PARTNER-LEVEL INDUSTRY SPECIALIZATION AND EARNINGS QUALITY: AN ANALYSIS OF INDUSTRY DIVERSITY IN CLIENT PORTFOLIOS

BY

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ABSTRACT

This study focuses on the auditor industry specialization for U.S. audit partners. I examine the relationship between such auditor industry expertise and earning quality by incorporating industry diversity in client portfolios to better understand the relevant factor that drives industry specialization development for auditors. The empirical results indicate that industry-specialist partners can constrain earnings management by reducing discretional accruals due to their industry-specific knowledge. In addition, industry diversity in client portfolios can inhibit earnings management due to knowledge leverage across client industries. However, industry diversification has the moderating effect due to its negative effect on earnings quality only for industry-specialist auditors who highly rely on audit experiences from client industries to develop their personal industry expertise. This study contributes to the auditor industry specialization literature several ways. First, the audit partner effect for industry specialization in U.S. compliments the existing at the audit office and audit firm levels. Second, such industry expertise is driven by industry diversification in client portfolios of auditors. Lastly, this study provides the practical contribution for audit partner assignment practices in audit firms by considering the characteristics of client industries in partners' portfolios.

Keywords: Industry specialization, Industry expertise, Audit partner, Audit quality, Earnings quality

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CHAPTER 1
INTRODUCTION

1.1 Auditor Industry Specialization

Audit quality is a complicated notion that this is difficult to have a single universal definition as different parties, such as auditors, managers, shareholders, investors, capital providers, and regulators, may perceive this term from various perspectives (Francis 2011; DeFond and Zhang 2014; IAASB 2014). Thus, we should view audit quality as a multi-dimensional construct that incorporates several components contributing to a high-quality audit service (W. R. Knechel, et al. 2013). One of the important determinants of audit quality is knowledge and expertise of auditors. This factor is largely recognized in many well-acceptable definitions of audit quality that portray the role of auditors in detecting financial misstatements[1], whereas an auditor's ability to discover accounting errors directly relates to auditor competence and expertise (Bonner and Lewis 1990; Libby and Tan 1994).

Additionally, some theoretical frameworks of audit quality emphasize auditor expertise as an important input for audit quality. This auditor expertise includes auditor's skills and personal qualifications (FRC 2008), auditor expertise as a characteristic of audit partners or audit firms (Francis 2011), domain-specific knowledge in audit tasks, client firms and client industries (W. R. Knechel, et al. 2013), and auditor expertise to supply a client demand of audit services (DeFond and Zhang 2014). Taken together, auditor expertise plays an important role in determining the quality of audit outputs.

In the auditor industry expertise domain, familiarity with client industries contributes to auditor expertise from the accumulation of industry-specific knowledge of operations and related accounting practices when auditors perform audits to their

[1] DeAngelo (1981) provides the seminal definition of audit quality as "the market-assessed joint probability that a given auditor will both discover a breach in the client's accounting system and report the breach". Most subsequent studies define audit quality based on the DeAngelo (1981)'s definition with a dual nature of detecting and reporting misstatements and an inclusion of auditor competency as one of the important drivers for detecting misstatements (e.g. Titman and Trueman 1986).

clients (W. R. Knechel, et al. 2013). Craswell, Francis and Taylor (1995) develop the agency-based theoretical framework to illustrate the role of industry in a demand and supply of audits. Subsequent scholars have considerably examined the association between auditor industry expertise and audit quality, but extant empirical findings are still inconclusive. A large body of the literature suggests that specialist auditors provide higher audit quality than non-specialist auditors do. For example, companies audited by industry specialists have lower discretionary accruals (Balsam, Krishnan and Yang 2003; Krishnan 2003; Reichelt and Wang 2010), a higher possibility of going-concern audit opinions (Lim and Tan 2008), the superior quality of corporate disclosure (Dunn and Mayhew 2004) and a shorter audit report lag (Habib and Bhuiyan 2011). On the other hand, few studies do not observe the impact of industry specialization on audit quality as such effect is sensitive to research methodologies (Minutti-Meza 2013) or countries (Garcia-Blandon and Argiles-Bosch 2018).

1.2 Research Gaps in the Auditor Industry Specialization Literature

The existing auditor industry specialization literature has two major limitations. First, researchers often use a national audit firm or a local audit office as the unit of analysis. This firm- or office-level analysis heavily relies on the presumption that the quality of audit services is uniform across all auditors in each audit firm or office. Unsurprisingly, this argument is likely to be irrational because audit engagements are managed by individual audit partners (Chi and Chin 2011; Lennox and Wu 2018).

Second, some researchers assume that all industry-specialist auditors are identical. This assumption is also questionable because each auditor may experience the different industry expertise development processes (Cahan, Jeter and Naiker 2011). In terms of a research design, the most popular approach to determine specialist auditors heavily relies on a within-industry market share (Audousset-Coulier, Jeny and Jiang 2016). Under this approach, an auditor who has the highest market share in an industry is considered to be a specialist in that industry. However, the accumulation of market shares is not a satisfactory condition for identifying industry specialists because this approach does not properly reflect how auditors gain industry expertise (Minutti-Meza

2013) or erroneously includes some irrelevant factors, including a sudden increase in a market share from a merger and acquisition (M&A) between two clients in the same industry (Gaver and Utke 2019).

1.3 Research Motivations

This study is motivated by two trends in existing research to mitigate the two limitations above. These trends are the analysis at the audit partner level and the investigation of expertise drivers that demonstrate how auditors develop industry specialization.

1.3.1 Industry Expertise at the Audit Partner Level

First, there is an increasing number of the archival audit literature using individual audit partner data (Lennox and Wu 2018). One important reason for this boom is the availability of engagement partner data due to the changes in audit regulations in the U.S. (Sarbanes-Oxley Act (SOX) 2002) and other regions after the Enron and WorldCom scandals (DeFond and Francis 2005). This study follows this trend by analyzing industry expertise of U.S. audit partners. In the U.S., the Public Company Accounting Oversight Board (PCAOB) issued the Rule 3211 to mandate the disclosure of audit partner information for U.S. public companies since Februrary 2017 (PCAOB 2015).

A scrutiny at the partner level is consistent with the real audit practice since audit judgment is finally made by audit partners, neither by audit firms nor by audit city offices. The partner-level analysis also suggests the difference in audit outcomes across partners as individual characteristics of auditors have a massive effect on audit quality (Nelson and Tan 2005).

1.3.2 Industry Expertise Drivers

My second motivation is driven from a call for incorporating expertise drivers in the measurement of industry specialists. As discussed in the previous section, the popular one-dimensional identification approach that focuses on industry market shares has some drawbacks because the market share alone does not demonstrate whether an industry leader have a sufficient grasp for being an industry specialist and how auditors evolve industry expertise. Therefore, some researchers supplement their analysis by considering underlying expertise drivers that portray how auditors develop industry specialization. As auditors have different industry experiences from their clients (Libby and Luft 1993; Libby and Tan 1994), the discrepancy in individual expertise development processes could induce the dissimilarity in the quality of audit outcomes among industry specialists and better capture the auditor industry specialization construct (Gaver and Utke 2019).

The existing literature unveils that the impact of auditor industry specialization depends some industry expertise drivers, including auditor strategies to obtain high market shares through product differentiation or low-cost strategies (Mayhew and Wilkins 2003; Cahan, Jeter and Naiker 2011) or on how long an auditor has been a specialist (Gaver and Utke 2019). Recently, scholars more directly examine expertise drivers from client industries in auditor's portfolios. Some examples are industry operational homogeneity (Bills, Jeter and Stein 2015; Cairney and Stewart 2015; Stewart and Cairney 2019) and industry diversification (Asthana 2017; Beardsley, Goldman and Omer 2020).

1.4 Research Objectives

This study has three research questions (RQs) or research objectives. The first research question (RQ1) is to investigate whether audit quality, measured by industry specialization of audit partners, relates to earnings quality, proxied by discretionary accruals. Basically, the monitoring role of audit functions in constraining earnings manipulation profoundly relies on the quality of audits (Becker, et al. 1998). As auditor industry expertise is one of the input-based indicators of audit quality, partner-level industry specialization should magnify audit quality by enhancing an auditor's capability to curb earnings management due to his or her deep understanding in unique accounting practices in an industry (DeFond and Zhang 2014).

The second research question (RQ2) is to further examine whether industry diversity in client portfolios of audit partners associates with earnings quality. Industry diversity in partner's portfolios is another important driver for industry expertise development because auditor expertise is determined by experiences from an audit of clients in auditor's portfolios (Bonner and Lewis 1990; Libby and Luft 1993; Libby and Tan 1994). So, the dissimilarity in industry diversification in auditor's portfolios should differently influence audit quality.

The last research question (RQ3) is to explore whether the association between industry specialization of audit partners and earnings quality depends on industry diversity in their client portfolios[2]. This question is grounded on the possible difference within a group of industry specialists due to various individual factors for expertise development. Because each auditor may experience different industry expertise development processes, the magnitude of industry expertise among industry specialists should differ, resulting in the difference in audit quality from these specialist auditors. In other words, expertise drivers are likely to moderate the influence of auditor industry specialization on earning quality.

Note that RQ2 and RQ3 are quite related as they examine the effect of industry diversity in client portfolios on earnings quality (proxied by discretionary accruals). But RQ2 examines the direct effect of industry diversity on earning quality (industry diversity is another independent variable on discretionary accruals), while RQ3 focuses a group of industry specialist auditors and investigates the indirect effect of industry diversity through the relation between industry expertise and earnings quality (industry diversity is a moderating variable on the relation between industry specialization and discretionary accruals that is examined in RQ1).

1.5 Research Contributions

In line with the above three research questions or research objectives, this study will contribute to the auditor industry specialization literature in three important ways. First, this is the first study that examines industry expertise of U.S. audit partners. Second, this study further examines the role of industry diversity in client portfolios of partners in developing industry expertise. This factor suggests a deviation in audit quality among specialist auditors and, thus, can be a moderator in the relationship

[2] The association between industry specialization of audit partners and earnings quality is examined in the first research question (RQ1).

between partner-level industry specialization and earnings quality. Lastly, a better understanding in industry diversification in client portfolios of audit partners is useful to audit firms in managing client portfolios of audit partners or in assigning engagement partners to clients. The remaining of this section will discuss these contributions in more details.

1.5.1 Partner-level industry specialization in the U.S.

Extant research of industry expertise in the U.S. generally employs an audit firm (e.g., Balsam, Krishnan and Yang 2003; Krishnan 2003; Dunn and Mayhew 2004; Carcello and Nagy 2004; Casterella, et al. 2004; Huang, et al. 2007; Gul, Fung and Jaggi 2009; Lim and Tan 2008; Cahan, Jeter and Naiker 2011; Gaver and Utke 2019) or an audit office (e.g., Francis, Reichelt and Wang 2005; Reichelt and Wang 2010; Fung, Gul and Krishnan 2012; Numan and Willekens 2012; Minutti-Meza 2013) as the unit of analysis. There is no empirical study of partner-level industry expertise in the U.S. setting due to the lack of public information for individual audit partners, although audit partners significantly influence audit quality as they hold an utmost responsibility of audits (Chi and Chin 2011).

An investigation of the role of U.S. audit partners in audit quality is important because, while there are empirical tests of partner fixed effects in China (Gul, Wu and Yang 2013) and the U.K. (Cameran, Campa and Francis 2016), the effect of partners on audit works may be not observable in the U.S. context. This is because U.S. partners are highly subjected to several firm-level quality control mechanisms[3], stringent external inspections by the PCAOB and the Securities Exchange Commission (SEC) (Carcello, Hollingsworth and Mastrolia 2011), and a high litigation risk from a rigorous law enforcement (La Porta, et al. 2000). This unique institutional and legal environment in the U.S. possibly limits the influence of individual audit partners on audit engagements (W. R. Knechel, et al. 2013). Thus, we need an archival study to confirm whether the effect of U.S. partners on earnings quality exists.

Fortunately, the PCAOB Rule 3211 offers the great opportunity to conduct archival research using U.S. partner data. Researchers can now extend any

[3] Some examples are independence monitoring, partner rotation and a peer review (Jeppesen 2007).

research domain to an analysis at the partner level. As individual attributes of auditors highly affect audit quality (Nelson and Tan 2005), the direct examination of partner characteristics, such as industry expertise in this study, could enhance our understanding in audit quality in terms of audit inputs from audit partners (Francis 2011).

1.5.2 An Industry Expertise Driver: Industry diversity in client portfolios

The second contribution is that this study extends the literature by exploring industry expertise drivers. The analysis of expertise drivers typically provides better understanding in determinants and consequences of industry specialization from both conceptual and empirical perspectives. Conceptually, these factors suggest the variation of audit quality within specialist auditors because each auditor may differently experience a process of industry expertise development. Empirically, the expertise drivers complement research approaches for determining industry-specialist auditors to make sure that they have adequate industry knowledge. These factors probably explain some mixed findings in prior papers as they may moderate the effect of industry specialization.

In this paper, I examine one industry expertise driver, namely industry diversity in client portfolios of audit partners, for the extent to which such industry diversification directly influences earnings quality (RQ2) or indirectly moderates the relationship between partner-level industry specialization and earnings quality (RQ3). While some extant U.S. studies examine industry diversity at the audit office level (Asthana 2017; Beardsley, Goldman and Omer 2020), such industry diversity is never investigated at the partner level. In line with a recent call for the partner-level analysis discussed above, the evaluation of expertise drivers at the partner level should help us to better understand the nature of industry expertise of audit partners by providing direct insights of how individual auditors develop their industry expertise.

1.5.3 Audit Partner Assignment

In terms of practical contribution, a better understanding in industry diversification in partner's client portfolios is beneficial to auditor assignment practices for building client-auditor alignment. Specifically, industry concentration, which is one of the characteristics of client portfolios, demonstrates both demand- and supply-side factors for audit partner selection and assignment processes (Lee, Nagy and Zimmerman 2019). For the demand side, the management or board of directors appear to prefer engagement partners with some certain characteristics in audit partner selection. These characteristics include the auditor experience or reputation in certain industries. On the other hand, for the supply side, audit firms can consider this client preference or industry concentration in managing client portfolios of audit partners or assigning engagement partners to clients (Chen, et al. 2016). In sum, the proper match between client preference and auditor competency is likely to improve audit quality (Wu, et al. 2023).

CHAPTER 2
REVIEW OF LITERATURE

This study aims to examine auditor industry expertise at an individual U.S. audit partner level. Most of the extant archival literature on audit partners employ partner data from Asian countries, such as China and Taiwan, where engagement partner names have been publicized for a long time. During the past decade, there is a change in laws and regulations requiring the disclosure of partner names in many territories, including the European Union (EU)[4] countries, the United Kingdom (U.K.)[5], and the United States of America (U.S.). This trend offers the great research opportunity for archival research on audit partners. This chapter begins with a brief description of the new U.S. rule mandating the disclosure of audit partner names and the unique U.S. audit environment that may limit the role of U.S. audit partners.

2.1 Audit Partner Disclosure Requirement in the U.S.

In the U.S., auditors are required to disclose only the name of their audit firms, not the name of audit partners, in audit reports. However, on December 15, 2015, the Public Company Accounting Oversight Board (PCAOB) adopted the final rule (Rule 3211 "Auditor Reporting Certain Audit Participants"), which was later approved by the Securities and Exchange Commission (SEC) on May 9, 2016[6].

This rule compels the disclosure of engagement partners name for audit reports issued on or after January 31, 2017 in the new filing document called 'Form AP' (PCAOB 2015; SEC 2016). Note that audit partners reveal their names only in the Form AP. But, in audit reports, there is still the name of audit firms as normal.

The PCAOB claims that the disclosure of partner identities should heighten audit quality in the U.S. through two channels **Invalid source specified.**. First, it

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[4] Article 28 of the Eighth Company Law Directive of EU (effective since 2006) (European Parliament and the Council of the European Union 2006)

[5] The U.K. Companies Act of 2006 (effective since April 2009)

[6] The regulatory demand to disclose audit partner names in the U.S. was originated in 2009 when the PCAOB issued the concept release to solicit initial opinions of partner name disclosure from different parties. Please see Cunningham et al. (2019) for a detailed background of the standard-setting process for the PCAOB Rule 3211.

directly enhances the partner's sense of accountability for personal responsility (DeZoort, Harrison and Taylorc 2006) or reputation concerns (Basu and Shekhar 2018) because stakeholders can know who signs audit reports (PCAOB 2015). So, auditors is likely to enhance their professional due cares and efforts to avoid audit failures that normally have severe negative consequences on their individual reputation (King, Davis and Mintchik 2012). Second, the partner identification also improves the transparency of audits about who is responsible for performing the audit. For example, the U.S. Council of Institutional Investors argue that institutional investors can better evaluate audit quality at the individual level rather than the audit office level (CII 2009).

Not unexpectedly, many audit firms oppose to the PCAOB Rule by arguing that disclosing partner names may not have the expected benefits in the U.S. audit market. Their arguments are that U.S. audit partners are highly subjected to both internal firm-level quality control mechanisms, including independence monitoring, partner rotation, and engagement quality control review (EQCR), and rigorous external inspections by the PCAOB and the SEC (Jeppesen 2007).

Interestingly, the distinctive strong regulatory environment in the U.S. audit market is highly possible to restrict an influence of individual auditors on audit outcomes (W. R. Knechel, et al. 2013). For example, the PCAOB performs an independent inspection for auditors of U.S. public companies to uncover any deficiencies in audit works that signify poor audit quality. This PCAOB inspection supplements the traditional self-regulation quality control mechanisms within audit firms (e.g., internal peer review) that often lack independence because audit firms select their own reviewers (Lennox and Pittman 2010; M. L. DeFond 2013; Gunny and Zhang 2013).

Therefore, the effect of U.S. audit partner characteristics on audit quality seems to be questionable and may be unobservable as compared to other countries that have less strict control environments. The unique nature in the U.S. setting strongly emphasizes the importance of U.S. partner-level analysis to find out whether inputs from individual audit partners, who are ultimately responsible for an audit, influence quality of audit outcomes.

2.2 Audit Quality: Auditor industry expertise

Although the quality of audit works has been an interest of many parties, including audit professions, investors and regulatory bodies, for several decades, there is no universal definition for audit quality as people may perceive this term in different viewpoints (Francis 2011; W. R. Knechel, et al. 2013; DeFond and Zhang 2014).

