PARTMALE	+	0.079	(0.74)
PARTWORK	?	1.291***	(15.93)
PARTFEE	?	0.661***	(10.95)
PARTNAS	−	-0.882*	(-1.67)
BIG4	+	1.099***	(7.57)
S&P500	−	-0.250*	(-1.88)
ICFR	+	0.363***	(3.56)
LEV	−	-0.099	(-1.30)
SALEGR	+	-0.053	(-1.34)
LITIG	−	-0.256**	(-2.07)
ACSIZE	?	0.013	(0.47)
ACEXP	?	-0.046	(-0.53)

Table 5. (Continued)

FE	Industry, Year
Observations	11,422
Pseudo R^2	0.204

Table 5 reports the results of logistic regression of the multi-office partner assignment on audit partner, audit office, and client characteristics. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity.

CHAPTER 3

MULTI-OFFICE PARTNERS AND AUDIT QUALITY

3.1 Hypothesis Development

The multi-office partner assignment analyses in Chapter 2 show that audit firms assign partners to multiple offices to 1) match partner expertise with clients' needs and 2) manage audit office resource constraints. In this chapter, I examine how these two factors jointly impact the audit quality of multi-office partners.

Partner industry expertise and professional experience contributes to their competencies and affect audit outcomes (Francis 2011). Chapter 2 analyses show that MOPs are more likely to be industry specialists in the financial sector, which demands specialized knowledge. MOPs also report more skills on their LinkedIn profiles. Prior literature suggests that audit partners' industry experience, pre-client and client-specific experience are valuable (Chin and Chi 2009; Bell et al. 2015; Chi et al. 2017). Audit partners with higher expertise and more experience are associated with better quality, proxied by restatement, discretionary accruals, and interest rate spreads (Chin and Chi 2009; Bell et al. 2015; Chi et al. 2017). On the other hand, some studies document a negative association between partner age and audit quality as the most senior partners have less career concern and lower motivation to provide high quality audits (Sundgren and Svanstrom 2014; Goodwin and Wu 2016). Since MOPs are more likely to be experienced but not the most senior partners, I expect them to have the expertise and experience, as well as strong career motivation, to deliver higher quality audits.

Audit office resource constraints also impact audit quality. Chapter 2 analyses show that smaller audit offices, offices with lower partner to client ratio, and offices without industry specialization are more likely to use MOPs. Bills et al. (2016) documents a negative association between greater human resource constraints and audit quality. Although audit offices can use MOPs to mitigate local partner shortages, they may not fully alleviate the negative impact of resource constraints on audit quality. Audit offices staff engagement teams from local offices (Francis 2011). Aobdia, Choudhary, and Newberger (2024) document the importance of mid-level managers in audit outcomes. Choi, Kim, Kim, and Zang (2010) argue that larger offices have a larger pool of capable audit personnel, allowing them to share knowledge across engagements to increase audit quality and efficiency. When small offices are constrained by a lack of capable audit managers and staff, audit quality suffers. Similarly, if local audit personnel do not exhibit sufficient in-house industry specialized knowledge, audit quality is negatively impacted (Reichelt and Wang 2010). Therefore, I expect audit office resource constraints may hinder MOPs from delivering high-quality audits.

Overall, it is unclear whether the partner expertise and experience and audit office resource constraints discussed above will aggregately improve or impair quality. Therefore, I state the following null hypothesis:

HYPOTHESIS*: Audit quality is not different for clients of multi-office partners and clients of single-office partners.*

3.2 Empirical Model

I estimate the following logistic regression model with robust standard errors clustered by clients to examine the association between MOP and audit quality. I define all variables in Appendix A and describe them briefly below.

$$\Pr(Restatement_{it}) = \beta_0 + \beta_1 MOP_{it} + \beta_2 Partner\_Variables_{it} + \beta_3 AuditOffice\_Variables_{it} + \beta_4 Client\_Variables_{it} + Fixed\ Effects + e_{it} \quad (2)$$

I use restatement to proxy for audit quality (DeFond and Zhang 2014; Aobdia 2019). The dependent variable restatement has four variants: RESTATE, GAAPRESTATE, NEGRESTATE, and POSRESTATE. RESTATE is an indicator variable for all restatements, GAAPRESTATE indicates restatements due to a GAAP failure, NEGRESTATE (POSRESTATE) indicates restatements due to a GAAP failure, with negative (positive) effects on financial statements (Newton, Wang, and Wilkins 2013). The main variable of interest is MOP, set equal to one if the audit partner is associated with more than one audit office, and zero otherwise. Following prior literature, I include both year and industry-fixed effects.

Control variables include partner, audit office, and client characteristics that impact audit quality (Francis and Yu 2009; Choi et al. 2012; Newton et al. 2013; Francis et al. 2022). I include two partner workload controls, PARTWORK and PARTFEE. I use PARTSPEC to indicate whether the partner audits clients only in one industry in my sample, thus an industry specialist. I also include PARTEXP, PARTSR, PARTSKILL to capture professional experience and skills. In addition, I use PARTLEAD to indicate whether the partners hold a leadership position within the audit firm. For audit office controls, I include a Big 4 indicator (BIG4), audit office size (OFFSIZE), office industry specialization (OFFSPEC), and the extent of audit office NAS fees (OFFNAS). For client factors, I include client size (TA), whether the client is subject to an integrated audit (ICFR), leverage (LEV), sales growth (SALEGR), whether a firm is in a high litigation industry (LITIG), audit committee size (ACSIZE), and whether the audit committee has a higher percentage of designated financial expert (ACEXP), discussed in detail in the previous chapter. I introduce additional client characteristics that may influence financial reporting quality, including return on assets (ROA), book-to-market ratio (BM), the existence of a net loss (LOSS), restructure (RESTRUC), merger or acquisitions (MERGER), whether the client discloses at least one internal control material weakness in compliance with SOX 404a and/or SOX 404b (ICMW), whether the client announced a restatement in the prior year (LAGRESTATE), and the distance between client headquarter and audit office (DISTANCE). I winsorize all continuous variables at the 1st and 99th percentiles to minimize the potential influence of outliers.