One of the seminal definitions of audit quality is given by DeAngelo (1981) who defines audit quality as the market-assessed joint probability that auditors are able to detect and report a material misstatement. This definition requires auditors to be both competent (to be able to discover misstatements) and independent (to report detected misstatements) to provide a high level of audit quality. Another stream of the definition of audit quality focus on an accuracy of accounting information disclosed in financial statements (Titman and Trueman 1986). Regulatory agencies often concentrate on the degree to which auditors comply with generally accepted auditing standards (GAAS) (GAO 2003). In overall, the DeAngelo (1981)'s definition provides a binary foundation for other definitions that directly or indirectly include auditor competence and independence as important factors for constituting a high degree of audit quality.

The above definitions underscore the multi-dimensional nature of the audit quality construct that consists of several components contributing to a high-quality audit service (W. R. Knechel, et al. 2013). One of the important determinants of audit quality is knowledge and expertise of auditors as the auditor's ability to discover accounting errors directly relates to auditor competency or expertise (Bonner and Lewis 1990; Libby and Tan 1994).

Furthermore, some well-known theoretical frameworks of audit quality emphasize auditor expertise as an important input indicator for audit quality. For example, the U.K.'s Financial Reporting Council include auditor's skills and personal qualifications as one of the common drivers of audit quality (FRC 2008). Moreover, W. R. Knechel, et al. (2013) categorize audit quality indicators into four categories: input, process, output and context. As this study is the partner-level analysis, I focus on the audit input category because it is primarily reflected in the individual characteristics of audit professionals and because the quality of audit inputs significantly influences other three categories and, thus, overall audit quality (W. R. Knechel, et al. 2013). More precisely, auditor attributes, including knowledge and expertise, have a direct impact on audit quality because domain-specific knowledge in audit tasks, clients and industries improves auditor judgment (Bonner 1990).

In line with the audit quality framework by DeFond and Zhang (2014), audit quality is determined by both a client demand and an auditor supply since the authors view an audit as the economic goods. For the demand side, audit quality is needed from client incentives to reduce the agency problem between the owners and managers of a firm and driven by client competencies to support this demand by employing audit committee and internal audit functions. For the supply side, audit quality is affected by auditor incentives to provide high-quality audits and by auditor competencies to meet the client demand of an audit. While auditor incentives are determined by litigation concerns from regulatory agencies and by reputation concerns from auditors themselves, auditor competencies are reflected in the knowledge and expertise of auditors. In this study, I focus on the supply side of audit quality because I am interested in examining consequences of auditor industry expertise, which is one of the aspects of audit quality (DeFond and Zhang 2014), on finanical reporting quality at the individual partner level.

Taken together, auditor expertise plays an important role in determining the quality of audit outputs, such as financial statements. The auditing literature presents two forms of expertise that can influence audit quality: industry-specific and task-specific expertise (Moroney and Carey 2011; McGuire, Omer and Wang 2012). This paper concentrates on only industry expertise because task-specific expertise involves some specific accounts, such as income tax (Goldman, Harris and Omer 2022). The task-specific expertise research normally proxies audit quality based on ex-post measures of audit failures in related accounts (Dechow, Ge and Schrand 2010). However, as U.S. audit partner names have been disclosed since 2017, the number of financial restatements in a particular account is too limited for archival research. Thus, I leave task-specific expertise for a future study.

2.3 Audit Industry Expertise: Three Levels of Analysis

As this study focuses on the analysis at the partner level, this section provides the development of units of analysis in the audit industry expertise literature for demonstrating the importance of partner-level research. These three hierarchical units include a national audit firm, a local audit office, and an individual audit partner.

2.3.1 Audit Firm Level

Early auditor industry expertise research generally uses a whole national audit firm as the unit of analysis by assuming that audit partners provide a similar level of quality across all engagements within the same audit firm. This assumption heavily relies on standardized firm-wide audit methodologies and practices, such as quality control review and training programs, in each audit firm (Simunic & Stein 1987). Researchers find that, at the national level, industry-specialist auditors provide higher audit quality, relative to non-specialist auditors, as evidenced by lower abnormal accruals (Balsam, Krishnan and Yang 2003; Krishnan 2003), larger possibility of going-concern audit opinions (Lim and Tan 2008), greater disclosure quality (Dunn and Mayhew 2004), lower occurrence of fraudulent financial reporting (Carcello and Nagy 2004), and better compliance with auditing standards (O'Keefe, King and Gaver 1994).

Not surprisingly, such assumption has a substantial weakness because standardized policies from national audit firms are difficult to equally impact all engagements as audit works are managed by audit partners at local audit offices.

2.3.2 Audit Office Level

Scholars have attempted to mitigate the above firm-level limitation and the unavailability of engagement partner names in many jurisdictions by analyzing at the audit office level, which is closer to the individual partner level, Basically, auditor industry expertise among local offices is possibly different in spite of similar standardized firm resources because these resources are investment in human capital for professional staffs at city offices.

The critical assumption for the local office study is that audit partners must share or transfer knowledge to other partners for maintaining the same level of audit quality in each office. Again, this presumption is not reasonable because it requires sophisticated knowledge management systems to allow uniform knowledges and skills across all partners within the same audit office (DeFond and Zhang 2014).

The empirical evidence from the office-level studies complements the firm-level studies by demonstrating that the effect of industry specialization depends on whether industry specialization is measured at the firm or office level. For example, Australian auditors who are industry specialists at both national and local office levels earn the highest audit fee premium (Ferguson and Stokes 2002; Ferguson, Francis and Stokes 2003). In addition, some researchers directly examine the effect of industry expertise on audit quality and find that U.S. firms audited by industry specialists at both national and local office levels have the lowest abnormal accruals (Reichelt and Wang 2010).

2.3.3 Audit Partner Level

While the study at the audit firm or audit office level heavily relies on organizational behavior theories[7] to constrain equivalent quality across all engagements, the study at the partner level often employs individual characteristic and behavioral theories, which have been extensively utilized in judgment and decision-making (JDM) auditing research.

Nonetheless, the challenge of the partner-level analysis is a coherent theoretical foundation to conceptualize how industry expertise of audit partners can influence audit quality. I argue that the partner-level study should incorporate individual behavioral theories, as opposed to organizational behavior theories that are usually employed in the firm-level study (Vera-Munoz, Ho and Chow 2006), for two reasons. First, an individual framework is more consistent with a real audit process than an organizational framework since judgment in auditing is made by people (audit partners or other members in an engagement team), not by audit firms. Second, there is

[7] Some examples are strategic management (Asthana, Diversification by the audit offices in the US and its impact on audit quality 2017), resource allocation and knowledge sharing theories (Beardsley, Goldman and Omer 2020).

the difference in audit outputs across partners because audit quality is affected by individual auditor attributes (Knechel 2000; Nelson and Tan 2005).

Theoretically, according to a series of theoretical models that illustrate the determinants of auditor expertise (Bonner and Lewis 1990; Libby and Luft 1993; Libby and Tan 1994), auditor experience drives auditor knowledge, and auditor knowledge finally influences auditor expertise. The Bonner and Lewis (1990)'s model for the determinants of auditor expertise suggests that industry expertise of audit partners is an input-based measure of audit quality because auditors gather industry-specific knowledge of businesses and accounting practices to offer greater audit quality (Solomon, Shields and Whittington 1999).

Then, Libby and Luft (1993) and Libby and Tan (1994) strenghten the Bonner and Lewis (1990)'s model by focusing on the knowledge acquisition process. Libby and Luft (1993) hypothesize that auditor knowledge is determined by auditor experience and ability. Later, Libby and Tan (1994) conduct an experiment to test and confirm such hypothesis by showing the superior auditor performance in audit tasks for auditors who have higher expertise that is driven by their individual knowledge, problem-solving ability and experience.

More closely to this research, auditor knowledge is classified into general (e.g., accounting and auditing standards) and specific (e.g., industry-specific knowledge, understanding in financial derivatives) knowledge. Auditors can gain latter knowledge through experiences with certain clients or industries. Consequently, industry-specialist auditors are expected to provide higher audit quality because they accumulate knowledge of industry-specific businesses and accounting practices (Solomon, Shields and Whittington 1999).

The evidences from the behavioral literature highlight the benefits of auditor knowledge of client industries in audit risk assessment (Low 2004), in error detection (Owhoso, Messier and Lynch 2002) and in performing analytical procedures (Green 2008). Collectively, audit quality may depend on some characteristics of audit partners who are ultimately responsible for audits (Chi and Chin 2011).

Although audit partners play an important role in auditing, archival research at the partner level is limited because of the unavailability of engagement partner data in many jurisdictions. The following paragraphs summarize of archival findings in the auditor industry specialization literature from the U.S. and other countries.

2.3.3.1 Empirical Evidence in Non-U.S. Setting

The extant literature for the effect of industry specialization at the partner level on audit quality usually employ Asian and European markets where audit partner names has been publicly disclosed for decades. The empirical findings generally indicate that partner-level industry expertise has the positive impact on audit quality due to the extensive industry knowledge and experience. For example, there is the positive association between partner-level industry expertise and an audit fee, which is a harsh proxy of audit quality, in Sweden (Zerni 2012), Australia (Goodwin and Wu 2014), and Korea (Bae, Choi and Lee 2019). Other studies examine such effect on more-direct audit quality proxies. For example, in Taiwan, clients audited by industry specialist partners exhibit lower likelihood of restatements (Chin and Chi 2009), lower discretionary accruals and higher tendency to receive modified audit opinions (Chi and Chin 2011), and better disclosure quality (Lee, Lee and Wang 2017) than those audited by non-specialist partners. In China, industry expertise is negatively associated to discretionary accruals (Yuan, Cheng and Ye 2016). In addition, industry expertise is driven by partner-level expertise or a combination of firm-level and partner-level expertise, but not by firm-level expertise alone (Chin and Chi 2009; Chi and Chin 2011; Lee, Lee and Wang 2017). But some researchers fail to find the significant relationship between industry specialists and audit quality in some countries, such as Spain (Garcia-Blandon and Argiles-Bosch 2018).

The above findings suggest that industry specialization could be a partner-level phenomenon and underscore the importance of the analysis of industry expertise at the partner level in different countries where partner data is feasible (DeFond and Francis 2005; Bedard 2012; Gul, Wu and Yang 2013).

2.3.3.2 Generalization from non-U.S. to U.S. Setting

The observed impact of partner-level auditor industry specialization in the non-U.S. settings may be not generalized to the U.S. due to the following three reasons. First, there is no an empirical test of partner fixed effects in the U.S. because of the unavailability of U.S. audit partner data in the past, while there are empirical studies confirming that individual audit partners matter for audit quality in China (Gul, Wu and Yang 2013) and the U.K. (Cameran, Campa and Francis 2016),

Second, the U.S. institutional and legal environments are more vigorous than those of other jurisdictions. U.S. partners are greatly contingent on firm-level quality control systems, including independence monitoring, partner rotation and a peer review, and external regulatory inspection programs by the PCAOB and the SEC (Jeppesen 2007; Carcello, Hollingsworth and Mastrolia 2011). Moreover, a litigation risk in the U.S. is more severe than other countries due to a stringent legal system and a class action lawsuit[8] (La Porta, et al. 2000; Seetharaman, Gul and Lynn 2002). Researchers should consider the difference in legal environments when examining the role of auditor industry specialists in a cross-country analysis as the effect of audit industry specialists may be constrained by country-level litigious factors (Carcello and Li 2013; Blay, et al. 2014). For example, the pioneer work at an international setting by Kwon, Lim and Tan (2007) indicates that the association between industry expertise and earnings quality depends on legal environments and investor protection. Collectively, the unique institutional and legal environments in the U.S. possibly limits the influence of individual audit partners on audit engagements (W. R. Knechel, et al. 2013). Thus, we need an archival study to confirm whether the effect of audit partners on audit quality exists in the U.S. setting.

Finally, the location of partner disclosure in the U.S. is distinct from other countries. While the partner identification rules in other countries require partners to directly sign their names in audit reports, U.S. partners reveal their names in separate fillings named Form AP. Some investors argue that separate disclosure in Form AP may not provide the same sense of accountability as when partners sign their name in audit reports (Cunningham, et al. 2019).

2.3.3.3 Empirical Evidence in U.S. Setting

Because there was no direct public data source of engagement partners in the U.S. before 2017, some researchers employ other indirect sources, such as SEC comment letters and related correspondences[9], for examining audit partner

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[8] The class action lawsuit is prevalent in the U.S. legal system. It enhances the level of investor protection by facilitating the prosecution against the group of management or auditors.

[9] SEC comment letters sometimes include the name of engagement partners.

rotation (Laurion, Lawrence and Ryans 2016) and partner characteristics (Lee, Nagy and Zimmerman 2019). However, these indirect data sources have generalization and self-section problems because of a small sample size that limits to firms that have SEC comment letters. These firms may have the low quality of earnings as they are suspected to the SEC monitoring process.

Fortunately, the PCAOB Rule 3211 offers the great opportunity to conduct archival research using U.S. partner data. Currently, researchers can extend any research domain to an analysis at the partner level. As individual attributes of auditors highly affect audit quality (Nelson and Tan 2005), the direct examination of partner characteristics, such as industry expertise, could enhance our understanding in audit quality in terms of audit inputs from engagement partners (Francis 2011).

2.4 Relationship between Auditor Industry Expertise and Earnings Quality

Figure 2.1 illustrates a conceptual framework for the relationships among three variables of interest in this study. These variables consist of (1) partner-level industry specialization, (2) discretionary accruals (a proxy of earnings quality that signifies the degree of earnings management[10]), and (3) industry diversity in client portfolios of audit partners.

[Insert Figure 2.1 here]

As my first research question (RQ1) examines the relation between partner-level industry specialization and earning quality (H1 in Figure 2.1), I adopt the DeFond and Zhang (2014)'s audit quality framework that illustrates how the quality of audits correlates to the quality of financial reporting. The authors propose that financial reporting quality is a function of audit quality, firm financial reporting system quality and firm innate characteristics. By conditional on firm financial reporting systems and firm innate charateristics, audit quality is positively related to financial reporting quality

[10] I will discuss the rationale to use discretionary accruals to proxy earnings quality in Section 3.3 (Earnings quality model).

by offering greater assurance that financial statements faithfully reflect firm underlying economics (DeFond and Zhang 2014).

The next question is how audit quality can be measured by auditor industry expertise. As discussed earlier, the determinants of auditor expertise models by Bonner and Lewis (1990), Libby and Luft (1993) and Libby and Tan (1994) conclusively suggest that industry expertise of audit partners can be used as an input-based measure of audit quality. Hence, I measure audit quality by using partner-level industry specialization and examine its relation to earnings quality.

Although the association between industry specialization and earnings quality may be unobservable for U.S. audit partners due to the rigorous quality control, and institutional and legal environments in the U.S., as mentioned previously, I expect that, consistent with a sheer volume of industry expertise research for audit firms and audit offices, the role of auditor industry expertise in improving earnings quality is still valid for U.S. audit partners because audit partners are ultimately responsible for an audit, and their judgment and attributes should be more directly influence the quality of audit than external surveillance from other parties (Nelson and Tan 2005). Industry-specialist partners should constrain earnings management by reducing discretionary accruals. Therefore, I formulate the first hypothesis (H1) to test the negative relationship between partner-level industry expertise and discretionary accruals as follows.

Hypothesis 1: Industry specialization of audit partners is *negatively* related to discretionary accruals.

This hypothesis (H1) addresses my first research question (RQ1) that investigates whether audit quality, measured by audit partner industry specialization, is related to earnings quality, proxied by discretionary accruals, as depicted in the H1 relationship in the above conceptual framework (Figure 2.1).

Next, I further examines the effect industry diversity in client portfolios on earnings quality. In the following sections, I will discuss the relevant literature related to auditors experience from industry diversity in their client portfolios as a driver for industry expertise development. The understanding in industry expertise drivers is useful in formulating the second and third hypotheses that test whether the direct relation between industry diversity and earnings quality exists (RQ2) and whether industry diversity indirectly moderates the relation between partner-level industry expertise and earnings quality (RQ3), respectively (as portrayed in the H2 and H3 associations in Figure 2.1).

2.5 Difference among Industry Specialists: How do auditors develop industry expertise?

The prevalent assumption of most auditor industry specialization literature is that all industry specialists are identical. Many researchers scrutinize the effect of industry specialists on their variables of interest by using the dummy variable of specialist auditors and comparing such effect between specialists (dummy = 1) and non-specialist auditors (dummy = 0).

In recent years, some scholars challenge this assumption by proposing that all industry-specialist auditors are not similar because each auditor may differently experience the process of industry expertise development (Cahan, Jeter and Naiker 2011). By treating same industry expertise across all industry specialists, the power of empirical tests is low because researchers may ignore some drivers for industry expertise development (Cahan, Jeter and Naiker 2011).

2.5.1 Industry Expertise Drivers

The ignorance of expertise drivers in the literature is heavily grounded on the limitation in the two traditional empirical approaches for identifying industry specialists[11]. The first one is the ‘market share approach’ that focuses on client industries. For a particular industry, an auditor who is the market leader (e.g., the highest market share) is classified as a specialist in that industry. The second approach is called the ‘portfolio share approach’. It focuses on client portfolios and determines an auditor as a specialist in the largest industry in portfolios. However, both methods do not reflect ‘how’ auditors become industry specialists. Minutti-Meza (2013) and Gaver and Utke (2019) strongly underscore that the accumulation of market or portfolio

[11] I will discuss the industry specialization identification approach in more details in Chapter 3.

share is not a sufficient condition for industry expertise classification. Similarly, DeFond and Zhang (2014) suggest that auditing a large proportion of clients in an industry market or an auditor portfolio alone may not allow auditors to gain greater industry expertise. For example, if auditors become the market leader for the first year, expertise is not archived immediately because they need time to develop industry-specific knowledges and skills (Gaver and Utke 2019). Another example is the sudden increase in a market share form some exogenous events (e.g., merger and acquisition (M&A) in the same industry) that unrelated to expertise improvement.

Since there is the difference in the underlying process of how auditors develop industry expertise, researchers should consider these expertise drivers when investigating the effect of industry specialists (Aobdia, Siddiqui and Vinelli 2021). In terms of research designs, Gaver and Utke (2019) suggest that the empirical measure of specialization should not solely rely on the market or portfolio share alone but incorporate the factors describing how auditors progress their expertise. The examination of these expertise drivers may help us to better understand the nature of auditor industry specialization and to explain the inconclusive findings in prior research as there might be a discrepancy within specialist auditors[12].

In my opinion, a recent call for a study within specialist auditors is warrant but challenging because we need a comprehensive understanding of the nature and characteristic of industry specialists to identify relevant factors for industry expertise development.