3.3 Descriptive Statistics

Table 6 presents descriptive statistics for the MOP and SOP subsamples. About 5.5 percent of client-year observations audited by MOPs and 5.1 percent audited by SOPs have restatements. The GAAPRESTATE rate is also higher for MOPs' clients versus SOPs' clients (5.2 vs 5.0 percent). The majority of the GAAP restatements have a negative net effect on the financial statement. About 4.3 percent (3.9 percent) and 0.9 percent (1.2 percent) of MOPs' (SOPs') clients have NEGRESTATE and POSRESTATE, respectively. Although clients of MOPs have a higher rate of RESTATE, GAAPRESTATE, and NEGRESTATE, and a lower rate of POSRESTATE, the differences in means are not statistically significant. MOPs audit about 17.4 percent (1,923/(1,923+9,160)) of client-years in the restatement sample.

Table 6. Descriptive Statistics for Audit Quality Model

	MOP (N=1,923)					SOP (N=9,160)					
Variables	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Diff in Mean
RESTATE	0.055	0.228	0.000	0.000	0.000	0.051	0.220	0.000	0.000	0.000	0.004
GAAPRESTATE	0.052	0.222	0.000	0.000	0.000	0.050	0.219	0.000	0.000	0.000	0.002
NEGRESTATE	0.043	0.203	0.000	0.000	0.000	0.039	0.192	0.000	0.000	0.000	0.004
POSRESTATE	0.009	0.094	0.000	0.000	0.000	0.012	0.108	0.000	0.000	0.000	-0.003
Partner Factors											
PARTSPEC	0.382	0.486	0.000	0.000	1.000	0.449	0.497	0.000	0.000	1.000	-0.067***
PARTEXP	0.495	0.500	0.000	0.000	1.000	0.428	0.495	0.000	0.000	1.000	0.067***
PARTSR	0.258	0.438	0.000	0.000	1.000	0.247	0.432	0.000	0.000	0.000	0.001
PARTSKILL	0.488	0.500	0.000	0.000	1.000	0.469	0.499	0.000	0.000	1.000	0.019
PARTLEAD	0.340	0.474	0.000	0.000	1.000	0.354	0.478	0.000	0.000	1.000	0.014
PARTMALE	0.864	0.343	1.000	1.000	1.000	0.833	0.373	1.000	1.000	1.000	0.031***
PARTWORK	0.934	0.371	0.693	0.693	1.099	0.548	0.558	0.000	0.693	1.099	0.386***
PARTFEE	15.034	1.005	14.379	15.128	15.779	14.518	1.248	13.748	14.619	15.383	0.516***
Audit Office Factors											
BIG4	0.690	0.463	0.000	1.000	1.000	0.645	0.479	0.000	1.000	1.000	0.045***
OFFSIZE	16.641	1.805	15.240	16.978	18.060	16.900	1.944	15.476	17.266	18.513	-0.259**
OFFSPEC	0.308	0.462	0.000	0.000	1.000	0.278	0.448	0.000	0.000	1.000	0.030***
OFFNAS	0.083	0.060	0.041	0.075	0.109	0.082	0.057	0.041	0.073	0.107	0.001
Client Factors											
TA	7.358	2.019	6.274	7.549	8.738	6.795	2.428	5.206	7.012	8.441	0.563***
ICFR	0.815	0.388	1.000	1.000	1.000	0.731	0.444	0.000	1.000	1.000	0.084***
LEV	0.296	0.353	0.079	0.250	0.418	0.325	0.602	0.060	0.237	0.437	-0.029***
SALEGR	0.167	0.586	-0.002	0.076	0.186	0.206	0.802	-0.019	0.071	0.199	-0.039
LITIG	0.197	0.398	0.000	0.000	0.000	0.289	0.453	0.000	0.000	1.000	-0.092***
ICMW	0.080	0.271	0.000	0.000	0.000	0.091	0.288	0.000	0.000	0.000	-0.011***
LOSS	0.256	0.437	0.000	0.000	1.000	0.369	0.483	0.000	0.000	1.000	-0.113***
ROA	-0.036	0.520	-0.003	0.019	0.058	-0.155	1.088	-0.065	0.013	0.056	0.119***
BM	0.532	0.815	0.247	0.510	0.781	0.452	0.937	0.190	0.423	0.741	0.080***
RESTRUC	0.008	0.088	0.000	0.000	0.000	0.009	0.094	0.000	0.000	0.000	-0.001
LAGRESTATE	0.051	0.221	0.000	0.000	0.000	0.045	0.208	0.000	0.000	0.000	0.006
MERGER	0.080	0.271	0.000	0.000	0.000	0.093	0.291	0.000	0.000	0.000	-0.013
DISTANCE	3.069	1.803	1.960	2.760	3.976	3.166	1.873	1.988	2.815	3.953	-0.097***
ACSIZE	3.945	1.415	3.000	4.000	5.000	3.725	1.335	3.000	4.000	4.000	0.220***

Table 6. (Continued)

	MOP (N=1,923)					SOP (N=9,160)					
Variables	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Diff in Mean
ACEXP	0.260	0.439	0.000	0.000	1.000	0.264	0.441	0.000	0.000	1.000	-0.004

Table 6 reports descriptive statistics for the variables used in the audit quality analyses. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Variable definitions are provided in Appendix A.

3.4 Main Results

Table 7 reports the results for the relation between multi-office partners and audit quality. The coefficient on MOP is positive and significant in column (1), which indicates that MOPs are associated with a higher likelihood of restatement. The odds ratio for MOP in column (1) is 1.34 (untabulated), suggesting that when switching from a SOP to a MOP, the client is 1.34 times more likely to have a restatement. The results are consistent in columns (2) and (3) that MOPs are positively associated ($p < 0.1$ in both columns) with restatements relating to a GAAP failure (GAAPRESTATE) and GAAP restatements with a negative effect (NEGRESTATE). I do not find MOPs to be associated with restatement that had a positive effect (POSRESTATE). Overall, the results reject the null hypothesis and provide evidence that MOPs are, on average, associated with lower audit quality. Among the control variables, the Big 4 indicator (BIG4) has a significant negative coefficient suggesting that Big 4 firms perform higher audit quality, consistent with findings in prior work (e.g., Becker, DeFond, Jiambalvo, and Subramanyam 1998; Robin, Wu, and Zhang 2016). The coefficients on audit office size (OFFSIZE) are positive and significant, which is unexpected but consistent with Francis et al. (2022). Furthermore, consistent with prior research, firms with material weakness in internal control (ICMW) and those located further away from the audit office (DISTANCE) are more likely to have restatements (Choi et al. 2012; Newton et al. 2013).