2.5.2 The Moderating Role of Industry Expertise Drivers on the Effect of Industry Expertise

As each specialist auditor differently experience the process of expertise development, the degree of industry expertise among industry specialists should be different. Thus, expertise drivers should moderate the influence of industry specialization on audit outputs. Recent papers advance the industry specialization literature by including industry expertise drivers as a moderating variable in an analysis. These drivers can be classified into the following two groups.

[12] The literature normally compares audit outcomes between the groups of specialist and non-specialist auditors.

2.5.2.1 Client-related Drivers

Industry expertise is probably not similar across client firms, even they are in the same industry, because client firms are distinct in several dimensions, including characteristics, strategies, or operations. For instance, Bills, Jeter and Stein (2015) study the homogeneity in client operations and find that auditors can lower audit fee to clients in industries with homogenous operations due to economies of scales and the ease of expertise development across several clients with similar operational patterns. They also show that this audit fee reduction does not sacrifice audit quality. Moreover, Yuan, Cheng and Ye (2016) observe that the effect of Chinese partner-level specialization is more pronounced when client strategies deviate from an industry norm because industry specialists are familiar with a wide range of business and accounting practices.

2.5.2.2 Auditor-related Drivers

Industry expertise may be not equivalent across auditors because of the difference in characteristics or preferences of auditors. Firstly, Cahan, Jeter and Naiker (2011) argue that specialist auditors can pursue different competitive strategies, such as product differentiation and cost minimization (Porter 1985), to obtain a high market share in an industry. On the one hand, auditors may prefer a small proportion of large firms in an industry to become a market leader. They can differentiate from other specialist auditors to offer high quality audits and charge extra audit fees under the product differentiation strategy. On the other hand, auditors may attract a large proportion of relatively small firms in an industry by lowering audit fees. The latter group of auditors is likely to not exhibit superior audit quality because they focus on economies of scales rather than the quality of services under the cost minimization strategy.

Secondly, the distinct roles of audit partners can influence the effect of industry expertise (Chi and Chin 2011). In Taiwan, audit reports of public companies are signed by both lead (primary responsibility for the audit) and concurring (secondary level of review) partners. The authors find that high audit quality can be only observed in lead, not concurring, auditor specialists.

Thirdly, the recent paper by Gaver and Utke (2019) shows that the association between U.S. auditor industry specialization and audit quality, which is proxied by discretionary accruals and a book-tax difference, depends on specialist tenure (or how long auditors have been a specialist). Particularly, audit quality of auditors who recently become industry specialists is lower than that of auditors who have been specialists for a number of years. Furthermore, these first-year specialist auditors do not provide the different level of audit quality from non-specialist auditors. The authors estimate that the learning process for becoming specialists takes about two to three years.

Lastly, Beardsley, Goldman and Omer (2020) focus on the industry diversity in auditor's client portfolios. They hypothesize that specialist auditors who have concentrated portfolios from few industries (low industry diversity) easily develop their industry expertise than those who have diversified portfolios from many industries (high industry diversity). The empirical work supports their hypothesis.

In conclusion, both client-related and auditor-related drivers manifest the divergent nature and process of industry expertise development. As a result, there would be some difference across specialist auditors and, thus, audit outcomes (e.g., financial reporting quality) from these auditors. In addition, the study of expertise factors could help us to better understand the determinants and consequences of auditor industry specialization (Neal and Riley 2004). This study focuses on an auditor's client portfolio as one of the important sources of industry expertise due to auditor experience in a particular industry of his clients.

2.6 Industry Expertise Driver: Industry diversity in client portfolios

Because industry specialization closely relates to how auditors accumulate industry-specific knowledge whey they perform an audit to their clients, auditor experience in client industries highly contributes to the acquisition of industry knowledge. Industry-specific experience can be acquired through a duration that auditors service in an industry (Gaver and Utke 2019) or through the client industries. For the latter, client portfolios provide a good opportunity for auditors to gain understanding in client industries (Asthana 2017; Beardsley, Goldman and Omer 2020). However, the characteristic of auditor portfolios has not been widely examined in the literature.

2.6.1 Difference between Industry Diversity and Industry Expertise

We should understand that, while industry diversity and industry specialization are closely related, these two terms are dissimilar. On the one hand, industry specialization focuses on auditor specific knowledge and experiences in client industries (Asthana 2017). It is suitable for the study of either a client demand of auditors[13] or an auditor supply of excellent audit services (DeFond and Zhang 2014).

On the other hand, industry diversity refers to the spread of client industries in auditor's portfolios. For instance, given that an auditor has ten client firms, a diversified portfolio (high industry diversity) is composed of many industries (e.g., ten different industries). Whereas a concentrated portfolio (low industry diversity) consists of few industries (e.g., all ten firms are from the only one industry). Industry diversity is appropriate for a study of an auditor supply because clients do not generally know a whole auditor's client portfolio, while auditors do (DeFond and Zhang 2014).

In sum, the presence or absence of specialization does not necessarily imply the presence or absence of diversification (Asthana 2017). For example, industry-specialist auditors can have clients with high or low industry diversity depending on the divergence in client industries. Therefore, the study of industry diversity in client portfolios should enhance our understanding in how auditors evolve industry specialization.

2.6.2 Industry Diversity at the Audit Office Level

To the best of my knowledge, the existing U.S. literature on industry diversity is only conducted at the city office level. Researchers utilize industrial organization frameworks to examine whether industry diversity affects the auditor's ability to manage knowledge or resources within local offices to provide high audit quality.

For example, according to the strategic management theory, Asthana (2017) hypothesize that, if audit offices have clients from a wide range of industries, audit quality is detrimental because audit offices need to spread their resources across many industries. He simply measures industry diversity by the number of unique

[13] The auditor superior knowledge is one of the determinants of auditor choices.

industries in client portfolios of audit offices. The results support his hypothesis based on the five proxies of audit quality. Similarly, the diverse audit office's client portfolio also lessens audit quality because of the limited opportunity to transfer knowledge among client industry bases (Beardsley, Goldman and Omer 2020).

2.6.3 Industry Diversity at the Audit Partner Level

My study extends the recent papers by Asthana (2017) and Beardsley, Goldman and Omer (2020) that examine the industry diversity of audit city office's portfolios. My second and third research questions further examines whether industry diversification in client portfolios of audit partners directly influences earnings quality (RQ2) or whether it indirectly moderates the relationship between industry expertise and earnings quality (RQ3). I argue that industry diversity in partner's portfolios is another important driver for industry expertise development because auditor expertise is determined by auditor knowledge and experience (Bonner and Lewis 1990; Libby and Luft 1993; Libby and Tan 1994). As auditors gain experiences through an audit of clients in their portfolios, the difference in industry diversification in auditor's portfolios should differently influence industry expertise development for each auditor.

The next issue is to anticipate how such industry diversity influences earnings quality. I draw the strategy management literature to predict the direction of such industry diversity effect on earnings quality in the formulation of second hypothesis. Basically, diversification can have either positive or negative effect on output quality (Rumelt 1982; Palepu 1985; Geringer, Tallman and Olsen 2000; Asthana 2017), depending on the characteristics of diversification. On the one hand, if the diversification has a 'narrow' focus ('related' diversification), it offers the positive impact to performance due to knowledge leverage and knowledge spillover among connected constituencies (Rumelt 1982). On the other hand, if the diversification has a 'wide' focus ('unrelated' diversification), it is beneficial to the firm growth and profitability due to a diversified business risk and an enhanced business opportunity (von Nordenflycht 2011), but it may have a detrimental effect on performance due to the lack of specialized knowledge in a specific area (Rumelt 1982). In sum, the relationship between diversification and performance could be nonlinear (Lubatkin and Chatterjee 1994) and follows an inverted-U shape (Rumelt 1982).

By applying the concept of related and unrelated diversification to the audit setting, auditors can diversify horizontally by adding clients from new industries. I argue that, although auditors may have clients from several industries, such client industry diversity should be considered as 'related' diversification because there are several common audit methodologies for all engagements. The examples are bank and accounts receivable confirmation, and a physical count for inventories and tangible assets. Industry-specific knowledge is essential for some industry-specific accounts, including fair value accounting and loans receivable for a banking industry (Taylor 2000). In contrast, if auditors diversify vertically by providing non-audit services, such as tax consulting and internal audit, to existing clients. This vertical diversification is 'unrelated' diversification.

Recently, Hao, Liu and Xu (2018) utilize this theory to Chinese audit firms and find that clients with narrow diversification have higher audit quality (proxied by a propensity to detect misstatements) than those with wide diversification. Collectively, these findings indicate that there is a knowledge leverage effect among clients within the closely related industries, and that there is the difference in audit quality between narrow and wide diversification in auditor's client portfolios. Thus, as I use discretionary accruals as a proxy of earnings quality (to measure the degree of earnings management), I expect the negative association between industry diversity and discretionary accruals. This negative sign demonstrates the positive effect of industry diversity in partner's client portfolios in enhancing earnings quality by reducing discretionary accruals. I formulate the second hypothesis (H2) as follows.

Hypothesis 2: Industry diversity in client portfolios of audit partners is *negatively* related to discretionary accruals.

However, for industry-specialist auditors, industry diversity in their client portfolios is a driver for industry expertise development through an accumulated audit experience in their specialized industries. If specialist auditors have many clients from other industries that they are not specialized, this industry diversification is detrimental to auditor industry expertise. Therefore, I anticipate the adverse effect of industry diversity for a group of industry-expert auditors and develop the following third hypothesis (H3).

Hypothesis 3: Industry diversity in client portfolios of *industry-specialist* partners is *positively* related to discretionary accruals.

The third hypothesis (H3) represents a moderating effect of industry diversity on earnings quality for industry-specialist auditors (H1). Specifically, I expect a *negative* relationship between discretionary accruals and industry-specialist partners (H1) or industry diversity in partner's client portfolios (H2).

However, the *negative* association between industry specialization and discretionary accruals in H1 should change to be *positive* in H3 for industry diversity of industry-specialist partners (ISPDIV) as high industry diversification impairs industry expertise development.

Note that both hypotheses address my research questions to examine whether industry diversity in client portfolios of audit partners influences earnings quality as an independent variable (RQ2) or as a moderator to the association between audit partner industry specialization and earnings quality (RQ3), as illustrated as the H2 and H3 relations, respectively, in the conceptual framework in Figure 2.1.

CHAPTER 3
RESEARCH METHODOLOGY

One of the most critical debates for auditor industry specialization literature is the selection of research designs as there are several research designs for measuring industry specialization, and these design alternatives highly influence empirical findings. This chapter begins with the description of sample period, scope and selection process, and data sources. Then, I discuss the three important empirical issues for a proxy of industry specialization. These issues consist of a measurement approach, a measurement variable, and a classification criteria for measuring auditor industry expertise. Next, I review the proxies for earnings quality and discuss the earnings quality model used to estimate discretionary accruals, which is the dependent variable in this study. In section 3.4, I introduce the industry diversity measure developed by Beardsley, Goldman and Omer (2020) that demonstrates the diversification of client industries in audit partner's client portfolios. I adopt this measure to answer the second and third research questions that investigate industry diversity of client industries. Finally, the multivariate regression model used to test the three hypotheses is presented in section 3.5.

3.1 Sample and Data

3.1.1 Sample Period

The sample of this study is the U.S. public companies that have the fiscal years ended during 2016 – 2019 and that disclose engagement partner names through Form AP fillings. The beginning year of the sample period is 2016 because the PCAOB Rule 3211 has been effective since January 31, 2017. So, the earliest availability of U.S. partner name information consists of companies with the fiscal year ended in 2016 and submitted annual fillings to the SEC and Form AP to the PCAOB after January 31, 2017[14].

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[14] The SEC deadline for 10-K (annual reports) fillings depends on a company size. If a company is a large accelerated filler, accelerated filler or non-accelerated filler, the company has to filled Form 10-K within 60, 75 or 90 days, respectively, after the end of the fiscal year. Thus, the sample excludes

3.1.2 Sample Scope

This paper extends the auditor industry specialization literature by covering 'non-Big 4' audit firms. Although large audit firms (Big 4) tend to be industry specialists (DeFond and Zhang 2014), I would like to contain non-Big 4 firms in the sample because my study also aims to analyze how audit partners develop industry expertise. This paper would offer beneficial insights of the difference in industry expertise development of audit partners in between Big 4 and non-Big 4 firms. There are few papers examining industry specialization of non-Big N auditors. For example, DeFond, Francis and Wong (2000) study an audit fee premium for both Big 6 and non-Big 6 auditors in Hong Kong. They find that one large local audit firm, namely Kwan Wong Tan & Fong (KWTF), could be a market leader in the property industry and that KWTF does not earn any industry specialist premium for audit fees, contrasting to the Big N literature that usually observes a fee premium from industry specialization. This study highlights the importance of considering non-Big N auditors in the audit research to better understand the difference in audit quality between Big N and non-Big N auditors.

Nonetheless, the critical problem of including non-Big 4 firms is the 'self-selection bias' from auditor choices (Francis 2011). In the audit context, this bias refers to the problem that some companies are more likely to choose certain types of auditors because auditors are not randomly assigned to clients in the real world. This non-random matching between auditors and clients is likely to cause an inference problem that a statistical interpretation drawn from econometric techniques is biased toward the characteristics of sample firms. For example, in the earnings quality literature, large companies, which generally have superior accounting systems and governance mechanisms, tend to appoint auditors from large (Big N) audit firms (DeFond and Zhang 2014). Thus, high earnings quality of these companies may be not mainly due to auditor attributes but partially due to client characteristics (Gul, Fung and Jaggi 2009). Lawrence, Minutti-Meza and Zhang (2011) confirm the self-selection dilemma for discretionary accruals and suggest that this problem is difficult to control

some companies that have the end of the fiscal year during 2016 and complete the SEC fillings before January 31, 2017 because these companies have a year-end date in the early of 2016 (the deadline is due before January 31, 2017) or have a year-end date in the late 2016 but file the SEC fillings before the deadline. Most of the sample companies in 2016 have the fiscal year ended in December 2016.

when a clientele difference is large (for instance, there is an extreme dissimilarity between the largest client of Big 4 firms and the smallest client of non-Big 4 firms). Thus, most studies limit the sample to only Big-N auditors to constrain the similar attributes of sample companies within Big-N firms.

Fortunately, the self-selection bias can be mitigated by restricting the non-Big 4 sample to only the second-tier audit firms. This restriction helps us to reduce the difference among clients of these top audit firms and a severe confounding effect of audit firm sizes in earnings quality models (Boone, Khurana and Raman 2010; Eshleman and Guo 2014). I identify two non-Big 4 firms, namely 'Grant Thornton' and 'BDO Seidman', as the second-tier audit firms based on the following procedures. First, I rank all audit firms by the number of audit partners because this study focuses on the audit partner level. The four largest firms are Big 4 auditors (EY, Deloitte, PWC and KPMG) as expected. Then, I classify the fifth and sixth largest audit firms (Grant Thornton and BDO Seidman, respectively) as the second-tier audit firms. Further, I look at other audit firms and note that the number of audit partners of the seventh and eighth largest firms (RSM and Crowe) is clearly lower than that of Grant Thornton and BDO and is less than 100 partners per firm. The lower number of audit partners results in the substantially higher numbers of clients and engagements per partner. As these two numbers demonstrate the characteristics of audit partners' client portfolios, which are the key element in this study, I exclude the seventh and eighth largest auditors from the sample to reduce the dissimilarity within my sample data and to alleviate the self-selection problem as discussed previously. In sum, I identify only Grant Thornton and BDO Seidman as second-tier auditors. The inclusion of Grant Thornton and BDO as the second-tier audit firm is consistent with Boone, Khurana and Raman (2010) and Carson (2009)[15].

Another issue of the scope of sample is the client industries of sample firms. Contrary to prior research that mostly exclude financial and insurance companies (SIC code between 6000 and 6999) because of the unique nature of accruals and special regulations (Payne 2008; Reichelt and Wang 2010; Liu, et al. 2017; Gaver and Utke 2019), I include financial companies in my sample because the financial industry can

[15] Carson (2009) considers Big 4, as well as Grant Thornton and BDO, as the six global audit firm networks.

be one of the specialized industries for auditors. Furthermore, I can later partition the full sample into two sub-samples (financial and non-financial industries) for a supplementary analysis. However, as there are various forms of financial institutions, I exclude financial funds, including investment funds, mutual funds, and employee benefit plan funds, because these funds are substantially smaller than ordinary financial companies and have different audit report types as disclosed in Form AP.

3.1.3 Data Sources

All variables are obtained from two sources, including the Compustat database for financial information and the SIC industry classification and the AuditorSearch database in the PCAOB website for Form AP fillings and engagement partner name information. AuditorSearch is a public database of engagement partners for an audit of U.S. public companies. This database contains all Form AP fillings for U.S. public companies since February 2017 (the effective date of partner name disclosure under the PCAOB Rule 3211) and is updated daily.

All continuous variables are winsorized at 1% and 99% to lessen an outlier effect. This 1% winsorization is just an initial remedy for removing outlier observations. However, when I perform the descriptive statistics analysis, I note some variables, including the market value (MV) and absolute discretionary accruals (ADACC), still have extreme values after this 1% winsorization. Consequently, I further remove more observations with the MV or ADACC values higher than the 95th percentile[16]. Although I delete few observations with extreme MV and ADACC values, this additional data removal hugely improves the multivariate result[17].

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[16] I believe that the 95th percentile is appropriate from the distribution of these variables (average, 90th, 95th and 99th percentiles). I do not want the remove too many observations to preserve my low sample size.

[17] See more details of this additional data winsorization in the sample selection process for the MV variable (Section 3.1.4) and the multivariate analysis for the ADACC variable (Section 4.3).

3.1.4 Sample Selection

Table 3.1 summarizes the following sample selection process. I began with 31,849 firm-year observations in the AuditorSearch database. This initial sample set consists of all companies that have filled Form AP to the PCAOB since the PCAOB Rule 3211 was effective (for all audit reports issued after January 31, 2017).

[Insert Table 3.1 here]

Next, I removed 1,092 records for the observations for the fiscal years other than 2016, 2017 2018 and 2019. Note that 221 audit reports were issued after January 31, 2017 (auditors need to file Form AP to the PCAOB as the Rule 3211 has been effective), but these reports are for the audits for the fiscal year before 2016 (e.g., 2015, 2014). Additionally, the remaining items are recent filings for the audits for the fiscal year after 2019 (e.g., 2020, 2021).