Table 7. Multi-office Partner and Audit Quality: Main Results

	RESTATE	GAAPRESTATE	NEGRESTATE	POSRESTATE
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
MOP	0.291**	0.252*	0.291**	0.042
	(2.21)	(1.89)	(1.98)	(0.14)
Partner Factors				
PARTSPEC	-0.306**	-0.315**	-0.348**	-0.177
	(-2.42)	(-2.47)	(-2.40)	(-0.71)
PARTEXP	0.102	0.084	0.044	0.179
	(0.88)	(0.71)	(0.33)	(0.75)
PARTSR	0.130	0.144	0.158	0.064
	(0.97)	(1.07)	(1.04)	(0.23)
PARTSKILL	0.043	0.037	0.098	-0.158
	(0.42)	(0.36)	(0.84)	(-0.70)
PARTLEAD	-0.193*	-0.177	-0.181	-0.137
	(-1.71)	(-1.56)	(-1.42)	(-0.59)
PARTMALE	0.072	0.040	-0.061	0.424
	(0.50)	(0.28)	(-0.38)	(1.30)
PARTWORK	-0.480***	-0.505***	-0.474***	-0.545**
	(-3.93)	(-4.08)	(-3.49)	(-2.03)
PARTFEE	0.106	0.109	0.131	0.042
	(1.19)	(1.21)	(1.31)	(0.22)
Audit Office Factors				
BIG4	-0.627***	-0.639***	-0.549**	-0.895**
	(-3.17)	(-3.18)	(-2.38)	(-2.40)
OFFSIZE	0.118**	0.112**	0.042	0.334***
	(2.36)	(2.21)	(0.74)	(3.31)
OFFSPEC	0.066	0.065	0.153	-0.266
	(0.55)	(0.53)	(1.13)	(-1.01)
OFFNAS	-0.276	-0.168	0.021	-0.554
	(-0.31)	(-0.18)	(0.02)	(-0.25)
Client Factors				
TA	0.030	0.033	0.060	-0.062
	(0.59)	(0.65)	(1.04)	(-0.62)
ICFR	-0.378**	-0.387**	-0.370**	-0.443
	(-2.43)	(-2.44)	(-2.01)	(-1.50)
LEV	-0.102	-0.136	-0.065	-0.364
	(-1.13)	(-1.38)	(-0.61)	(-1.52)
SALEGR	-0.106*	-0.127*	-0.071	-0.375
	(-1.65)	(-1.95)	(-1.19)	(-1.21)

Table 7. (Continued)

	RESTATE	GAAPRESTATE	NEGRESTATE	POSRESTATE
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
LITIG	-0.091	-0.104	0.062	-0.669**
	(-0.55)	(-0.63)	(0.33)	(-2.18)
ICMW	1.316***	1.295***	1.260***	1.189***
	(10.71)	(10.44)	(9.16)	(4.71)
LOSS	0.241*	0.244*	0.304**	0.096
	(1.84)	(1.85)	(1.98)	(0.38)
ROA	0.152*	0.131	0.256	0.009
	(1.65)	(1.58)	(1.54)	(0.25)
BM	0.038	0.029	0.025	0.032
	(0.46)	(0.35)	(0.26)	(0.32)
RESTRUC	-0.285	-0.255	0.014	0.000[a]
	(-0.56)	(-0.50)	(0.03)	(.)
LAGRESTATE	0.380**	0.409**	0.345*	0.503
	(2.25)	(2.43)	(1.77)	(1.49)
MERGER	0.307**	0.328**	0.176	0.749***
	(2.25)	(2.38)	(1.13)	(2.68)
DISTANCE	0.066**	0.065**	0.059*	0.082*
	(2.33)	(2.28)	(1.75)	(1.68)
ACSIZE	-0.036	-0.036	-0.044	-0.017
	(-0.80)	(-0.79)	(-0.84)	(-0.19)
ACEXP	0.138	0.160	0.092	0.350
	(1.09)	(1.26)	(0.61)	(1.49)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.070	0.070	0.064	0.110

Table 7 reports the results of a logistic regression of the audit quality on multi-office partners. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at p < 0.10, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

[a] RESTRUC has no variation in predicting POSRESTATE and is therefore dropped from the regression.

3.5 Entropy Balanced Sample

Chapter 2 provides evidence that partner, audit office, and client characteristics impact MOP assignments. To mitigate the concern that the negative association between MOP and audit quality is driven by MOP selection bias from observable characteristics, I re-estimate equation (2) using an entropy balanced sample (Hainmueller 2012). I reweigh the observations so that all control variables in equation (2) are balanced in means across the treatment (MOPs) and control groups (SOPs). The results using an entropy balanced sample (untabulated) are consistent with the main results. I find that MOPs are significantly positively associated with RESTATE, GAAPRESTATE, and NEGRESTATE (p <0.05 in all three models).

3.6 SOPs Who Transition to MOPs

Since MOP is a partner-year measure, a partner can be an MOP in some years but an SOP in other years. In my sample, about 80% of partners have never been MOPs. To mitigate the concern that time-invariant but unobservable partner characteristics impact both MOP assignment and audit quality outcome, I identify client-years audited by SOPs, who in other years within my sample serve as MOPs.[11] I introduce a new dummy variable MOPSOP in equation (2) to capture this subgroup of client-year observations and report the results in Table 8. The coefficients on MOPSOP are not significant in any of the models. The results suggest that, on average, the audit quality of SOPs, who in

[11] For example, partner A in 2017 conducted three audits from two different MSAs: client A and B - Albany (New York) and client C - Memphis (Tennessee). This partner is an MOP in 2017. In 2018, partner A rotates of client C and only conducts audits in one MSA. This partner becomes a SOP in 2018. MOPSIN equals 1 for client A and client B in 2018.

other years might serve as MOPs, is not different from that of SOPs who are never MOPs.