Then, I deleted 15,100 observations for client firms audited by audit firms other than Top 6 audit firms. As discussed earlier, the scope of my sample is composed of Big-4 audit firms and the second tier U.S. audit firms (Grant Thornton and BDO Seidman).

Next, I eliminated 1,240 records in Form AP that do not contain necessary details for further analysis or are redundant withing the same firm in the same year (each firm should have only one filling in each year). First, there are 33 items that do not have ‘Central Index Key (CIK) number’ (CIK number is used to match financial data in Compustat). Second, I removed 812 items that have ‘dual-dated’ audit reports. If auditors issue dual-dated audit reports (two audit reports that have different audit report dates for the same firm in the same fiscal year), they need to file the separate Form AP for both audit reports. Thus, these dual-dated audit reports are duplicated for a company. I deleted a subsequent filling for dual-dated reports and keep an original filling in the sample. Third, I also deleted 395 items representing ‘an amendment to the previously filed Form AP’. If auditors realize that a previously submitted Form AP contains some incorrect information or omits required information, they can file a new (amended) Form AP. The amended Form AP must supply not only correct or additional information but also all information in the original Form AP. Thus, I need to delete both original and subsequent fillings and keep a latest filling for each company in each year that contain the most correct information.

Next, I exclude 4,879 firm-year observations, which are audited by audit partners who have only one public firm client per each year. Specifically, there are 1,159, 1,244, 1,216 and 1,260 fillings in Form AP that were audited by partners who have only one listed company client in 2016, 2017, 2018 and 2019, respectively. The reason to exclude these firms is that my study focuses on industry specialization of audit partners. Thus, audit partners with only one client would be considered as a specialist in an industry belonged to such client in their portfolio. However, they do not demonstrate any industry expertise because they provide audit services to only one public client in each year. Hence, I remove these observations, and I can study this data set separately later.

When matching data in Form AP to Compustat, I need to clean data by removing a total of 3,820 observations due to three data problems. First, I remove 1,568 records that lack Standard Industrial Classification (SIC) code in Compustats (SIC code is used to identify an industry of a company). Second, I exclude 3,816 records that do not have necessary variables in Compustat (total assets and total revenues) to compute an industry specialization proxy or that have missing data to compute variables (e.g. discretionary accruals which is my dependent variable) in the empirical models[18]. Third, I check outlier data and other unusual characteristics in the data set and remove some observations with extremely high or low outlier values for some variables. I screen the distribution and descriptive statistics[19] of all continuous variables and note that there are some variables, such as the market value (MV), that still have extremely high or low values. The extreme values signal some errors in raw data or variable calculation. Therefore, I clean my data set before analyzing data.

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[18] To do so, I focus on all firms with no total assets or total revenues data in the Compustat database. When removing these firms, I also delete all other firms that have a same audit partner in each year. For instance, if Compustat does not have total assets or total revenues data for Firm A in 2016, and Firm A is audited by Partner X who has four clients (Firm A, B, C & D) in that year, I remove all four observations from my data set. This is because the calculation of industry specialization proxy is hugely based on the proportion of total assets or total revenues in partner's client portfolios. If I simply remove only Firm A, Partner X will have three remaining clients (while he actually has four clients) and the proportion of total assets or total revenues in his portfolio will be distorted, although this procedure highly reduces the sample size.

[19] I examine the histogram, mean, minimum, maximum and the 25th, 50th and 75th percentiles.

Eventually, I get the final sample of 3,945 firm-year observations which consist of 730, 1,125, 1,110 and 980 firms from fiscal years 2016, 2017, 2018 and 2019, respectively.

3.2 Proxy of Auditor Industry Specialization

Similar to other archival research, the main challenge for the auditor industry specialization literature is how to proxy industry specialization because this construct is not directly observable. As there is a variety in research design choices in measuring industry specialization, this section will review three critical research issues related to industry specialization measurement. These three issues are (1) measurement approaches, (2) measurement variables and (3) operationalized criteria to determine auditor industry expertise.

This section will deliberate underlying concepts, advantages, as well as disadvantages of each measurement choice. I also briefly review prior findings to supplement each research alternative as I already thoroughly present the effect of auditor industry specialization by partitioning on three units of analysis (audit firm, audit office and audit partner) in the literature review. For a detailed review, please refer to Audousset-Coulier, Jeny and Jiang (2016) who provide the excellent summary of different industry specialization metrics used in the existing research.

Most importantly, Neal and Riley (2004) and Audousset-Coulier, Jeny and Jiang (2016) strongly encourage researchers to carefully decide the appropriate research designs to their research contexts because design alternatives considerably influence empirical findings. They also point out that a battery of sensitivity analysis based on several metrics is not an efficient way to deal with the choices in research design because researchers may simply choose one main metric without a clear rationale. So, I will end each research issue with my rationales of the selected research designs in this study. I believe that my chosen designs are appropriate for the partner-level analysis.

3.2.1 Measurement Approaches

The most controversial issue is how to define industry specialization as different definitions lead to different identifications of industry specialists. In the literature, there are two prevalent approaches for measuring industry specialization as follows.

3.2.1.1 Market Share Approach

According to this approach, an industry-specialist auditor refers to an auditor who has the largest market share in an industry (only one specialist auditor per industry) (Palmrose 1986). This definition can extend to cover the second or third largest share (more than one specialist auditor per industry) as long as these top-rank auditors can differentiate from other auditors in the industry (Palmrose 1986). This approach is grounded on the 'within-industry' perspective that focuses on auditors' market shares in industries. The justification is that the leading market share reflects an auditor industry-specific knowledge base. This valuable body of knowledge is gained from providing audit services to many clients in the same industry and from audit firm investments in audit supporting tools to develop such industry knowledge for becoming market leaders.

In terms of a mathematical expression, the auditor's industry market share can be formulated as follows (Krishnan 2003).

$$Market\ Share = \frac{\sum_{j=1}^{J_{ik}} X_{ijk}}{\sum_{i=1}^{I_k} \sum_{j=1}^{J_{ik}} X_{ijk}} \qquad (1)$$

Note that the variable X in the above equation refers to a measurement variable, such as total assets or audit fees[20], used to calculate an auditor's market share in a particular industry. The numerator is the sum of a measurement variable (X) from all *J* clients in industry *k* for auditor *I* (the market share of one auditor in one industry). The denominator is total amount of a measurement variable from all *J* clients over all *I* auditors in industry *k* (the scale factor of all auditors in each industry).

[20] This issue will be discussed in Section 3.2.2 Measurement variables.

Researchers usually employ a market share as a primary measurement approach in investigating the effect of industry specialization on earnings quality[21] or audit fees[22].

The market share approach has some advantages. First, by focusing on auditor rankings within industries, this technique straightforwardly depicts how industry experts can differentiate from other auditors (Audousset-Coulier, Jeny and Jiang 2016; Neal and Riley 2004), consistent with the argument that industry specialization is a differentiation strategy enhancing auditor's competitive advantages in audit markets (Casterella, et al. 2004). Second, because the market share is easily recognized by clients, this approach is suitable for the study of industry specialization audit fee premium.

However, the main limitation of the market share approach is that it does not consider an 'industry size' (Neal and Riley 2004; Minutti-Meza 2013; Audousset-Coulier, Jeny and Jiang 2016). This would result in the over-identification and under-identification problems in small and large industries, respectively. In small industries, market leaders who are classified as specialist auditors may not be truly disparate from other non-specialist auditors because there is no exclusive expertise needed for an audit in such uncomplicated industries. Thus, researchers may over-identify industry specialists as there may be no real specialists for small-sized industries. On the contrary, large industries attract all Big-4 audit firms because these industries are important sources of revenues for audit firms, and large audit firms usually have some clients from these competitive industries. However, this approach designates one specialist (the largest market share) per industry. The problem is whether this specialist auditor really differentiates from other non-specialist auditors as all Big-4 firms are capable for huge investments in expertise and technology development. Thus, researchers may under-identify industry specialists as all Big-4 firms may be qualified as industry specialists for large-sized industries[23].

[21] Most studies use discretionary accruals as a dependent variable based on U.S. (Francis, Reichelt and Wang 2005; Huang, et al. 2007; Gul, et al. 2009; Reichelt and Wang 2010; Fung, Gul and Krishnan 2012; Minutti-Meza 2013), Taiwan (Chin and Chi 2009; Chi and Chin 2011), or international data (Kwon, et al. 2007; Carson 2009).

[22] The examples of audit fee studies are Cahan, Jeter and Naiker (2011) and Fung, Gul and Krishnan (2012) for U.S. data, and Zerni (2012) for Swedish data.

[23] To the best of my knowledge, there is only one exception that a local audit firm in Hong Kong (namely Kwan Wong Tan & Fong) was the market leader in the property industry in 1992 (DeFond, Francis and Wong 2000).

The market-share proxy also causes the self-selection problem because auditors with large market shares are likely to have large clients. Thus, the within-industry market share generates two auditor groups (industry specialist vs. non-specialist) with distinct client attributes (large vs small clients), and client sizes are simultaneously related to the industry specialization variable and to audit quality proxies (Minutti-Meza 2013).

3.2.1.2 Portfolio Share Approach

According to this approach, an auditor is defined as a specialist for the largest industry in his or her client portfolio. This classification is based on the 'within-auditor' perspective that concentrates on an auditor and the distribution of client industries in each auditor's portfolio (Gramling and Stone 2001). Thus, auditors are not necessarily to be the market leader to become industry specialists under the portfolio share approach. The intuition is closely related to auditors' economic risks and welfares. Because the industry with a high portfolio share is an important source of revenues for auditors, they have incentives to develop a body of industry-specific knowledge for providing high audit quality in order to avoid audit failures that could have severe negative consequences to their reputation and incomes (DeAngelo 1981). Moreover, auditors can enjoy economies of scale in developing industry expertise as the cost of expertise development is spread among many clients in their portfolios (Fung, Gul and Krishnan 2012).

Mathematically, the auditor's portfolio share calculation is below (Krishnan 2003).

$$Portfolio\ Share = \frac{\sum_{j=1}^{J_{ik}} X_{ijk}}{\sum_{k=1}^{K} \sum_{j=1}^{J_{ik}} X_{ijk}} \qquad (2)$$

The numerator is the sum of a measurement variable (X) from all *J* clients in industry *k* for auditor *i*. This denotes the total value of a corresponding variable for all clients of one auditor in one industry. On the other hand, the denominator is the sum of a variable of all *J* clients from all *K* industries for auditor *i*. It represents for the scale factors of all clients in the portfolio of each auditor. Note that the numerators of Equation 1 (market share) and Equation 2 (portfolio share) are identical (only the denominators are dissimilar).

The advantage of this approach is that it demonstrates auditors' economic incentives to develop industry expertise as discussed above. Unfortunately, few studies apply a portfolio share as a primary measurement approach in investigating the effect of industry specialization on audit quality or audit fees (Numan and Willekens 2012).

However, it has some drawbacks. First, similar to the market share approach, the portfolio share approach is influenced by the size of industries (but in the opposite way). Researchers are possibly not able to identify any expert in small industries (under-identification) because small industries are difficult to gain the highest share in auditor's portfolios. On the other hand, there may be too many specialists in large industries (over-identification) as these industries normally attract many auditors (Neal and Riley 2004; Cahan, Jeter and Naiker 2011). Second, although this measure centers on auditors' incentives and endeavors to become industry specialists, this measure does not reflect any auditor effort for developing industry expertise. Lastly, the economies of scale may either prompt auditors to develop industry expertise (for high audit quality) or to reduce audit fees (by lowering audit quality) (Fung, Gul and Krishnan 2012; Audousset-Coulier, Jeny and Jiang 2016)[24].

3.2.1.3 Measurement Approach in this Study: Portfolio share

According to the seminal empirical work of Neal and Riley (2004), the market and portfolio shares represent different aspects of industry specialization. Consequently, these measures should not be used a substitute in a sensitivity analysis. In this paper, I measure industry specialization by adopting the 'portfolio share approach' because it is appropriate to the partner-level analysis for three reasons.

[24] To address the limitations of both market share and portfolio shares, Neal and Riley (2004) propose the 'weighted market share approach' by adding a weight of a portfolio share to the market share measure. It directly dilutes the problem of industry sizes. Although small industries rarely gain a high scale in auditors' portfolios, auditors can be industry specialists in these industries if they pursue marketing strategies to gain higher market shares within industries (a low portfolio share is compensated by a high market share). For large industries that normally have specialists from Big-4 firms, the weight of portfolio shares allows non-Big 4 auditors to be industry specialists if their clients are highly concentrated on few industries (a low market share is compensated by a high portfolio share). Unfortunately, few papers employ this measure (e.g., Kwon, Lim and Tan (2007)) because this weighted technique does not take into account why the two measures from distinct underlying viewpoints should be combined together.

First, the portfolio share depicts auditors' economic and reputation incentives to develop industry expertise for protecting their critical source of revenues. While the market share reflects the auditor differentiation strategy from other non-specialist auditors (Casterella, et al. 2004), the economic and reputation incentives are more closely related to the individual unit than the organization unit in the audit context (Lennox and Wu 2018).

Second, the market share approach focuses on the dominance of auditors in an industry and the economies of scale in industry expertise development to gain such market power (Audousset-Coulier, Jeny and Jiang 2016; Dekeyser, Gaeremynck and Willekens 2019). The industry leadership is not sensible when applying to the individual partner level as this smallest unit rarely holds a notable portion of market shares in an industry.

Third, a focus on within-auditor portfolios is consistent to my second and third research questions that investigate industry diversity in client portfolios contributes to industry expertise development.

3.2.2 Measurement Variables

The second empirical controversy is the variables used in measuring industry specialization. There are few commonly used variables for the calculation of market and portfolio shares.

3.2.2.1 Audit Fees

Gramling and Stone (2001) assert that auditor's market shares in an industry should be operationalized by audit fees and scaled by total audit fees within one industry (for the market share approach) or within one auditor (for the portfolio share approach).

Proponents of using audit fees contend that this variable is consonant with the industrial organization literature that focuses on industry outcomes because audit fees reflect audit hours and audit efforts in the production of auditor reports, which is an outcome of audit works (DeFond, Francis and Wong 2000; Audousset-Coulier, Jeny and Jiang 2016).

However, the use of audit fee has two common drawbacks. First, audit fees may contain the industry premium bias because some industries have innate characteristics, such as complexity and riskiness, that are more difficult to audit than others and, thus, require higher audit fees (Simunic 1980; Pearson and Trompeter 1994).

Second, audit fees may suffer from the heterogeneity of audit pricing strategies among auditors. Conceptually, auditors are likely to adopt their own pricing strategies because an audit market is a competitive market that allows for price competition (Numan and Willekens 2012; Lemonakis, Ballas and Balla 2018; Gunn, Kawada and Michas 2019; Asthana, Khurana and Raman 2019). The extant audit fee literature presents empirical evidence to confirm the divergence in audit pricing strategies among auditors. The early works usually treat Big N auditors as a homogenous group and examine the difference in audit pricing between Big N and non-Big N auditors. Hay, Knechel and Wong (2006) conduct the comprehensive meta-analysis and conclude that the Big N auditors charge the higher audit fees than non-Big N auditors (commonly referred as the 'Big N fee premium'). However, Hay (2013) later notices a price premium for PricewaterhouseCoopers (PWC) in more recent studies. This 'PwC fee premium' phenomenon suggests the possible audit pricing practice even among a Big 4 audit firm.

The pioneer work that considers different audit pricing practices among Big N auditors is Mayhew and Wilkins (2003). They utilize the Porter (1985)'s theory of competition and differentiation and argue that auditors may employ dissimilar competitive strategies, including the 'product differentiation' or 'cost minimization' strategies, that differently influence the levels of audit fees[25]. In addition, auditors may strategically lower audit fees to obtain potential business opportunities under the 'low-balling' strategy[26](DeAngelo 1981; Chan 1999).

There are two recent studies suggesting the heterogeneity in audit pricing practices among auditors in U.S. Big-4 audit firms. First, Moon et al. (2019) disentangle audit fee premiums into two components, namely auditor and

[25] Auditors who employ the product differentiation strategy focus on providing the superior quality of audit services to differentiate form other competitors. As a result, they charge higher audit fees to compensate with higher audit costs. However, for the cost minimization strategy, auditors focus on cost savings and economy of scales in audit works to offer lower audit fees to attract clients.

[26] The low-balling strategy refers to when auditors propose unusual low audit fees to new clients and expect an increase in audit fees in the future to recover loss in the first year

engagement premiums. The auditor premium relates to auditor reputation, resources, and qualifications, and reflects the difference in pricing structures among auditors. They identify a 6% variation in auditor premiums across individual U.S. Big-4 audit firms. Second, Hrazdil, Simunic and Suwanyangyuan (2020) observe the systematic pricing differences across U.S. Big-4 firms due to individual brand names of each audit firm. Interestingly, both papers find that PwC and KPMG earn the highest and lowest auditor premiums among Big-4 firms, respectively[27].

In the domain of auditor industry specialization, the evidence of audit pricing is inconclusive. On the one hand, industry specialist auditors offer a fee discount because they have cost efficiency and economy of scale from perform an audit to several clients in a similar industry (Ettredge and Greenberg 1990; Chan 1999). On the other hand, they charge higher audit fees due to a premium from industry expertise (Francis, Reichelt and Wang 2005).

More closely to this study that focuses on the individual audit partner level, most studies that show the difference in audit pricing decisions among audit partners are from the behavioural literature[28]. For archival research, Taylor (2011) discovers the different fee premiums (or discounts) among individual audit partners in Big-4 and three second-tier audit firms (namely BDO, Grant Thornton and PKF) in Australia that cannot be totally explained by audit firm or client characteristics. Additionally, Che, Langli and Svanström (2018) argue that the assumption that each engagement partner uses the similar billing policy for all of his or her clients may be impractical in some circumstances that need audit partners to highly involve[29].

In sum, although audit fees demonstrate audit hours and audit efforts, audit fees simultaneously consist of other factors that are not directly related to audit efforts to become industry specialists and are affected by the heterogeneity in

[27] These findings are consistent with early studies by Simunic (1980) and Hay (2013) who find higher-average fee premiums for Price Waterhouse (later as PwC) or PricewaterhouseCoopers due to superior reputation and by Moizer (1997) who documents below-average fee premiums for Peat Marwick (later as KPMG) as a price cutter under price competition.

[28] Audit partners differ in their individual behaviours, attitudes, perceptions and decisions. These personal differences significantly influence audit quality and audit fees (Nelson and Tan 2005).