Table 8. Multi-Office Partner and Audit Quality: SOPs Who Transition to MOPs

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
MOP	0.317**	0.278**	0.332**	0.020
	(2.30)	(2.00)	(2.15)	(0.07)
MOPSOP	0.182	0.183	0.279	-0.197
	(1.09)	(1.08)	(1.51)	(-0.56)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.070	0.064	0.110

Table 8 reports results of a logistic regression to test the audit quality on multi-office partners and address self-selection bias. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

CHAPTER 4

ADDITIONAL ANALYSES

4.1 Cross-Sectional Tests

The main results show that MOPs are associated with lower audit quality, suggesting that audit office resource constraints dominate partner expertise and experience, resulting in a net negative impact on the quality of audits conducted by MOPs. In this chapter, I examine partner and audit office characteristics that may *intensify or mitigate the negative association between MOP and audit quality.*

4.1.1. Partner Workload

In this section, I examine whether the effect of MOP on audit quality varies conditionally on the MOP workload. On one hand, the workload creates an incentive for MOPs to provide higher quality audits. Using a theoretical framework, DeAngelo (1981) argues that audit partners with a larger client base have stronger incentives to provide high-quality audits. In the event of audit failures, audit partners face the risk of losing all clients. A larger number of clients serve as greater total collateral against opportunistic behavior (DeAngelo 1981). Audit partner compensation is positively associated with the number of public clients and has been shown to be negatively associated with restatements (Knechel et al. 2013). Mande and Son (2013) show that restatements lead to auditor changes. Therefore, MOPs with a higher workload should have a stronger motivation to provide high quality audits.

On the other hand, a higher workload imposes greater challenges. Some prior studies find that high workload pressure is associated with impaired audit quality (Lopez and Peters 2012; Sundgren and Svanstrom 2014; Chen, Dong, Han, and Zhou 2020). In addition, audit firms have internal quality control systems to monitor audit quality and can rotate partners off the engagement before the end of the five-year mandatory term if their work quality fails to meet the standard (Gipper, Hail, and Leuz 2022). The partner's workload may ultimately reflect an equilibrium such that more capable partners have heavier workloads (Lennox and Wu 2018). MOPs with higher workloads may have higher competencies to manage a larger workload. The coefficient on PARTWORK (reported in Table 7) is negative, suggesting that the greater incentives and capabilities from managing a large workload dominate higher workload stress for partners. Therefore, I expect MOPs with a higher workload to provide higher audit quality.

I partition MOP into high workload (HPARTWORK) and low workload (LPARTWORK) groups using the median split of workload, measured by the number of clients PARTWORK. The median of PARTWORK is 2 in my sample. I replace the main test variable MOP in equation (2) with HPARTWORK and LPARTWORK.

As shown in Table 9, the low workload MOP group (LPARTWORK) is positively associated with three restatement measures, RESTATE, GAAPRESTATE, and NEGRESTATE. However, I do not find a significant association between high workload MOP (HPARTWORK) and audit quality. When directly comparing the coefficients on LPARTWORK and HPARTWORK in columns (1) – (3), I find the coefficient on LPARTWORK to be statistically greater than the coefficient on HPARTWORK in columns (1) and (2) using a one-tailed test ($p<0.1$). These results provide some evidence that MOPs with a higher workload provide 1) better quality audits than MOPs with a lower workload and 2) similar quality audits as SOPs do.

In untabulated analyses, I use two alternative measures of high workload MOP group (HPARTWORK) and low workload MOP group (LPARTWORK), 1) using the 75th percentile of workload in terms of the number of clients (PARTWORK) as the cutoff and 2) using the median split of workload in terms of total audit fees (PARTFEE). For these two alternative measures, I do not find the coefficients on LPARTWORK to be statistically greater than the coefficients on HPARTWORK. Overall, there is some evidence that MOPs with a higher workload provides better quality audits than MOPs with a lower workload and greater partner incentives mitigate MOPs' lower audit quality although these results are sensitive to alternative specification.

Table 9. Cross-Sectional Test: Workload

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
HPARTWORK	0.069	0.041	0.175	-0.618
	(0.33)	(0.20)	(0.80)	(-0.95)
LPARTWORK	0.406***	0.361**	0.351**	0.328
	(2.75)	(2.40)	(2.10)	(1.07)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.070	0.064	0.112

Table 9 reports results of a logistic regression to test whether the effect of MOP on audit quality varies conditionally on the MOP workload. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

4.1.2 Partner Expertise and Experience

In this section, I examine whether the negative relation between MOPs and audit quality is affected by the partner expertise and experience. The negative coefficients on partner industry specialization (PARTSPEC) in Table 7 are consistent with prior studies that document that industry specialists are associated with higher audit quality (Chin and Chi 2009; Bell et al. 2015). Partners with years of experience auditing clients in the same industry develop more in-depth knowledge about the specific industry and deliver higher quality audits. Although MOPs, on average, provide lower quality audits than SOPs, the MOPs with industry specialization, because of their superior industry knowledge, can still maintain their work quality. I expect industry specialist MOPs to provide higher quality audits than MOPs who are not industry specialists.

I partition the MOP into two groups (specialist MOP - SPECMOP and non-specialist MOP- NONSPECMOP) by interacting MOP and partner industry specialization (PARTSPEC). I use the same model specification as the primary audit quality model and replace the main test variable MOP in equation (2) with specialist MOP (SPECMOP) and non-specialist MOP (NONSPECMOP). As shown in Table 10, NONSPECMOP is positively associated with RESTATE, GAAPRESTATE, and NEGRESTATE. I do not find a significant association between SPECMOP and audit quality. When I compare the coefficients on SPECMOP and NONSPECMOP in columns (1) – (3), I find that the coefficients on NONSPECMOP are statistically greater than the coefficients on SPECMOP using a one-tailed test ($p<0.03$ in all three models). These results suggest that industry specialist MOPs provide consistent audit quality as SOPs do and better quality than non-specialist MOPs. Therefore, MOPs' competencies, proxied by industry specialization, mitigate the negative relation between MOP and audit quality.