[29] The examples are audit issues related to asset impairment or fair value measurement. These client-specific or industry-specific issues require extensive professional judgment, experiences and additional works from high-level audit staffs, such as audit partners or managers. Thus, billing rates (audit fee per hour) of these engagements are likely to be higher than those of other engagements even for the similar audit partners.

audit pricing strategies among auditors, especially at the audit partner level that is the smallest unit in audit firms.

3.2.2.2 Client Sizes

Due to the unavailability of audit fee information in some countries, some researchers must employ variables of client sizes instead. The size of clients can be proxied by total assets (Carson 2009; Gul, Fung and Jaggi 2009; Zerni 2012; Minutti-Meza 2013), the square root of total assets[30] (Mayhew and Wilkins 2003; Payne 2008; Bruynseels, Knechel and Willekens 2011) or total revenues (Kwon, Lim and Tan 2007; Lim and Tan 2008; Chi and Chin 2011). Unfortunately, client-size variables are not linked to auditor efforts in heightening audit quality due to industry expertise (Audousset-Coulier, Jeny and Jiang 2016). Moreover, audit fees already capture client-size factors and other factors (e.g., complexity and risks) that influence audit quality (Simunic 1980).

3.2.2.3 Measurement Variable in this Study: Client sizes

I calculate the portfolio share of each audit partner based on total assets of clients because of the following four reasons. Firstly, an audit fee is a function of not only auditor efforts (audit hours) but also other several factors (e.g., client complexity and business risks) (Simunic 1980). In addition, as discussed above, there is the difference in audit pricing strategies among auditors (Hrazdil, Simunic and Suwanyangyuan 2020) and economies of scale from audit efficiencies due to industry expertise (Bills, Jeter and Stein 2015). These determinants are difficult to disentangle across auditors, especially in the very small unit analysis as an audit partner. Therefore, an audit fee may be a noisy measurement of audit efforts because it is contaminated from other factors that do not directly reflect auditor efforts in expertise development.

Secondly, audit production, in terms of an audit hour, is more directly related to audit efforts than audit fees. Although audit hour information is usually not publicly available, previous studies show that a client size is a critical determinant of an audit hour[31] and that there is a strong positive relationship between

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[30] Simunic (1980) shows that the square root of total assets can be used as a proxy of audit fees when audit fee information is not available.

[31] Client size alone explains more than 50% of the cross-sectional variation in audit hours (O'Keefe, Simunic and Stein 1994).

audit hours and client sizes (O'Keefe, Simunic and Stein 1994; Caramanis and Lennox 2008).

Thirdly, a client size plays an important role in the analysis of the selection of industry specialist auditors by client firms as it is one of the primary drivers of audit quality (Minutti-Meza 2013). Fourthly, the portfolio share approach used in this study does not directly focus on audit production processes and audit efforts to become specialists as this approach grounds on auditors' economic incentives (Audousset-Coulier, Jeny and Jiang 2016).

In summary, I argue that the size of clients in partners' portfolios straightforwardly drives industry expertise development for audit partners.

3.2.3 Measurement Variables Criteria

After researchers determine the empirical approach and variable to proxy industry specialization, they need to consider the following two operationalized criteria for separating between specialist and non-specialist auditors (Audousset-Coulier, Jeny and Jiang 2016).

3.2.3.1 Relative Value

Auditors can be classified as industry specialists if they possess the largest market share or portfolio share without considering the value of shares. This criterion can be further applied to the second or third largest share. The weakness of this technique is that the value of auditor's industry or portfolio shares may be too low for representing a genuine specialist position. Therefore, some scholars also require that the largest share must be higher than the second largest share by at least a certain percentage, such as 10 percent (Minutti-Meza 2013). This more rigid requirement helps us to make sure that identified specialist auditors are really distinct from other non-specialist auditors.

3.2.3.2 Absolute Value

Another way to codify industry specialists relies on the absolute value of an auditor's share given that the share is higher than a specific value. For example, if the cut-off threshold is 25 percent[32], all auditors whose shares are

[32] The 25% threshold is conceptualized from the argument that all Big 4 audit firms uniformly divide an industry among them.

greater than 25 percent will be classified as specialists. Thus, this means does not limit to a single specialist in one industry as long as auditors can surpass the given value. However, the designation of the cut-off level is hugely subject to researcher discretion.

3.2.3.3 Measurement Variable Criteria in this Study: Relative value

In this study, I classify an auditor as a specialist in an industry that (1) has the highest share (based on total assets) in a client portfolio, and (2) such highest share must be 20% greater than the second-highest industry share.

In my view, the primary advantage of this relative criterion for the partner-level analysis is that there will be no more than one specialized industry per audit partner[33]. As an individual audit partner is the smallest unit of analysis, his or her portfolio is normally small and does not have a wide range of industries compared to a portfolio of audit firms or city offices[34]. So, many specialized industries in one partner seems to be irrational and may not truly signal industry expertise at the audit partner level.

In addition, I add the second criterion that the difference in the portfolio share between the largest industry and the closet industry must be at least 20% to make sure that identified (largest) industries truly signify industry specialization by separating from other industries in the partners' portfolio.

However, the intrinsic limitation of the use of threshold is that the higher threshold results in the lower number of industry specialists because of the requirement of larger difference between the largest and the second-largest shares in auditors' portfolios. Thus, researchers should carefully determine the appropriate level of threshold.

While the prior industry expertise literature at the audit firm or office levels widely uses the 10% threshold for the difference between the largest and the second-largest industry (Minutti-Meza 2013; Audousset-Coulier, Jeny and Jiang 2016), such cut-off value may be too small for the individual audit partner level that

[33] If industry specialization is determined based on an absolute value of portfolio shares, auditors may be classified as industry specialists in more than one industry as long as the proportion in their portfolios is above the pre-defined threshold. Additionally, the absolute value basis heavily depends on researcher judgment in establishing such cut-off value.

[34] In this study, the average number of client firms and engagements (firm-year observations) per partner are 1.72 and 4.09, respectively. The minimum, maximum and average number of client industries per partner is 1, 7 and 2.15, respectively.

normally has the large gap among industry ranks in partner's portfolio. Thus, I argue that I should use higher threshold (to be consistent with the analysis of audit partners), but it should be too high (to avoid the under-identification of industry specialists from the above intrinsic limitation). Therefore, I believe that the 20% threshold is reasonable for partner-level analysis[35].

Taken together, based on these two rules, each audit partner can be a specialist in either zero (not be specialized in any industry if partners do not pass the above 20% difference threshold) or one industry.

3.3 Earnings Quality Model

This paper focuses on the consequence of auditor industry expertise on the quality of earnings. Earnings is an important indicator of firm performance that are relevant to a specific decision by a variety of users of financial statements (Healy 1985; Bradshaw and Sloan 2002) and better than cash flows in performance measurement (Dechow 1994). Thus, the quality of earnings is closely conditional on the informativeness of reported earnings for a firm financial performance and the decision-relevance of this information (Dechow, Ge and Schrand 2010). The accounting literature provides many definitions or concepts of earnings quality. These definitions include earnings persistence (under the time-series properties of earnings), the accurate representation of the economic transactions, and the relation between accruals and cash flows (Dechow and Dichev 2002). Therefore, there are several proxies of earnings quality depending on the extent to which high-quality earnings should offer to financial statement users. Dechow, Ge and Schrand (2010) categorize these proxies into three major categories, including the (1) properties of earnings, (2) investor responsiveness to earnings (earnings response coefficient (ERC)), and (3) external indicators of errors in disclosed earnings (e.g., restatements, internal control weakness, and Accounting and Auditing Enforcement Releases (AAER) by the SEC).

I argue that the earnings quality proxy that demonstrates the earnings properties is mostly suitable to this paper because the other two groups may be

[35] I can perform a sensitivity analysis for other threshold values in Section 4.4 (Robustness test).

problematic in my research setting. First, a study of ERC is basically appropriate for an event study to see a market response to some circumstances, such as the issuance of new rules or policies. However, my paper precisely investigates the effect of partner-level auditor industry specialization on earnings quality, rather than the comparison of such effect before and after the mandatory disclosure of partner name in the U.S.[36]. Thus, an ERC is not directly relevant to my research setting. Second, a study of external indicators of financial misstatements is not practical for a short-period study (2016 – 2019) due to a low sample size from ex-post errors in earnings.

Therefore, I rely on the properties of earnings to proxy the quality of earnings. The next question is which earnings properties should be employed in the setting of auditor industry specialization. I decide to use discretionary (abnormal) accruals, which represent the distortion in reported earnings or earnings management, for two reasons.

First, an auditor understanding in client industries can enhance an auditor's ability to detect earnings management or irregular managerial discretion in financial reporting (Barth, Landsman and Lang 2008). The behavioral literature shows that auditor's industry-specific knowledge can improve earnings quality through audit risk assessment and error detection because industry specialists are familiar with the nature of industry-specific financial statement accounts, such as loans receivable for a banking industry (Taylor 2000) or with the pattern of errors that pertain to some industries (Maletta and Wright 1996; Owhoso, Messier and Lynch 2002; Hammersley 2006).

Second, other earnings properties proxies, including earnings persistence, smoothness, and conservatism, that also demonstrate the properties of earnings are not relevant to the auditor industry specialization context. For instances, earnings persistence and earnings smoothness are more pertinent to a decision-making context by equity investors as the time-series properties of earnings directly relates to a stream of cash flows in equity valuation, such as a discounted cash flows-based model (Dechow, Ge and Schrand 2010). Moreover, these two proxies may not closely

[36] Recently, some researchers conducted the event study to compare the effects of audit partner name disclosure before and after the effective date of the PCAOB Rule 3211. They find that audit quality and audit fees increase after the disclosure (Dao, Xu and Liu 2019; Burke, Hoitash, and Hoitash 2019). Nonetheless, these findings are sensitive to research methodologies (e.g., a difference-in-difference design), audit quality proxies and company characteristics (Cunningham, et al. 2019).

demonstrate earnings quality because earnings persistence and smoothness can be contaminated by artificial or temporary earnings manipulation, not a real fundamental performance of firms (Barth, Landsman and Lang, et al. 2012). Further, earnings conservatism or timely loss recognition (TLR) (Basu 1997) is one of the well-known earnings quality proxies that depict an asymmetric recognition of gains and losses in accounting systems in which losses are realized in an accounting system more quickly than gains. However, the construction of TLR model is mainly developed from an earnings-return regression that heavily relies on the market efficiency assumption (Dechow, Ge and Schrand 2010).

Consistent with a sheer volume of the literature, I use discretionary accruals to proxy earnings quality, I estimate discretionary accruals based on the modified Jones model (Dechow, Sloan and Sweeney 1995) adjusted for firm performance (Kothari, Leone and Wasley 2005)[37] by including a return on assets (ROA) to control for firm financial performance as follows.

$$TACC_{it} = \beta_0(1/(TA_t+TA_{t-1})/2)) + \beta_1(\Delta REV_{it} - \Delta AR_{it}) + \beta_2 PPE_{it} + \beta_2 ROA_{it} + \varepsilon_{it} \quad (3)$$

Where:

$TACC_{it}$	=	Total accruals defined as (net operating income before extraordinary items - operating cash flow) / average total assets (for year *t*)
ΔREV_{it}	=	A change in revenues (sales) for firm *i* from prior year ($sales_t - sales_{t-1}$) / average total assets (for year *t*)
ΔAR_{it}	=	A change in accounts receivable for firm *i* form prior year ($AR_t - AR_{t-1}$) / average total assets (for year *t*)[38]
PPE_{it}	=	Gross amount of property, plant and equipment (for firm *i* at the end of year *t*) / average total assets (for year *t*)
ROA_{it}	=	Return on assets calculated as net income (for firm *i* for year *t*) / average total assets (for year *t*)

[37] I argue that the cash flows-based model, such as Dechow and Dichev (2002), is not appropriate for industry specialization research because this kind of models is built on accounting concept, not accrual drivers, while specialist auditors should be better able to evaluate the drivers of accrual items to distinguish between non-discretionary and discretionary accruals that signal the low earnings quality and a high likelihood of earnings management.

[38] Dechow, Sloan and Sweeney (1995) modify the Jones (1991)'s model by deducting a change in accounts receivable from a change in revenues to remove a growth in credit sales, which can be manipulated. So, the residuals (ε) better demonstrate the discretionary component of accruals.

Note that all variables, including an intercept, are scaled by average total assets (Reichelt and Wang 2010). I estimate the parameters in Equation (3) by using ordinary least square (OLS) regression. Based on the estimated coefficients of Equation (3), I compute expected total accruals (ETACC). Finally, I calculate discretionary accruals (DACC) as total accruals minus expected total accruals (TACC - ETACC) and compute the absolute value of discretionary accruals (ADACC). This ADACC variable is my proxy of earnings quality.

3.4 Industry Diversity at Auditor's Client Portfolios

The second research question addresses how auditors develop industry expertise by directly examining the extent to which clients in their portfolios vary by industries. To measure industry diversity in client portfolios of audit partners, I adopt the industry diversity index (DIV)[39] by Beardsley, Goldman and Omer (2020) and Beardsley, Lassila and Omer (2019). The steps in calculation are as follows.

1. Assign a diversity weight to each client. This weight is the number of clients audited by an audit partner in a different industry divided by total number of clients audited by that partner. Conceptually, this weight demonstrates how many clients in partner's portfolios belong to dissimilar industries.
2. Sum the weights of all clients in each partner's portfolio to aggregate industry diversity measure at the partner level.
3. Scale by the total number of clients audited by the partner again to mitigate the effect from the difference in the number of clients of each partner.

As a result, the value of the industry diversity measure (DIV) is between zero and one. The difference in the value is not due to the size of portfolios, but due to the scale or industry diversity in portfolios. Intuitively, the higher number implies

[39] Although this measure is originally employed at the audit office level, I maintain that its conceptual and mathematical justification can be appropriately applied to the audit partner level because the nature of industry diversification in portfolios of audit offices and audit partners is not greatly different. Rather, the key difference is the size of portfolios in which we can scale by the number of clients in portfolios to reduce the size effect on the calculation of the industry diversity index.

greater degree of industry diversity of clients from a wide range of industries (See Appendix for a calculation example).

3.4.1 The Construction of Industry Diversity (DIV) Proxy

I use 'Form AP' as a primary source for calculating the industry diversity (DIV) variable because it contains engagement partner information for all public-firm fillings since February 2017 (the effective date of the PCAOB's Rule 3211). Thus, Form AP well demonstrates the client portfolios of audit partners in the U.S.

After removing some records in Form AP that do not meet sample selection requirements (Section 3.1.4), the total number of audit partners as per the remaining Form AP data is 860 partners. Then, I separately calculate the DIV variable at the audit partner level for each year (2016, 2017, 2018 or 2019). The calculation is based on the proportion of two-digit SIC of clients in each year. So, the DIV value of each audit partner can vary year by year to reflect the dynamic in client portfolios[40] and to be consistent with the characteristic of panel regression models for multivariate analysis. Note that client portfolios of audit partners must contain total assets and total revenues data from Compustat database to be used in constructing the industry specialization (ISP) variable.

3.5 Multivariate Regression Model

Consistent with Reichelt and Wang (2010) and Minutti-Meza (2013), the regression model for testing the three hypotheses in this study is shown below.

$$ADACC_{it} = \alpha_0 + \alpha_1 ISP_{it} + \alpha_2 DIV_{it} + \alpha_3 ISPDIV_{it} + \alpha_4 BIG4_{it} + \alpha_5 LOSS_{it} + \alpha_6 SIZE_{it} + \alpha_7 LEV_{it} + \alpha_8 MTB_{it} + \alpha_9 CFO_{it} + \alpha_{10} ROA_{it} + \alpha_{11} GROWTH_{it} + \alpha_{12} LOGSDSALES_{it} + \alpha_{13} AO_{it} + \alpha_{14} AOIC_{it} + \omega_{it} \quad (4)$$

Where:

[40] In each year, auditor's client portfolios can change for some reasons, including the mandatory auditor rotation, the acceptance of new clients or the voluntary auditor change by clients. As this study focuses on an audit partner, which is the smallest unit, any change in audit partners' portfolios may have a significant impact on industry diversification in portfolios. So, I calculate DIV for client portfolios of audit partners for each year. For instance, one audit partner may have different four values of the DIV variable during the four-year sample period.

ADACC	=	The absolute value of discretionary accruals calculated from the modified Jones model (Dechow, Sloan and Sweeney 1995) adjusted for firm performance (Kothari, Leone and Wasley 2005) in Equation (3)
ISP	=	1 if an audit partner is an industry specialist, and 0 otherwise
DIV	=	Industry diversity in audit partner's client portfolios (Beardsley, Goldman and Omer 2020) (See Appendix for the example of calculation)
ISPDIV	=	The interaction term between ISP and DIV[41]
BIG4	=	1 if a firm is audited by a Big 4 auditor, and 0 otherwise
LOSS	=	1 if net income is negative, and 0 otherwise
SIZE	=	The natural logarithm of market value of equity at the end of year *t*
LEV	=	Total liabilities (at the end of year *t*) divided by average total assets (for year *t*)
MTB	=	Market-to-book ratio calculated as market value of equity divided by the book value (total assets – total liabilities) of equity
CFO	=	Cash flow from operations (for year *t*) divided by average total assets (for year *t*)
ROA	=	Return on assets calculated as net income (for firm *i* for year *t*) / average total assets (for year *t*)
GROWTH	=	Sales growth calculated as $(sales_t – sales_{t−1})/sales_{t−1}$
LOGSDSALES	=	The natural logarithm of standard deviation of sales in the past four years (from *t – 4* to *t*)
AO	=	1 if an audit opinion is other than an unqualified opinion, and 0 otherwise (AO = 0 for an unqualified (clean) opinion)
AOIC	=	1 if an audit opinion on internal control is other than effective, and 0 otherwise (AOIC = 0 for an effective internal control (no material weakness))

[41] This interaction term represents the moderating effect of industry diversity (DIV) on the relationship between industry specialization (ISP) and discretionary accruals (ADACC). I will explain the expected signs of related coefficients (α_1, α_2 & α_3) in Section 3.5.1.

I employ the 'absolute value' of discretionary accruals (ADACC) as a dependent variable and ignore the 'sign' of discretionary accruals because I focus on the role of industry expertise in constraining earnings management (by lowering discretionary accruals), not the directions of earnings management (e.g., income-increasing or income-decreasing)[42]. The independent variables (variables of interest) are ISP, DIV and ISPDIV.