In untabulated analyses, I use two alternative measures of specialist MOP group (SPECMOP) and non-specialist MOP group (NONSPECMOP), 1) interacting MOP and partner reported LinkedIn skills (PARTSKILL) and 2) interacting MOP and partner disclose being in leadership positions in online profiles (PARTLEAD). For these two alternative measures, I do not find the coefficients on SPECMOP to be statistically greater than the coefficients on NONSPECMOP. Overall, the results suggest that partner industry specialization plays a more important role in mitigating lower quality of MOPs compared to their overall skills and leadership experience.

Table 10. Cross-Sectional Test: Industry Specialization

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
SPECMOP	-0.202	-0.315	-0.336	-0.271
	(-0.71)	(-1.06)	(-0.98)	(-0.43)
NONSPECMOP	0.428***	0.405***	0.455***	0.126
	(2.92)	(2.73)	(2.80)	(0.38)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.071	0.065	0.110

Table 10 reports results of a logistic regression to test whether the effect of MOP on audit quality varies conditionally on the MOP industry specialization. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

4.1.3. Information Friction

In this section, I examine whether the effect of MOP on audit quality varies conditionally on the distances among different MOP offices. MOPs work with engagement teams based in different audit offices. This unique setting creates two challenges for them. First, geographic distance creates information friction and reduces audit quality (Choi et al. 2012; Francis et al. 2022). Both Choi et al. (2012) and Francis et al. (2022) find that longer geographic distance between the auditor and client locations impairs audit quality. Similarly, the geographical separation between multiple offices hinders MOPs' ability to acquire detailed knowledge about their clients. It also reduces the opportunities for MOPs to bond with clients and supervise engagement team members. SOPs can have in-person interactions with audit teams of different clients in the same audit office, while it is not feasible for MOPs to have such interactions. As a result, audit clients in multiple offices may negatively impact the audit quality for MOPs' clients.

The results of DISTANCE in Table 7 are consistent with prior literature that greater distance causes greater information friction (Bhattacharya and Chakraborty 2005; Choi et al. 2012; Francis et al. 2022). I use the distance between different MOP offices to proxy for information friction unique to MOPs. I calculate the distances between various offices of MOPs (MOPDIS). As a majority of MOPs have audits based in two different offices, the distance is simply miles between Office A and Office B. For MOPs with three different offices, I compute the distance between Offices A and B, B and C, C and A and then add them up to obtain the total distance. I followed the same logic to compute

MOPDIS for MOPs with four different offices. The average (median) distance between audit offices for MOPs is 492 (224) miles (untabulated).

I partition the MOP into those with long distances between audit offices (LDISMOP) and those with short distances between audit offices (SDISMOP) using the median split of MOPDIS. I expect LDISMOP to provide lower quality audits than SDISMOP. I use the same model specification as the primary audit quality model and replace the main test variable MOP in equation (2) with LDISMOP and SDISMOP and report the results in Table 11 Panel A. I find that LDISMOP is positively and significantly associated with restatement in columns (1) – (3). Although the coefficients on SDISMOP are positive in columns (1) and (3), they are not statistically significant. I find that coefficient on LDISMOP is statistically greater than the coefficient on SDISMOP in columns (1) – (3) using a one-tailed test (*p* ranging from 0.02 to 0.09 in the three models). These results show that as the distance between audit offices increases for MOPs, the audit quality suffers, consistent with information friction literature.

In addition, I explore whether the information friction only imposes costs on non-local audits. I partition the MOP clients into those in the MOP's local office (LOCALMOP) and those in the MOP's non-local office (NLOCALMOP). I replace the main test variable MOP in equation (2) with LOCALMOP and NLOCALMOP and report the results in Table 11 Panel B. I find some evidence that both LOCALMOP and NLOCALMOP are significantly and positively associated with RESTATE and I do not find coefficients on NLOCALMOP to be statistically greater than the coefficients on NLOCALMOP in any models. Therefore, I conclude that both MOP's local and non-local clients suffer from lower audit quality.

Table 11. Cross-Sectional Test: Information Friction

Panel A: Distances among different MOP offices

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
LDISMOP	0.490***	0.478***	0.441**	0.560
	(2.97)	(2.88)	(2.38)	(1.60)
SDISMOP	0.075	-0.002	0.131	-0.773
	(0.43)	(-0.01)	(0.70)	(-1.44)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.071	0.064	0.114

Panel B: Local vs Non-Local MOP offices

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
LOCALMOP	0.284*	0.292*	0.293	0.243
	(1.69)	(1.72)	(1.57)	(0.64)
NLOCALMOP	0.299*	0.212	0.289	-0.243
	(1.67)	(1.14)	(1.46)	(-0.54)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.070	0.070	0.064	0.110

Table 11 reports results of a logistic regression to test whether the effect of MOP on audit quality varies conditionally on the distances among different MOP offices (Panel A) and local versus non-local MOP offices (Panel B). Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

4.1.4. Audit Office Focus (NAS)

In this section, I examine whether the effect of MOP on audit quality varies conditionally on the extent of non-audit service (NAS) work by different MOP offices. Audit office leaders oversee all audits and personnel in the office. Prior studies show that office leaders of the same firm may have various leadership cultures and strategies (Beardsley et al. 2021; Anding, Mowchan, Seidel, and Zimmerman 2024; Mowchan 2023). In particular, some audit offices emphasize and provide more non-audit services (NAS) to audit clients. Both Mowchan (2023) and Beardsley et al. (2021) find that audit quality decreases for audit offices who focus on NAS. Therefore, I expect that when MOPs conduct audits in offices with a greater focus on NAS, their audit quality suffers because the offices allocate more time and resources to NAS work for audit clients (Beardsley et al. 2021; Mowchan 2023).

I partition MOPs into those working in audit offices with NAS (NASMOP) and without NAS focus (NONNASMOP) using the median split of the extent of audit office NAS fees (OFFNAS). I use the same model specification as the primary audit quality model and replace the main test variable MOP in equation (2) with NASMOP and NONNASMOP. As shown in Table 12, the coefficients on NASMOP are positive and significant in columns (1) – (3). The coefficients on NONNASMOP are not significant in all models. When directly comparing the coefficients on NASMOP and NONNASMOP from columns (1) – (3), I do not find the coefficients on NASMOP to be statistically greater than the coefficients on NONNASMOP ($p>0.1$). Therefore, I conclude that there is no difference in the audit quality of MOPs who work in audit offices with and without NAS focus.

In untabulated analyses, I used two alternative measures of office NAS fees to construct NASMOP and NONNASMOP: 1) total NAS fees, including tax-related fees, and 2) only tax-related NAS fees. When I use the first alternative measure, I do not find the coefficients on NASMOP to be statistically greater than the coefficients on NONNASMOP. However, when I use the second alternative measure, I find the coefficients on NONNASMOP to be significant and positive, while the coefficient on NASMOP is not significant. This is consistent with the prior literature that auditor-provided tax services improve audit quality through knowledge spillover (Robinson 2008). However, only in the GAAPRESTATE model is the coefficient on NONNASMOP statistically greater than that on NASMOP, using a one-tailed test ($p<0.1$). Overall, I conclude that there is no evidence to suggest that audit quality of MOPs varies depending on whether they are in an audit office with a greater or lesser NAS focus.

Table 12. Cross-Sectional Test: Office Focus (NAS)

	RESTATE	**GAAPRESTATE**	**NEGRESTATE**	**POSRESTATE**
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
NASMOP	0.363**	0.332**	0.334*	0.292
	(2.36)	(2.14)	(1.95)	(0.86)
NONNASMOP	0.115	0.054	0.191	-0.933
	(0.50)	(0.23)	(0.77)	(-1.26)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.070	0.064	0.112

Table 12 reports results of a logistic regression to test whether the effect of MOP on audit quality varies conditionally on non-audit service (NAS) work by different MOP offices. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

4.1.5. Knowledge Sharing

In this section, I examine whether the negative relation between MOPs and audit quality is affected by knowledge sharing from the audit office to MOPs. Working in different offices can create knowledge transfer opportunities. Prior studies have shown the benefits of knowledge sharing within and across audit offices (Beck et al. 2019; Michas, Russomanno, and Zhao 2022). Office size, industry specialization, and audit quality are likely to impact knowledge transfer opportunities for MOPs. First, large audit offices tend to have better audit quality due to more collective experience and greater “in-house” expertise (Francis and Yu 2009). Second, an audit office can provide more industry-specific guidance to partners when problems arise for clients in the industry that the audit office specializes in. Third, audit offices with higher quality are likely to have adequate office-level quality control, better trained audit personnel, and better audit practice.[12] MOPs have access to a greater aggregate knowledge pool from multiple offices and can apply best practices to improve audit quality for all clients. Thus, MOPs with greater knowledge sharing from the audit office may have better audit quality.

I use knowledge sharing (KS) to capture the three audit office characteristics that lead to better knowledge sharing from the office to the partner. KS is a discrete variable that ranges from zero to three. It is the sum of three audit office level dummy variables: whether the audit office size (OFFSIZE) is above the median, whether the office is an industry specialist of the MOP client (OFFSPEC), and whether the office is a high-quality office without any client restatements in the previous year. Because MOPs have access to

[12] Francis and Michas (2013) find that certain audit offices can have systematic quality problems that persist over time.

knowledge pools from multiple offices, I factor in the aggregate learning opportunities from all offices. For example, if an MOP audits clients in a large office A and a small office B, I assign one for the office size dummy for this MOP because of their access to greater collective knowledge from the larger office A. In contrast, an MOP who conducts audits in two small offices is less likely to benefit from the “in-house” expertise of a larger office. The median knowledge sharing (KS) is 2 (untabulated). I classify MOPs in offices with KS above 2 as high knowledge sharing MOP (HKSMOP) and the rest of them as low knowledge sharing MOP (LKSMOP). I use the same model specification as the primary audit quality model and replace the main test variable MOP in equation (2) with HKSMOP and LKSMOP.

As shown in Table 13, low knowledge sharing MOPs (LKSMOP) are positively associated with RESTATE, GAAPRESTATE, and NEGRESTATE. Although the coefficients on high knowledge sharing MOPs (HKSMOP) are negative, they are not statistically significant. These results indicate that MOPs with lower knowledge-sharing opportunities are associated with worse audit quality. I find that the coefficients on LKSMOP are statistically greater than the coefficients on HKSMOP in columns (1) - (3) using a one-tailed test ($p<0.05$ in all three models). These findings suggest that the negative relation between MOP and audit quality is mitigated by greater knowledge sharing opportunities from audit offices.

Table 13. Cross-Sectional Test: Knowledge Sharing

	RESTATE	GAAPRESTATE	NEGRESTATE	POSRESTATE
Variables	**Coefficient (t-statistic)**			
	(1)	(2)	(3)	(4)
HKSMOP	-0.050	-0.102	-0.068	-0.321
	(-0.22)	(-0.43)	(-0.27)	(-0.60)
LKSMOP	0.445***	0.409***	0.455***	0.183
	(3.07)	(2.79)	(2.80)	(0.55)
FE	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Controls	Yes	Yes	Yes	Yes
Observations	11,083	11,083	11,083	11,083
Pseudo-R^2	0.071	0.071	0.065	0.110

Table 13 reports results of a logistic regression to test whether the effect of MOP on audit quality varies conditionally on knowledge sharing from the audit office to MOPs. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity. t-statistics are reported in parentheses.

4.2 Audit Fee Results

In this section, I use audit fees as an alternative proxy for audit quality to support the robustness of the results. The audit fee is an input-based measure of audit quality (Asthana and Boone 2012; Hribar, Kravet, and Wilson 2014). Although this proxy has a higher measurement error compared to the restatement proxy, it is negatively associated with PCAOB inspection deficiencies (DeFond and Zhang 2014; Aobdia 2019). The main results show that MOPs are associated with lower audit quality. Therefore, I expect a negative association between MOPs and audit fees. In equation (2), I use audit fee (AUDFEE) in place of the restatement measures as the dependent variable and present the results in Table 14. Consistent with the results in the main analyses, I find a negative and significant coefficient on MOP in column (1), indicating that MOPs have lower quality. Results for other variables in the model are consistent with prior literature (Choi et al. 2010; Hribar et al. 2014).