The existing literature suggests several control variables that can be categorized into two main groups. The first group is 'auditor' characteristics. I control for whether sample firms are audited by Big 4 auditors (BIG4) as an auditor size immensely influences audit quality (DeAngelo 1981), and companies with Big N auditors usually have lower discretionary accruals than companies with non-Big N auditors (Becker, et al. 1998). However, I do not control auditor tenure because the number of years that each audit partner serves each client should not significantly different across the short-period sample (2016 – 2019).

Another group of control variables relates to 'client' characteristics. I include several firm-based attributes in the model. Normally, ADACC is positively related to LOSS, LEV, MTB, ROA, GROWTH, LOGSDSALES, AO and AOIC. Conversely, ADACC is negatively related to BIG4, SIZE and CFO. The following provides an explanation for the relationships between ADACC and client-based control variables.

First, firms with a negative profit (LOSS) are likely to have larger discretionary accruals because managers of poor-performance firms have incentives or pressures for earnings management to turn to profitability firms (Watts and Zimmerman 1990; Doyle, Ge and McVay 2007).

Second, large discretionary accruals are expected for high-leverage firms (LEV) because managers are likely to engage in income-increasing earnings

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[42] According to the positive accounting theory (Watts and Zimmerman 1990), the signs of discretionary accruals can be positive (income-increasing) or negative (income-decreasing). For the former, managers exercise their discretion to increase company earnings to meet their incentives. These incentives include meeting earnings targets to increase management compensation (the bonus plan hypothesis) or avoiding debt covenant violation (the debt covenant hypothesis). For the latter, managers may adopt accounting choices to reduce earnings because they would like to avoid regulatory or political scrutiny (the political cost hypothesis). However, this study does not concentrate on managerial incentives for earnings management. So, I use the absolute value of discretionary accruals in the empirical models.

management to inhibit the violation of debt covenants (Watts and Zimmerman 1990; DeFond and Jiambalvo 1994).

Third, higher discretionary accruals are expected for firms with high growth opportunities (MTB and GROWTH) and with extreme performance in which earnings are much higher than underlying operational assets (ROA). Furthermore, the high revenue volatility (LOGSDSALES) provides an opportunity to manipulate earnings as firm revenues are flucuated.

Lastly, the audit opinion (AO) other than unqualified (clean) opinion and the audit opinion on internal control under SOX404 (AOIC) other than effective internal control suggest the low quality in earnings or the deficiency in internal control systems.

For the negative relation with ADACC, large auditors (BIG4) are expected to have greater competencies to detect earnings management (DeAngelo 1981; Francis, Maydew and Sparks 1999). A larger size of clients (SIZE) can lower discretionary accruals due to superior governance and internal control mechanisms (Ge and McVay 2005; Doyle, Ge and McVay 2007; Ashbaugh-Skaife, et al. 2008). Finally, operating cash flows (CFO) are inherently negatively correlated to discretionary accruals under an accrual-based accounting system as managers have a lower opportunity to exercise their discretion in accrual choices if firm earnings consist of a large cash-flows component (Dechow and Dichev 2002).

3.5.1 Expected signs of regresion coefficients to test hypotheses

According to the direct effect of variables of intetrest on the magnitude of discretionary accruals, I anticipate the *negative* sign for ISP coefficient (α_1) for the first hypothesis (H1). This negative sign indicates that industry-specialist partners reduce discretionary accruals (or improve earnings quality) by enhacning the auditor ability to detect irregular accounting pracrtices or earnigns manipulation due to their extensive industry knowledge or experience. I also expect the *negative* sign for DIV coefficient (α_2) for the second hypothesis (H2). This negative coefficient signals that high industry diversity in client portfolios of audit partners is generally beneficial to auditors in constraining earnings management due to the leverage of knowledge across client industries while several general audit methodologies do not pertain to specific industries.

As the third hypothesis (H3) centers on the moderating role of industry diversification (DIV) on the relationship between industry specialization (ISP) and discretionary accruals (ADACC) in the first hypothesis (H1), I predict the *positive* sign for ISPDIV coefficient (α_3)[43]. Conceptually, although the superior industry-specific understanding of industry-specialist auditors can lower discretionary accruals, high industry diversification in client portfolios of industry-specialist auditors adversely impairs industry expertise development as direct experiences in auditing clients are spread across many industries.

I argue that the *negative* association between industry specialization and discretionary accruals in H1 should adversely reverse to be *positive* in H3 if we focus on industry diversity of industry-specialist partners (the ISPDIV interaction term) as high industry diversification impairs industry expertise development as direct experiences in auditing clients are spread across many industries.

[43] The coefficient sign of ISPDIV (the interaction term) should be positive, in contrast to the negative coefficient of ISP, due to the predicted moderating effect of DIV.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Descriptive Statistics

4.1.1 Industry Distribution

As this study focuses on the analysis of client industries, I present the industry distribution of the sample in Table 4.1. The sample firms are mostly from the manufacturing (50.3%), service (17.7%) and trading (10.2%) industries[44]. This sample distribution is similar to the Compustat distribution and to Asthana (2017) who studies the U.S. firms for the period 2003 – 2012. Therefore, the sample well represents client industries, which are the key interest in this study.

[Insert Table 4.1 here]

4.1.2 Descriptive Statistics of All Variables

Panel A of Table 4.2 presents the descriptive statistics (mean, minimum, maximum, and the 25th, 50th and 75th percentiles) for all variables in this study.

[Insert Table 4.2 here]

For the variables of interest, the average values of ADACC, ISP and DIV are 0.1623, 0.4129 and 0.4473, respectively. The average ADACC is quite high as I employ the absolute value of discretionary accruals that shows only the positive value. However, I notice some outlier items because the maximum value of ADACC is 6.16 while the mean, 75th percentile, 95th percentile and 99th percentile values are only 0.1623 and 0.19, 0.50 and 1.12, respectively. The histogram of ADACC (see Figure 4.1) clearly show several extreme values on the right side. As these outliers may cause

[44] The SIC codes for manufacturing, service and trading (wholesale & retail) industries begin with 2 & 3, 7 & 8 and 5, respectively.

the statistical problem in the regression analysis, I, thus, perform additional analysis by removing the outlier ADACC items that are greater than 0.5 (95^{th} percentile) in the multivariate analysis. The histogram of ADACC that has the value less than 0.5 (after data removal) is shown in Figure 4.1 for a comparison purpose.

[Insert Figure 4.1 here]

Additionally, the average ISP value (0.4129) suggests that approximate 41.29% of sample firms are audited by audit partners who are classified as industry specialists. This statistical number is different from the previous studies by Beardsley, Goldman and Omer (2020) and Asthana (2017) who report the mean value of auditor expertise at 0.333 and 0.5962, respectively. This difference is due to the different research designs for the auditor expertise proxy. Both Beardsley, Goldman and Omer (2020) and Asthana (2017) proxy industry expertise by using the market share appraoch at the audit office level, while this study proxies at the audit partner level based on the portfolio share apparoch. Also, Beardsley, Goldman and Omer (2020) uses the Fama-French 17 industry classfication, while this study and Asthana (2017) use the two-digit SIC code[45]. Overall, the high proportion of firms audited by industry-specialist partners in this paper is due to the following two main reasons. First, I measure auditor industry expertise by using the within-auditor portfolio share approach. Each auditor is designated to be a specialist for one industry (the largest industry in his or her portfolio), unless such largest industry does not distinguish from the second-largest share (the difference in portfolio shares between the largest and second-largest industry must be higher than 20%). Second, as client portfolios of audit partners are small and consist of few clients, the proportion of firms audited by industry-specialist partners is relatively high.

The mean industry diversity (DIV) of 0.4473 is less than that of Beardsley, Goldman and Omer (2020) and Asthana (2017) who report the mean value of 0.639 and 1.704, respectively. The possible reason is that this study measures industry diversity at the audit partner level while those two studies examine industry

[45] The two-digit SIC code is largely employed in the auditor industry specialization literature (Audousset-Coulier, Jeny and Jiang 2016).

diversity at the audit office level. As client portfolios of audit partners are usually smaller than those of audit offices (or audit firms), industry diversification in partners' portfolios should be lower than industry diversification in audit offices' portfolios. Another reason is that Asthana (2017) adopts the different measure of industry diversification as the natural logarithm of the number of unique two-digit SICs of clients in each audit offices. Thus, the Asthana (2017)'s measure can be higher than one. Note that I employ the similar industry diversity index with Beardsley, Goldman and Omer (2020) that limits the industry diversity value to be lower than one.

For other variables, 38.1% of sample firms report losses. This percentage is quite similar to Beardsley, Goldman and Omer (2020) and Asthana (2017) who use the U.S. data during 2002 to 2015 and find the average loss firms at 37.7% and 26.1%, respectively. The majority of sample firms (83.6%) uses auditors from Big 4 firms[46]. This proportion is significantly higher than the Big 4 proportion in Asthana (2017) (73.6%) and Beardsley, Goldman and Omer (2020) (64.2%). In addition, the average size of sample firms (based on the market value of equity) is $6.96 million. The client size is larger than Asthana (2017) ($6.25 million) and Beardsley, Goldman and Omer (2020) ($5.49 million)[47]. The possible reason for such a high proportion of Big 4 and larger size is that audit partners in Big 4 firms are less likely to be removed from my final sample due to the sample criteria that audit partners must have more than one publicly traded client in a year[48]. Thus, the remaining audit partners mostly comprise of auditors in Big 4 firms and the remaining sample firms are likely to be a large company.

The average return of assets (ROA) is -0.0424. Although this negative mean, which suggests the negative net income (losses) for sample firms, seems to be peculiar at the first glance, it is still coherent with the distribution of other variables and previous studies. First, as described earlier, 38.1% of sample report losses. Second, the average, minimum and maximum values of net income for sample firms

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[46] Total number of firm-year observations from Big 4 auditors is 3,503, relative to the total 4,150 firm-year observations in the sample (see Table 4).

[47] Asthana (2017) defines a client size as the natural logarithm of client's total market value of equity. While Beardsley et al. (2020) defines as the natural logarithm of the client's total assets. In this study, I use the similar definition of Beardsley et al. (2020).

[48] Auditors' portfolios with only one client do not demonstrate any industry diversity at all.

are \$83.79, \$-1,011 and \$6,230 million, respectively. Third, the distribution of ROA and net income shows that both variables concentrate near zero from the 50^{th} percentile of ROA (0.02) and income (\$22.98 million) (see Figure 4.2). Lastly, the average ROA in this study is not highly different from Asthana (2017) who reports mean value of 0.0147, which is closed to zero as well, for the similar country and period settings.

[Insert Figure 4.2 here]

4.1.3 Descriptive Statistics by Industry Specialization (ISP)

Panel B of Table 4.2 shows the basic statistics for variables of interest by conditioning on industry specialization (specialist partners vs non-specialist partners). Although the main ISP proxy is constructed based on total assets (TA) and the 20% threshold requirement (for the difference between the largest and the second largest share in auditor's portfolios), I also analyse for other measurement variables, including square root of total assets (SqTA) and total revenues (TR) and other cut-off values (10% and 30%) to perform a primary sensitivity analysis for choices of industry specialization measurement. These alternative thresholds are one-level below (10%) and upper (30%) from the main threshold (20%). As the higher threshold results in the lower chance to identify industry specialists, I believe that one-level deviation from the main threshold (20%) is sufficient for sensitivity analysis because the main threshold is already higher than the widely used 10% cut-off value in the industry expertise literature (Audousset-Coulier, Jeny and Jiang 2016)[49]. The followings are the compelling statistics when separating between specialist and non-specialist auditors (ISP vs. non-ISP).

Firstly, absolute discretionary accruals (ADACC) of audit partners who are classified as industry experts (mean ADACC = 0.149)[50] are significantly 'lower' than those of non-industry expert partners (mean ADACC = 0.173) for all ISP cut-off criteria (10%, 20% and 30%) (p-value < 0.05). This finding clearly signifies the

[49] As deeply discussed in Section 3.2.3.3, I upwardly adjust the threshold to 20% to reflect the small size of audit partners' portfolios, relative to the client portfolios of audit offices and audit firms.
[50] For the sake of brevity, I refer to statistics numbers only from the 20% cut-off threshold.

beneficial role of industry specialization of audit partners in improving earnings quality (by reducing discretionary accruals)[51].

Secondly, industry-specialist partners have 'lower' industry diversity (DIV) in their client portfolios than non-specialist partners do (mean DIV = 0.333 and 0.528 for ISP and non-ISP, respectively). This difference holds for all ISP measurement variables (TA, SqTA and TR) and all cut-off criteria (10%, 20% and 30%) (p-value < 0.001). This strong difference emphasizes that auditor direct experiences from client industries play an important role in industry expertise development. This finding is consistent with the model of determinants of auditor expertise by Libby and Luft (1993) and Libby and Tan (1994) that concentrates on the knowledge acquisition process through auditor experiences from clients in their portfolios. In sum, auditors are more likely to be industry specialists when they have concentrated client portfolios (low industry diversity).

However, some previous research find that industry specialists have 'higher' industry diversity than non-industry specialists at the U.S. audit office level (Beardsley, Goldman and Omer 2020) and at the Chinese audit partner level (Mao, Qi and Zhang 2023). Mao, Qi and Zhang (2017) argue that auditors who serve clients from various industries (high industry diversification) tend to be industry specialists because they are capable to do so without sacrificing audit quality. Their argument concentrates on auditor ability, which is one of the determinants of audit expertise (Bonner & Lewis 1990; Libby and Luft 1993; Libby and Tan 1994), in addition to auditor experience used in this study. Interestingly, either lower or higher industry diversification for industry experts confirms that industry specialization (ISP) and industry diversity (DIV) capture different auditor characteristics (Beardsley, Goldman and Omer 2020). If these two constructs are similar, there should be no different directions or correlations between them[52].

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[51] If I use square root of total assets (SqTA) or total revenues (TR), the mean difference of ADACC between ISP and non-ISP is significant for only SqTA at the 10% threshold (p-value < 0.05).

[52] As discussed in Chapter 2, industry specialization (ISP) and industry diversity (DIV) are developed from different perspectives. While industry specialization focuses on the leading client industry in auditors' portfolios, industry diversity focuses on the spread or proportion of client industries in auditors' portfolios.

4.1.4 Descriptive Statistics by Big 4 Audit Firms

As I include two non-Big 4 firms (Grant Thornton and BDO) in my study, Panel C of Table 4.2 presents the average values of some important variables by partitioning between Big 4 and non-Big 4 auditors. The following preliminary analysis provides some basic understanding for the differential role between Big 4 and non-Big 4 auditors that is generally consistent with the existing auditing research.

First, as expected, clients audited by Big 4 auditors have lower discretionary accruals (ADACC) and larger sizes (SIZE) than clients audited by non-Big 4 auditors (p-value < 0.01). These differences are consistent with the seminal theoretical background by DeAngelo (1981) who argues the positive correlation between an auditor size and audit quality.

Second, client portfolios of Big 4 partners have lower industry diversity (DIV) than those of non-Big 4 partners (p-value < 0.01). Such lower industry diversification in Big 4 partners' portfolios is analogous to the partner-level study by Mao, Qi and Zhang (2017), but contrast to Asthana (2017) who studies industry diversity at the audit office level and finds that the Big 4 audit offices have higher indstry diversity compared to non-Big 4 audit offices. This finding highlights the importance of empirical analysis at different units of analysis for auditors (audit firms, audit offcies or audit partners).

Third, Big 4 audit firms have a higher number of industry specialist partners (ISP) than non-Big 4 audit firms (p-value < 0.01)[53], consistent with the positive association between an auditor size and audit quality (DeAngelo 1981) and previous industry specialization literature at the audit firm and audit city office levels in the U.S. (Reichelt and Wang 2010) and at the audit partner level in China (Yuan, Cheng and Ye 2016). This finding indicates that non-Big 4 auditors are less likely to develop specific expertise in auditing (Ryo and Roh 2007).

[53] This finding holds for all cut-off thresholds (10%, 20% and 30%) for the ISP variable based on total assets.

4.1.5 Descriptive Statistics by Audit Partners

Because an audit partner is the main unit of analysis in this paper, I present the additional descriptive analysis for audit partners to further understand the differential role of individual audit partners in Table 4.3. According to Panel A of Table 4.3, the sample consists of 860 audit partners from the six audit firms. EY has the highest number of audit partners (230), followed by Deloitte (173), PWC (163), KPMG (156), BDO (73) and Grant Thornton (65). The total number of 722 audit partners from Big 4 firms represents 84.0% of the total number of audit partners in the sample. This proportion is very consistent with the mean value of BIG4 variable (83.6%), which is measured at the audit firm level.

[Insert Table 4.3 here]

Furthermore, if we further examine the number of firm-year observations (engagements) and the number of unique client firms of each audit firm, EY still dominates the full sample with 1,138 firm-year observations from 491 distinct client firms, followed by PWC, Deloitte, KPMG, BDO and Grant Thornton. The audit firm ranking of the number of firm-year observations is nearly identical to the ranking of the number of audit partners of each audit firm, except for the alternated ranking between Deloitte and PWC. Consequently, the unit of analysis at the audit partner level can well represent the full sample.

The average number of client firms per partner is 1.98 with the maximum and minimum numbers are seven and two clients per partner[54], respectively. Panel B or Table 4.3 shows that the distribution of number of clients per partner is 62%, 24%, 9%, 2.8%, 1%, and 0.2% for two, three, four, five, six and seven clients per partner, respectively. This distribution clearly reveals that more than half of the total audit partners have only two clients, resulting in the concentration in the value of industry diversity measure that will be discussed in next section.

The average number of engagements (firm-year observations) per partner is 4.59 with the maximum and minimum numbers are 16 and two engagements

[54] Note that I remove audit partners with only one client because their client portfolios do not demonstrate any industry diversity.

per partner, respectively. Approximate 25%, 21% and 12% of audit partners have two, four and six engagements (see Panel C or Table 4.3).

In addition, each client has the average of 2.32 engagements (firm-year observations) per partner (see Panel A of Table 4.3). This average number is less than four (for the four-year sample period) because I delete some observations that do not have necessary data in Compustat (missing data), not survive for the whole period (non-survival data) or not meet sample selection criteria.

4.1.6 Distribution of Industry Diversity (DIV)

Table 4.4 presents the distribution of the industry diversity (DIV) variable. There are only 14 different values of DIV, ranging from 0.00 to 0.80. Most of the DIV values are 0.50 (45%), 0.00 (16%) and 0.67 (15%). Overall, the sample has a low variation in industry diversity because the nature of small-sized client portfolios of audit partners. In addition, the concentration of DIV value at 0.50 and 0.00 is accounted for 61% of the total sample and results from the client portfolios with two clients[55]. Lastly, the industry diversity distribution is consistent with the distribution of number of clients per partner that reveals about 60% of audit partners who have two client firms in their portfolios.

[Insert Table 4.4 here]

4.1.7 Proportion of Industry-specialist Partners (ISP)

The inherent nature of industry specialization measurement is that the higher threshold for industry specialization identification directly induces the lower propensity for auditors to be classified as industry specialists (higher threshold requires the larger dispersion between the largest and the second-largest ranks in auditor's portfolios).

I further examine the proportion of industry-specialist partners in the sample by considering the effect of dissimilar identification threshold values[56]. First,

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[55] If the two clients are in different industries, DIV is 0.50. Otherwise, DIV is 0.00 as two clients are in the same industry, indicating no industry diversification at all.

[56] I employ the 20% threshold in the main analysis and perform a sensitivity analysis for the 10% and 30% thresholds, which are one-level deviation from the main threshold (20%).

Panel A of Table 4.5 shows that the numbers of audit partners who are classified as industry specialists (ISP) are 680, 610 and 556 partners for the 10%, 20% and 30% thresholds, respectively. These numbers account for 79%, 71% and 65% of the total number of audit partners in the sample (860 partners). The proportion of industry specialists is relatively high due to the innate characteristic of the portfolio share approach as each auditor normally has one specialized industry (for an industry that has the highest share in auditor's portfolio). However, an auditor may not be specialized in any industry if the difference between the largest and the second-largest industry does not surpass a predetermined percentage to ensure that the largest industry truly demonstrates auditor industry expertise.

[Insert Table 4.5 here]

Second, Panel B of Table 4.5 presents the ratios of the number of firm-year observations audited by industry-specialist partners over the total number of firm-year observations in the sample. The number of client-year observations audited by industry specialists declines from 1,763 to 1,629 and to 1,503 observations, and the proportions over the total number of firm-year observations are 45%, 41% and 38% for the 10%, 20% and 30% thresholds, respectively. I also partition the number of firm-year observations that are audited by industry-specialist partners who work in Big 4 vs non-Big 4 firms. The proportion of observations audited by Big-4 industry specialists (Big 4 ISP) is approximately 86% of the number of observations audited by industry specialists (ISP) for all cut-off thresholds.

Finally, I partition the number of firm-year observations that are audited by industry specialists by industry diversity (DIV). For a convenient purpose, I stratify 14 DIV values into five categories as shown in Panel C of Table 4.5. The proportion of firm-year observations in each category is not significantly different across three thresholds. The majority of sample records has a DIV value between 0.4 to 0.6 (mostly are 0.5).

In summary, the number of industry-specialist auditors declines when the cut-off threshold increases (Panel A). However, the choices of thresholds may not have a critical impact on research findings as there is a constant pattern along Big 4 auditors (Panel B) and industry diversity (Panel C). Moreover, the other threshold that is higher than 30% (e.g., 40% or 50%) may be too extreme for audit partners in which their client portfolios are small and consists of few clients. The very high threshold can lead to the under-identification problem because there will be no specialized industry for each partner.

4.2 Univariate Analysis

4.2.1 Correlation Analysis

Panel A of Table 4.6 shows the Spearman correlation coefficients among all variables in this study. The Spearman rank correlation coefficient (*rho*) is a measure of the strength of the monotonic association between two variables. The primary advantage of the Spearman measure is that it is a non-parametric statistic that does not rely on any assumption of the distribution of data set[57] (Hauke and Kossowski 2011). There are several interesting points to be discussed further.

[Insert Table 4.6 here]

First, as expected, the negative correlation between ISP and ADACC underscores the role of industry specialists in detecting earnings management (by lowering discretionary accruals) and supports the first hypothesis (H1).

Second, the negative relationship between DIV and ADACC suggests that the higher industry diversification in partners' portfolios, the lower discretionary accruals (the better quality of earnings). The negative relationship justifies my second hypothesis (H2) and implies the positive effect from knowledge leverage across different client industries. Diversity in client industries may be related diversification due to common audit procedures for all audit engagements (no matter of industries). Nonetheless, this negative association contradicts to Beardsley, Goldman and Omer (2020) who find the positive correlation between industry diversity (at audit

[57] I do not employ the 'Pearson' correlation coefficient because this measure evaluates the linear relationship between continuous variables. However, industry specialization (ISP) and industry diversity (DIV) are the dichotomous and discrete variables (there are only 14 different DIV values), respectively.

offices) and a propensity to restate financial statements, indicating that industry diversity lowers audit quality.

Third, the negative correlation coefficient between ISPDIV (the interaction term between ISP and DIV) and ADACC does not in line with the third hypothesis (H3) that expects the moderating effect of DIV on the relation between ISP and ADACC (the correlation of the interaction term should be reversed to positive if ISP is negatively related to ADACC). As a correlation coefficient is just a univariate analysis between two variables, I will test the third hypothesis in a multivariate regression analysis.

Fourth, ISP is negatively related to DIV, indicating that, if industry diversity in audit partners' client portfolios is higher, audit partners will be less likely to be industry specialists. This negative relationship is consistent with the literature review in which industry diversity in partners' client portfolios could be one industry expertise driver as a wide range of client industries may impair the industry expertise development of audit partners.

Additionally, the relationship between ADACC and BIG4 is negative as Big 4 auditors are better to constrain opportunistic earnings management than non-Big 4 auditors (Francis, Maydew and Sparks 1999; Kim, Chung and Firth 2003). Moreover, ADACC is positively related to LOSS because managers of firms with a poor financial performance have a pressure to manipulate earnings (Doyle, Ge and McVay 2007).

In addition, ADACC is negatively correlated to SIZE, suggesting that the large size of client firms have better earngins quality due to the better internal control, corporate governance and regulatory oversight (Ge and McVay 2005; Doyle, Ge and McVay 2007; Ashbaugh-Skaife, et al. 2008). Furthermore, ADACC is positively related to LEV as the higher leverage level induces managers to engage in earnigns management to avoid debt covenant violation (DeFond and Jiambalvo 1994).

Lastly, the modified audit opinion (AO = 1) positively relates to higher discretionary accruals (ADACC), consistent with the argument that firms with high accruals tend to receive a modified audit opinion due to financial misstatements from manipulated financial reporting (Bartov, Gul and Tsui 2000; Butler, Leone and Willenborg 2004).

4.2.2 Test for Multicollinearity

Although the correlation matrix does not exhibit any high correlation among variables, I perform the variance inflation factor (VIF) test to statistical diagnose whether multicollinearity exists. Panel B of Table 4.6 shows the VIF for all variables. None of VIF exceeds 10[58]. The high VIFs (between 5 – 9) are from the main variables (ISP and DIV) and their interaction term (ISPDIV). As expected, these VIFs are high becasuse they are from the variables that is constructed by interacting between two variables. However, these high VIFs are still in the acceptable threshold and the correlation coeffcients are not closed to 1 (perfectly positive correlation) or -1 (perfectly negative correlation). The VIFs for other control variables are less than five, which is a more conservative threshold for multicollinarity (Greene 2000), and the mean VIF for the model is 2.70. Overall, the data set does not suffer from the multicollinearity problem.

4.3 Multivariate Analysis

This section presents the results from the main analysis that is based on the industry specialization (ISP) proxy developed from the 20% cut-off threshold of audit partners' portfolio shares based on total assets (TA) of clients. For other ISP measurement alternatives, I will present in the robustness test section later.

4.3.1 Panel Regression

As the four-year sample period is short for the panel regression model that examines longitudinal data of the same firm (*i*) over time (*t*), I recheck the appropriateness of the data set for the panel analysis and note that 483 firm-year observations (12% of the total sample) have data for only one year. This time-invariant characteristic leads to a biased estimator in the panel analysis because these observations do not exhibit any variation across time for the same firm. Thus, I remove

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[58] A VIF under 10 implies that the model does not have serious multicollinearity problem (Greene 2000)

these observations before applying the panel regression[59]. The new sample size (called 'panel sample') is 3,462 firm-year observations[60].

By using the panel sample, Table 4.7 shows the random-effect (RE) panel estimators (Model 1) and a robust standard error (Model 2). Note that all analyses are based on a random effect (RE) model because a fixed effect (FE) estimator is biased and inconsistent in the short period data. This is due to the limited number of years (time) to consistently estimate a fixed effect estimator, which is a part of an intercept in the regression model[61]. Moreover, the panel models in this study are estimated from the generalized least square (GLS) technique. If I use the maximum likelihood (ML) estimation technique (untabulated), the result does not significantly change. Thus, I report the GLS result only.

[Insert Table 4.7 here]

The negative coefficient of ISP in Model 1 is significant at the 5% level (p-value = 0.013), supporting the first hypothesis (H1) and indicates the beneficial role of industry-specialist partners in constraining earnings management (by reducing discretionary accruals). This auditor function of mitigating earnings manipulation is conforming with the prior literature conducted at the U.S. audit firm (e.g., Balsam, Krishnan and Yang 2003; Krishnan 2003; Dunn and Mayhew 2004; Carcello and Nagy 2004; Casterella, et al. 2004; Huang, et al. 2007; Gul, Fung and Jaggi 2009; Lim and Tan 2008; Cahan, Jeter and Naiker 2011; Gaver and Utke 2019) and U.S. audit office (e.g., Francis, Reichelt and Wang 2005; Reichelt and Wang 2010; Fung, Gul and Krishnan 2012; Numan and Willekens 2012), as well as for audit partners in Taiwan (Chi and Chin 2011; Lee, Lee and Wang 2017).

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[59] I perform the ordinary least square (OLS) regression for these 483 observations as they seem to be cross-sectional data. None of main variables (ISP, DIV and ISPDIV) is significant.

[60] The panel sample has the average of 2.9 observations per firm (compared to 2.32 observations per firm from the full sample (see Table 4.3)). I estimate the panel regression from the full sample (3,945 observations) and find that only DIV coefficient is significant at the 5% level. Other main variables (ISP and ISPDIV) and some control variables are insignificant or have unusual signs. This is possibly due to the bias from the one-year observations in this panel regression.

[61] I also estimate the fixed-effect (FE) panel regression from the full sample and note that main variables (ISP, DIV and ISPDIV) and some control variables (e.g., BIG4) are insignificant. This finding confirms that a fixed-effect estimator is worse than a random-effect estimator.

The DIV coefficients are significantly negative for both panel models at the 0.1% significant level (p-value < 0.001). This negative coefficient of DIV confirms the second hypothesis (H2) and suggests the favourable effect of industry diversity in audit partner's client portfolios on inhibiting earnings management due to knowledge leverage across client industries.

While the coefficiets of ISP and DIV and negative, the coefficient of ISPDIV (the interaction term between ISP and DIV) is positive at the 5% significance level for Model 1 only (p-value = 0.045). This positive interaction effect can be interpreted that, although industry diversity of audit partners generally reduces discretionary accruals, higher industry diversity in client portfolios has the adverse effect for industry-specialist partners. In other words, industry diversification has the detrimental impact of earnings quality only for industry-specialist auditors who hughly rely on audit experiences from client industries to develop their personal industry expertise. Therefore, the third hypothesis (H3) is supported as industry diversity moderates the role of audit partner industry specialization on constraining earnings management by undermining the industry expertise development process of industry-specialist partners.

The signs of control variables in Model 1 are consistent with the prior research and with the correlation analysis above. The use of Big 4 auditors (BIG4) and a client size (SIZE) are negatively related to discretionary accruals (ADACC), suggesting the favorable effect of Big 4 auditors and superior governance controls of large-sized clients in constraining earnings management. In contrast, firms with poor performance (LOSS), a high leverage level (LEV), high growth (proxied by the market-to-book ratio (MTB) and sales growth (GROWTH)), returns on assets (ROA)), earnings volatility (SDSALES) and a modified audit opinion (AO) are likely to manipulate earnings to serve managerial incentives, including management compensation, debt covenant restriction and stock prices. All these signs are significant at the 5% level, except for LEV, MTB and AO that are weakly significant at the 10% level.

When using the robust standard error to mitigate the heterogeinity problem (Model 2), DIV is the only main varaible that yields the significant coefficient at the 5% level (p-value = 0.020), whereas ISP and ISPDIV do not. There is no substantial change in the signs and the significance degrees of control variables between

Model 1 and Model 2. These findings indicate that the statistical inference for variables of interest (ISP and ISPDIV) in Model 1 may be sensitive to heteroskedasticity. However, the inference for the postive effect of industry diversity in partner's client portfolios (DIV) in lowering discretionary accruals (ADACC) is valid and robust to heteroskedasticity[62].

Moreover, the short panel data set is less likely to contain the autocorrelation (serial correlation) problem because data is not carried over successive several years. To address the possible autocorrelation problem, I also run the linear regression with the first-order (AR1) disturbance that limits autocorrelation to the one time lag (one year) model. The untabulated AR1 result is not significantly different from Model 1, except for the higher significant level (up to 10%) for some variables (e.g., ISP). Thus, the sample does not suffer from the autocorrelation issue.

One of the statistical problem in my data set is that there are some remaining outliers (after the 1% and 99% winzorization) in the dependent variable (ADACC), I deal with this problem in two ways. First, I remove observations with ADACC greater than 0.5 (approximate the 95th percentile of ADACC) (Model 3). For this solution, although the result for main variables is stronger than that in the main analysis (Model 1) as the coefficients of ISP, DIV and ISPDIV are now all significant at the 1% level, the signs for some control variables, including CFO and ROA, are insignificant or have unusual directions. This is possibly because I remove additional 165 firm-year observations with extreme ADACC values. The relationship between ADACC and variables may be more apparent. However, the low sample size may cause other econometrics problems, especially when estimating a panel model. Second, I perform the panel tobit regression to fix the ADACC values of observations with high ADACC to be 0.5 (Model 4)[63]. The tobit result for variables of interest is quite as same as that of Model 1.

Overall, I rely on the analysis in Model 1 to test the hypotheses. The findings from the multivariate panel model supports all three hypotheses in this study (p-value < 0.05).

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[62] I try to use the generalized least square (GLS) panel regression to directly address the heteroskadasticity problem for panel data, but the sample size is too small.

[63] The tobit model does not reduce number of observations as it truncates observations with outliers to have the same certain upper (or lower) limit value.

4.3.2.1 Panel Regression: Without banking and insurance industries

As discussed earlier, the literature usually excludes the banking and insurnace industries in the empirical analysis because these industries have the unique nature of accruals and special regulations (Payne 2008; Reichelt and Wang 2010; Liu, et al. 2017; Gaver and Utke 2019). However, I include these industries in the preliminary analysis as this paper focuses on the industry specialization of auditors, and the financial and insurance sectors are one of the common specialized industries for auditors. The results of the analysis of the data set for all industries are presented in the previous section (Section 4.3.1) Then, I perform an additional analysis by excluding the financial and insurance industries (SIC code starting with 6) to be in line the sheer volume of prior research. The panel sample with no banking industry has 3,380 firm-year observations[64].

In general, the results when removing the financial and insurance firms (see Table 4.8) are not highly different from the main analysis. The coefficients of ISP and DIV are negative, while the coefficient of ISPDIV is positive (at the 5% significance level). Thus, the interpretation is similar to the main analysis. In sum, although the financial and insurance industries are excluded, the empirical results still support all three hypotheses.

[Insert Table 4.8 here]

[64] Note that the each firm in the panel sample must have data for more than one year in the four-year sample period to preserve the time variation for each firm in the panel analysis.

4.3.2 Cross-sectional Regression

The sample seems to be a cross-sectional data because the sample period is short (each client firm has approximate 2.32 engagements during the sample period). Thus, I re-estimate the Equation 4 by using cross-sectional models as shown in Table 4.9. In contrast to the longitudinal analysis in the previous section, the cross-sectional analysis can directly use the larger sample of 3,954 observations because we do not need to concern a time-invariant characteristic of sample data.

[Insert Table 4.9 here]

4.3.2.1 Ordinary Least Square (OLS) Model

Model 1 of Table 4.9 presents the result from the OLS regression to test the hypotheses. Consistent with the panel analysis, the OLS coefficients of ISP and DIV are negative and the 5% siginificant level. Such negative sign supports the first and second hypotheses (H1 and H2) that underscores the role of industry-specialist partners and industry diversity in mitigating earnings management.

Furthermore, the interaction effect between ISP and DIV (ISPDIV) is positive at 10% significance level (p-value = 0.07) and weakly supports the third hypothesis (H3) of the moderating effect of industry diversification on how industry-specialist audit partners constrain earnings management. Specficially, while the diversity of client industries generally reduces discretionary accruals, if audit partners are industry experts, such industry diversity heighten discretionary accruals (the positive sign of ISPDIV). Consequently, industry diversification has the adverse effect on earnings quality only for industry-specialist auditors. Lastly, the signs of other control variables in the OLS regression are analogous to those reported the previous panel regression.

Next, I test whether heterogeneity exists in the sample set. In an untabulated analysis, the relationship between fitted (predicted) values and residuals from the OLS regression shows the unconstant variance of residuals (large and upward dispersion from the zero mean value of fitted values). The Breusch-Pagan and White tests confirms the presence of heteroscedasticity (unconstant variance of residuals) in the sample data at the 1% significance level. Fortunately, heteroskedasticity does not provoke OLS coefficient estimates to be biased but the standard error of such estimates is biased, resulting in a wrong inference from statistics used in the hypothesis testing.

To mitigate the heteoskedasticity problem, I re-estimate the OLS model by using the robust standard error as shown in Model 2 of Table 10. Unfortunately, the coefficients of ISP and ISPDIV are not significant anymore. However, the cofficient of DIV is still significantly negative at the 5% level (p-value = 0.01), consistent with the OLS Model 1. This finding suggests that the coefficients of ISP and ISPDIV from the OLS regression are sensitive to the heteroskedasticity problem.

4.3.2.2 Linear Regression with Endogenous Treatment Effects

As the OLS model does not address the heteroskedasticity and endogeneity problems, I employ another cross-sectional model, namely the 'linear endogenous treatment effect' model, to alleviate these statistical issues. This model applies a maximum likelihood (ML) technique to estimate an average treatment effect (ATE) and other parameters of a linear regression model by including an endogenous binary treatment variable, which is industry specialization (ISP). The ISP variable is endogenous to a client size (SIZE) (proxied by the market value of equity) as the size of clients highly influences the use of industry-specialist auditors and discretionary accruals (Minutti-Meza 2013).