Table 14. Multi-Office Partner and Audit Fee

	AUDFEE	
Variables	**Coefficient**	**t-statistic**
	(1)	(2)
MOP	-0.040**	-2.47
PARTSPEC	-0.037***	-3.05
PARTWORK	-0.783***	-50.59
PARTFEE	0.705***	56.28
BIG4	-0.012	-0.61
OFFSIZE	0.028***	5.75
OFFSPEC	0.034***	2.86
OFFNAS	-0.281***	-3.32
TA	0.170***	27.16
ICFR	0.091***	6.09
LEV	0.029***	2.96
SALEGR	-0.008	-1.09
LITIG	-0.013	-0.78
ICMW	0.129***	6.94
LOSS	0.089***	6.93
ROA	-0.009*	-1.73
BM	-0.021***	-4.37
RESTRUC	0.071	1.62
LAGRESTATE	0.041**	2.30
MERGER	0.080***	5.77
DISTANCE	-0.001	-0.22
ACSIZE	-0.004	-0.91
ACEXP	0.009	0.76
FE	Industry, Year	
Observations	11,083	
Adj R^2	0.906	

Table 12 reports the results of an OLS regression of the audit fee on multi-office partner. Variable definitions are provided in Appendix A. *, **, and *** indicate two-tailed statistical significance at $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are robust to heteroscedasticity.

CHAPTER 5

CONCLUSIONS

As leaders of audit teams, audit partners can have a significant impact on audit quality. Some partners handle audits in multiple audit offices and become shared resources across offices. I refer to this as the multi-office partner (MOP) phenomenon. My study is the first to examine what drives MOP assignments, and the audit implications of these assignments. When examining the factors that impact the MOP assignments, I find that partners who specialize in the financial sector are in high demand and are more likely to be associated with MOP assignments. Furthermore, experienced but not the most senior partners are desirable because they have more experience than junior partners and stronger career motivation compared to the most senior partners. Audit offices are more likely to share partner resources when they face resource constraints, such as not having enough partners or lacking office-level industry expertise. The MOP phenomenon is more common among the Big 4 firms' clients. Furthermore, I document that more prestigious clients, less complex clients, and clients with greater litigation risk are less likely to use MOPs. These findings suggest that audit firms share partners across offices to manage partner resource constraints and match partner expertise to meet clients' needs.

However, MOP assignments can have negative audit quality implications as audit office resource constraints hinder experienced MOPs from delivering high quality audits. I find that MOPs are associated with lower audit quality, using multiple restatement measures and audit fees as proxies. In cross-sectional analyses, I document that the positive association between MOP and restatement is concentrated in MOPs who lack specialized industry expertise, face greater information friction as the distance between audit offices of MOPs increases, and have access to fewer knowledge sharing opportunities from audit offices. Overall, I provide evidence that there are costs associated with using MOPs. While sharing partners across offices can help alleviate resource constraints, audit firms need to weigh the benefits and costs.

My study has two caveats. First, my study does not speak to the optimal client-partner matching and audit quality outcome. An optimal decision may involve client retention, business growth, audit quality, independence, and other considerations. Assigning clients to SOPs while disregarding the partner resource constraints may be a suboptimal decision and impair audit quality as well. Second, the partner-client assignment is endogenous. Although I attempt to alleviate the concern by using an entropy-balanced sample based on the observable partner, audit office, and client factors, there could be other unobservable characteristics confounding the audit quality results.

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APPENDIX A

VARIABLE DEFINITIONS

Dependent Variables

MOP	Indicator variable, equal to one if the audit partner is associated with more than one office (MSA) in year *t* as reported, and zero otherwise. (Audit Analytics)
RESTATE	Indicator variable, equal to one if the client subsequently restated its year-end financial statements, and zero otherwise. (Audit Analytics)
GAAPRESTATE	Indicator variable, equal to one if the client subsequently restated its year-end financial statements due to a GAAP failure, and zero otherwise. (Audit Analytics)
NEGRESTATE	Indicator variable, equal to one if the client subsequently restated its year-end financial statements due to a GAAP failure and the restatement effect was negative, and zero otherwise. (Audit Analytics)
POSRESTATE	Indicator variable, equal to one if the client subsequently restated its year-end financial statements due to a GAAP failure and the restatement effect was positive, and zero otherwise. (Audit Analytics)
AUDFEE	The natural log of audit fees received from the client in a given year t. (Audit Analytics)

Partner Variables

PARTWORK	The natural log of the number of unique Compustat clients in a partner's portfolio in a given year t. (Audit Analytics)
PARTFEE	The natural log of audit fees received from all Compustat clients in a partner's portfolio in a given year t. (Audit Analytics)
PARTEXP	Indicator variable equal to one if the partner's number of years professional experience is between the 25th and the 75th percentile. The number of years professional experience is calculated from the start year of the first job after graduation/graduation year/CPA license year. (Online Profile)
PARTSR	Indicator variable equal to one if the partner's number of years professional experience is above the 75th percentile. The number of years professional experience is calculated from the start year of the first job after graduation/graduation year/CPA license year. (Online Profile)

PARTSPEC	Indicator variable equal to one if the partner audited clients in only in one industry (based on SEC office industry classification) in my sample period, and zero otherwise. (Audit Analytics)
PARTSKILL	Indicator variable equal to one if the number of skills reported on partners' LinkedIn profile is in the top quartile. (Online Profile)
PARTMP	Indicator variable equal to one if the partner discusses being in a managing partner position at the accounting firm. (Online Profile)
PARTHR	Indicator variable equal to one if the partner discusses being in a human capital related leadership position at the accounting firm, for example national chief talent officer, director of ethics, and national US well-being leader. (Online Profile)
PARTOL	Indicator variable equal to one if the partner discusses being in a leadership position (other than PARTMP and PARTHR) at the accounting firm, for example banking and capital markets sector leader, commercial services team leader, and greater Tri-State real estate industry leader. (Online Profile)
PARTLEAD	Indicator variable equal to one if the partner discusses being in a leadership position at the accounting firm. (Online Profile)
PARTFIN	Indicator variable equal to one if the partner audited clients in the financial sector (Real Estate and Finance SEC industry offices) in my sample period, and zero otherwise. (Audit Analytics)
PARTNONFIN	Indicator variable equal to one if the partner audited clients in the non-financial sector in my sample period, and zero otherwise. (Audit Analytics)
PARTNAS	The percentage of audit partner non-audit services fees (excluding tax-related fees) to total fees in a partner's portfolio in a given year t. (Audit Analytics)
PARTMALE	Indicator variable equal to one if the partner is male based on online profile picture or internet search if a partner's given (i.e., first or middle) name is more commonly given to baby girls than to baby boys. (Online Profile)
MOPSOP	Indicator variable equal to one if the partner is a SOP in year t and MOP in other years in the sample. (Audit Analytics)
HPARTWORK	Indicator variable equal to one if the partner is an MOP and PARTWORK is above median, and zero otherwise. (Audit Analytics)
LPARTWORK	Indicator variable equal to one if the partner is an MOP and PARTWORK is below median, and zero otherwise. (Audit Analytics)

SPECMOP	Indicator variable equal to one if the partner is an MOP and PARTSPEC equals one, and zero otherwise. (Audit Analytics)
NSPECMOP	Indicator variable equal to one if the partner is an MOP and PARTSPEC equals zero, and zero otherwise. (Audit Analytics)
MOPDIS	The distances between various offices of MOPs. For MOPs based in two different offices, the distance in miles is between office A and office B. For MOPs with three different offices, I compute the distance between Offices A and B, B and C, C and A and then add them up to obtain the total distance. (Audit Analytics)
LDISMOP	Indicator variable equal to one if the partner is an MOP and MOPDIS is above the median, and zero otherwise. (Audit Analytics)
SDISMOP	Indicator variable equal to one if the partner is an MOP and MOPDIS is below the median, and zero otherwise. (Audit Analytics)
LOCALMOP	Indicator variable equal to one if the audit opinion signing office is MOP's local office based on online profile search. (Online Profile)
NLOCALMOP	Indicator variable equal to one if the audit opinion signing office is not MOP's local office based on online profile search. (Online Profile)
NASMOP	Indicator variable equal to one if the partner is an MOP and OFFNAS is above the median, and zero otherwise. (Audit Analytics)
NONNASMOP	Indicator variable equal to one if the partner is an MOP and OFFNAS is below the median, and zero otherwise. (Audit Analytics)
KS	The sum of three audit office level dummy variables: whether the audit office size (OFFSIZE) is above the median, whether the office is an industry specialist of the MOP client (OFFSPEC), and whether the office is a high-quality office without any client restatements in the previous year. (Audit Analytics)
HKSMOP	Indicator variable equal to one if the partner is an MOP and KS is above the median, and zero otherwise. (Audit Analytics)
LKSMOP	Indicator variable equal to one if the partner is an MOP and KS is below the median, and zero otherwise. (Audit Analytics)

<u>Audit Office Variables</u>

BIG4	Indicator variable equal to one if the auditor is a Big 4 firm, and zero otherwise. The Big 4 firms are Deloitte, EY, KPMG, and PwC (Audit Analytics)

SOPRATIO	The ratio of the total number of single office partners to the total number of audit clients in the client's industry in an audit office (MSA) in a given year t. (Audit Analytics)
OFFGR	Indicator variable equal to one if the audit office (MSA) is in the top decile of growth rate in audit fees from year t-1 to year t, and zero otherwise. (Audit Analytics)
OFFSIZE	The natural log of total audit fees charged to all clients within an audit office (MSA) in year *t*. (Audit Analytics)
OFFSPEC	Indicator variable equal to one if the audit office (MSA) has an audit fee market share in a two-digit SIC code industry of 50% or more for a given city-year following Reichelt and Wang (2010), and zero otherwise. (Audit Analytics)
OFFNAS	The percentage of audit office (MSA) non-audit services fees (excluding tax-related fees) to total fees in an audit office's portfolio in a given year t. (Audit Analytics)

Client Variables

S&P500	Indicator variable, equal to one if the client is an S&P 500 company in a given year t, and zero otherwise. (Audit Analytics)
LEV	Long-term debt (DLTT+DLC) divided by total assets (AT) (source: Compustat).
LITIG	Indicator variable, equal to one if the client is in a high litigation risk industry following Francis et al. (1994), and zero otherwise; high litigation risk industries include pharmaceuticals and biotechnology (SIC 2833-2836 and 8731-8734), computers (SIC3570-3577 and 7370-7374), electronics (SIC 3600-3674), and retail (SIC 5200-5691).
TA	The natural log of total assets (AT). (Compustat)
ICFR	Indicator variable, equal to one if the client received an integrated audit in a given year t, and zero otherwise. (Audit Analytics)
SALEGR	The one-year growth rate in net sales (SALE) from year t-1 to year t. (Compustat)
ACSIZE	The number of members in the audit committee in a given year t. (BoardEx)
ACEXP	Indicator variable, equal to one if the percentage of designated financial experts to all members in an audit committee belongs to the highest quartile of its distribution in a given year t, and zero otherwise. (BoardEx)
ROA	The ratio of earnings (IB) to average (of beginning and ending) total assets (AT). (Compustat)
BM	Book to market ratio (CEQ/PRCC_F*CSHO) (Compustat).

LOSS	Indicator variable, equal to one if net income (NI) is less than zero, and zero otherwise (Compustat).
RESTRUC	Indicator variable, equal to one for companies with restructuring expenses (RCP > 0), and zero otherwise. (Compustat)
MERGER	Indicator variable, equal to one if the client has acquisition expenses (AQC) during the year, and zero otherwise (Compustat).
ICMW	Indicator variable, equal to one if the client has a material weakness under 404a or 404b in year *t*, and zero otherwise. (Audit Analytics)
LAGRESTATE	Indicator variable, equal to one if the client has a restatement announcement in year *t*-1, and zero otherwise. (Audit Analytics)
DISTANCE	The natural log of distance between the client's headquarters and the audit office. (Audit Analytics)