Models 5 and 6 of Table 4.9 are the empirical results from the linear endogenous treatment effect regression. According to Model 5 that employs the full sample set (3,954 firm-year observations), the coefficients of ISP and ISPDIV are significant but has a positive sign. This positive sign indicates that specialist partners adversely increase discretionary accruals and that there is no moderating effect of DIV on ISP. Thus, the first and third hypotheses (H1 & H3) are not supported. However, the positive sign may signal that, if we control for endogeneity, the beneficial effect of auditor industry specialization may not hold as Minutti-Meza (2013) does not find the effect of auditor industry specialization in discretionary accruals when he applies the propensity score matching (PSM) approach to address a functional form misspecification problem and other endogeneity issues. Then, I use the reduced sample

(3,748 firm-year observations) that removes some outliers in ADACC[65] (Model 6). The signs of ISP, DIV and ISPDIV are consistent with the panel analysis and support all three hypotheses at the 5% significance level.

4.4 Robustness Analysis

4.4.1 Alternative designs for ISP measurement

As discussed in Chapter 3, there are several research design choices for industry specialization measurement (Neal and Riley 2004; Audousset-Coulier, Jeny and Jiang 2016). Although I strongly believe that my selected design (ISP proxy constructed from total assets with the 20% cut-off threshold) is most suitable to the partner-level analysis in this study, this section presents a supplementary sensitivity test for other research choices in ISP measurement to confirm my empirical findings. The alternative research designs include the measurement variable (total assets (TA), square root of total assets (SqTA) or total revenues (TR)) and operationalized thresholds (10%, 20% or 30%). To be able to compare with the main analysis (in Section 4.3.1), all sensitivity models (Table 4.10) are estimated by using the GLS random-effect panel regression from the panel sample (after removing observations with one-year data).

[Insert Table 4.10 here]

First, I focus on the total assets (TA) measurement variable for alternative cut-off thresholds (10%, 20% and 30%) (Panel A of Table 4.10). The sign and significant degree of main variables are not notably different across three thresholds, except for the coefficient of ISPDIV that is stronger to 5% significance level under the 10% threshold.

Second, for the square root of total assets (SqTA) variable (Panel B of Table 4.10), ISP are weakly significant for the 20% and 30% thresholds, and ISPDIV is not significant for all thresholds. Third, for the total revenue (TR) variable, ISP and

[65] I deleted 197 observations that have a value of ADACC higher than 0.5, which is the 95th percentile. The reduced sample size is 3,748. The extreme ADACC may be due to an error in raw data or in ADACC calculation.

ISPDIV are not significant for the threshold of 30%. Finally, the result for control variables does not considerably vary across these nine research choices for ISP measurement.

Overall, the lower cut-off threshold for identifying industry specialization results in the higher likelihood for auditors to be classified as industry specialists as discussed in Section 4.1.7. The higher number of industry-specialist auditors makes the stronger relationship between ISP or ISPDIV and ADACC in the multivariate regression analysis due to the more variation in ISP auditors. Therefore, ISP and ISPDIV are sensitive to research designs. However, this sensitivity does not cause a serious inference problem because the higher significant level is still within the 10% level (weak significance), and it does not affect the DIV variable. Moreover, Neal and Riley (2004) and Audousset-Coulier, Jeny and Jiang (2016) point out the inherent limitation of research design in the auditor industry specialization literture in which design choices immensely influence research findigns. Thus, they emphasize the importance of a careful selection of appropriate research designs to research contexts.

4.4.2 Alternative proxies of industry diversity

I also develop two alternative proxies (DIV2 and DIV3) of industry diversity in client portfolios. First, DIV2 is constructed from the same way as DIV (Beardsley, Goldman and Omer 2020) except that I do not separate client portfolios for each year but combine all clients of each audit partner during 2016 to 2019. Although DIV2 ignores the dynamic in partners' portfolios, DIV2 provides a more variety of industry diversity than DIV due to the larger size of client portfolios from consolidating all client firms during the four-year period. Second, DIV3 relies on Asthana (2017) who utilizes the diversification measure from the strategic management literature to define industry diversity as the natural logarithm of the number of unique two-digit SIC of clients. In an untabulated work, DIV2 and DIV3 do not yield the signficant coefficients for all main variables (ISP, DIV and ISPDIV). The inappropriateness of DIV3 is possibly because the small size of partner's client portfolios make a low variation in number of unique two-digit SIC of clients. In sum, I use the Beardsley, Goldman and Omer (2020)'s industry diversity proxy (DIV) in the main analysis.

4.4.3 Propensity Score Matching (PSM)

Recently, some scholars recommend the propensity score matching (PSM) approach to deal with functional form misspecification, which is one of the common endogeneity problems in accounting research. The primary advantage of PSM is that it relaxes a functional form assumption by not relying on any specification of relationship between dependent and independent variables. The central idea of PSM is that PSM matches observations from treatment and control groups that have same observable characteristics based on an estimated likelihood to be a treatment (Shipman, Swanquist and Whited 2017). This matching can imitate an experimental setting where treatment is randomly assigned. Thus, any difference in dependent variables (e.g., audit quality) between these two groups should be highly due to a treatment effect, not existing firm characteristics or other relevant factors that are included or excluded in the regression model[66].

In the auditor industry specialization domain, Minutti-Meza (2013) employs the PSM approach to match clients of specialist and non-specialist auditors on client size[67] and does not find the difference in audit quality between these two auditor groups. His finding emphasizes the confounding effect of client attributes in investigating the effect of industry specialization on audit quality.

In an untabulated analysis, I estimate an average treatment effect (ATE) by using the logit regression to regress ISP on client size (proxied by a market value of equity). However, ATE is not statistically significant (p-value > 0.1). Thus, I do not employ PSM in this study.

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[66] The exclusion of control variables that influence dependent variables is the ‘omitted variable’ problem, which is another source of endogeneity.

[67] He empirically shows that client size is substantially related to the use of auditor specialists, audit quality proxies and audit fees.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

This study is to examine whether industry specialization of audit partners relates to earnings quality, whether industry diversity in client portfolios of audit partners associates with earnings quality, and whether the relationship between industry specialization of audit partners and earnings quality depends on industry diversity in their client portfolios. These questions are grounded on the idea that industry specialization enhances an auditors' capability to mitigate earnings management due to their rigorous understanding in unique accounting practices in a particular industry. Additionally, industry diversity in partner's portfolios is the industry expertise driver due to the auditor direct experiences in client industries, and this expertise driver possibly moderates the relationship between auditor industry specialization on earning quality.

The empirical results indicate that audit partners who are industry specialists can constrain earnings management by reducing the magnitude of discretional accruals. The industry-specific knowledge of auditors can help them to identify any irregular accounting practices or earnings manipulation. This finding signals the beneficial effect of industry specialization in improving audit quality at the audit partner level, in addition to the audit office and audit firm levels in the previous research.

By further examining the client portfolios of audit partners, I note that industry diversity in client portfolios can inhibit earnings management. This negative association between industry diversity in partner's client portfolios and discretionary accruals can be attributed to knowledge leverage across client industries. Moreover, industry diversity moderates the role of audit partner industry specialization on constraining earnings management by threatening the industry expertise development process of industry-specialist partners. In other words, industry diversification has the detrimental impact of earnings quality only for industry-specialist auditors who highly rely on audit experiences from client industries to develop their personal industry expertise.

This study contributes to the auditor industry specialization literature in three ways. First, I examine the industry expertise at the audit partner level in the U.S. setting. scholars call for the analysis of audit partner because audit partners play an important role in audits and they are ultimately responsible for audit tasks. While behavioral researchers have examined the judgment and decisions-making process made by individual audit partners for a long time, archival researchers cannot conduct audit partner research in some settings because audit partner information is not publicly disclosed in some countries. In the U.S., the PCAOB Rule 3211 mandates the Form AP fillings since January 2017 for the public disclosure of U.S. audit partner information.

Second, researchers have attempted to investigate expertise drivers that demonstrate how auditors develop industry specialization. The results in this study indicate that industry expertise at the audit partner level can constrain earnings management. This partner effect compliments the existing auditor industry specialization literature at the audit office and audit firm levels, especially in the U.S. setting where we have limited audit partner information. Furthermore, such industry expertise is driven by industry diversification in client portfolios of audit partners. Therefore, auditor experience plays an important role in the auditor industry specialization development process because a client portfolio of auditors is a primary source of experience accumulation.

Third, this study offers the practical contribution to audit firms in audit partner assignment practices. Audit firms may consider the characteristics of client industries in partners' portfolios when they assign audit partners to clients to finally develop the client-auditor alignment.

This study has several points for improving in future works. First, researchers can replicate this study for the longer sample period as the sample period in this study is short and covers only four years (2016 – 2019) because the disclosure of audit partner names in the U.S. just began in 2017. The short sample period results in the unreliable estimates from the panel regression because some firms have only one observation (year) in the sample period. So, these firms do not have a time-variation in the panel analysis. Future research may use the longer period to re-examine my research questions or to explore task-specific expertise that normally proxies audit quality based on ex-post measures of audit failures in related accounts (Dechow, Ge and Schrand 2010).

Second, researchers can employ other empirical alternatives related to the construction of auditor industry specialization proxy. The findings are likely to sensitive to the research designs selected by researchers. However, I employ the research designs that are suitable to the audit partner unit of analysis (Audousset-Coulier, Jeny and Jiang 2016; Neal and Riley 2004).

Third, researchers can use audit fees as an alternative variable to total assets (client size) in measuring auditor industry specialization. The result may be different if we develop the ISP variable based on audit fees. However, I cannot access to the public database of audit fees for U.S. firms through the Audit Analytics database.

The last limitation is that the sample includes only public companies due to the data unavailability of private companies. Thus, the industry diversity measure may be different if we have the full or complete client portfolios of audit partners.

Table 3.1: Sample selection

	No. of firm-year observations
Initial Sample (No. of filling records in Form AP to PCAOB since 2017)	31,849
Less: Fiscal years before 2016 or after 2019	(1,092)
	30,757
Less: Clients audited by audit firms other than Big 4, Grant Thornton & BDO	(15,100)
	15,657
Less: Records in Form AP that do not contain necessary details or for further analysis	(1,240)
	14,417
Less: Clients audited by audit partners who have only one public-firm client per each year	(4,879)
Sample before merging with Compustat	9,538
Less: No SIC in Compustat	(1,568)
Less: Do not have necessary variables or have missing data in Compustat or outlier values	(4,025)
Final Sample	**3,945**

Table 4.1: Industry distribution

One-digit SIC	Industries	No. of observations	%
0	Agriculture, Forestry and Fisheries	6	0.2%
1	Mining and Construction	343	8.7%
2	Manufacturing	929	23.5%
3	Manufacturing	1,056	26.8%
4	Transportation, Communication and Utilities	416	10.5%
5	Wholesale and Retail	401	10.2%
6	Finance, Insurance and Real estate	96	2.4%
7	Service	529	13.4%
8	Service	168	4.3%
9	Public administration	1	0.0%
	Total	**3,945**	**100.0%**

Table 4.2: Descriptive statistics

Panel A: Descriptive statistics of all variables

Variables	Mean	SD	Min	Max	P25	P50	P75
ADACC	0.1623	0.27	0.00	6.16	0.04	0.09	0.19
ISP	0.4129	0.49	0.00	1.00	0.00	0.00	1.00
DIV	0.4473	0.21	0.00	0.80	0.44	0.50	0.50
BIG4	0.8355	0.37	0.00	1.00	1.00	1.00	1.00
LOSS	0.3807	0.49	0.00	1.00	0.00	0.00	1.00
SIZE	6.9590	1.77	(0.88)	10.08	5.92	7.20	8.21
LEV	0.5967	0.41	0.03	9.65	0.39	0.56	0.73
MTB	2.9536	26.59	(807.49)	689.78	1.22	2.30	4.22
CFO	0.0324	0.22	(3.23)	0.98	0.03	0.08	0.13
ROA	(0.0424)	0.28	(2.83)	4.75	(0.06)	0.02	0.07
GROWTH	0.4603	5.18	(1.00)	168.44	(0.03)	0.06	0.17
LOGSDSALES	4.6193	1.78	(4.13)	10.17	3.56	4.76	5.80
AO	0.3351	0.47	0.00	1.00	0.00	0.00	1.00
AOIC	0.1790	0.38	0.00	1.00	0.00	0.00	0.00
NI**	83.79	335.00	(1,011.00)	6,230.00	(27.92)	22.98	136.56
MV**	3,186.02	4,674.69	0.41	23,934.83	372.52	1,335.93	3,672.05

* No. of firm-year observations (sample size) is 3,945.

** Although NI (net income) and MV (market value) are not the main variables used in the hypothesis testing. I present the descriptive statistics for these variables to additionally explain the distribution of ROA and MTB (market-to-book value) variables.

Panel B: Descriptive statistics by industry specialization (ISP)

Absolute discretionary accruals (ADACC)

	Total assets (TA)			**Square root of Total assets (SqTA)**			**Total revenue (TR)**		
	10%	**20%**	**30%**	**10%**	**20%**	**30%**	**10%**	**20%**	**30%**
ISP = 0	0.173	0.170	0.169	0.170	0.165	0.165	0.160	0.158	0.160
ISP = 1	0.149	0.151	0.152	0.151	0.156	0.156	0.165	0.169	0.166
Difference	(0.024)	(0.019)	(0.017)	(0.019)	(0.009)	(0.009)	0.005	0.011	0.006
p-value*	0.004	0.023	0.049	0.027	0.330	0.381	0.595	0.199	0.511

* p-value for the difference using a pairwise comparison of means

Industry diversity (DIV)

	Total assets (TA)			**Square root of Total assets (SqTA)**			**Total revenue (TR)**		
	10%	**20%**	**30%**	**10%**	**20%**	**30%**	**10%**	**20%**	**30%**
ISP = 0	0.528	0.528	0.527	0.528	0.527	0.523	0.524	0.524	0.522
ISP = 1	0.347	0.333	0.317	0.331	0.293	0.255	0.353	0.334	0.319
Difference	(0.181)	(0.195)	(0.211)	(0.197)	(0.234)	(0.268)	(0.171)	(0.190)	(0.203)
p-value*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

* p-value for the difference using a pairwise comparison of means

Panel C: Descriptive statistics by Big 4 auditors (BIG4)

	ADACC	**DIV**	**ISP**	**SIZE**
BIG4 = 0	0.236	0.511	0.359	5.433
BIG4 = 1	0.148	0.435	0.424	7.260
Difference	(0.088)	(0.076)	0.065	1.827
p-value*	0.000	0.000	0.002	0.000

* p-value for the difference using a pairwise comparison of means

Table 4.3: Descriptive statistics by audit partners

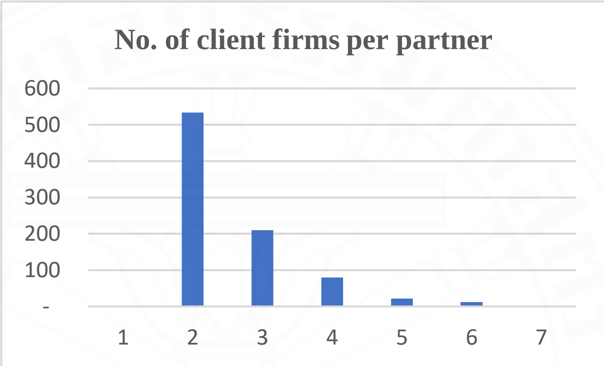
Panel A: Descriptive statistics of audit partners by audit firms

Audit firm	No. of partners	% of Big 4 & Non-Big 4	No. of unique client firms	No. of firm-year observations	% of Big 4 & Non-Big 4	No. of unique client firms / partner			No. of firm-year observations (engagements) / partner		
						Avg.	**Min**	**Max**	**Avg.**	**Min**	**Max**
EY	230		491	1,138		2.13	2	6	4.95	2	15
Deloitte	173		345	764		1.99	2	6	4.42	2	12
PWC	163		324	747		1.99	2	6	4.58	2	16
KPMG	156	84.0%	288	647	83.5%	1.85	2	4	4.15	2	11
BDO	73		160	334		2.19	2	7	4.58	2	12
Grant Thornton	65	16.0%	141	315	16.5%	2.17	2	2	4.85	2	12
Total	**860**	**100.0%**	**1,701**	**3,945**	**100.0%**	**1.98**	**2**	**7**	**4.59**	**2**	**16**

- Average firm-year observations (engagements) per client firm = 2.32 (3,945 / 1,701).
- The total number of unique client firms (1,701) is less than the sum of number of client firms from all audit firms (1,749). This is because some clients change auditors within these six audit firms. So, a single client firm may be counted for more than one audit firm.

Panel B: Distribution of the number of client firms per audit partner

No. of client firms per partner	Frequency	%
1	0	0%
2	534	62%
3	210	24%
4	80	9%
5	22	3%
6	12	1%
7	2	0%
Total	**860**	**100%**



Panel C: Distribution of the number of firm-year observations (engagements) per audit partner

No. of firm-year observations per partner	Frequency	%
1	0	0%
2	216	25%
3	112	13%
4	184	21%
5	78	9%
6	103	12%
7	56	7%
8	49	5%
9	18	2%
10	26	3%
11	16	2%
12	6	1%
13	3	0%
14	1	0%
15	1	0%
16	1	0%
Total	**860**	**100%**

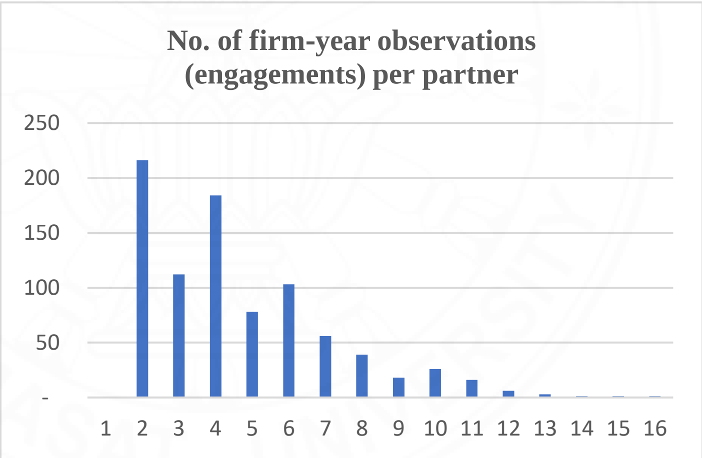


Table 4.4: Distribution of industry diversity (DIV) values

DIV values	No. of firm-year observations	%
0.0000	637	16%
0.2188	3	0%
0.2783	10	0%
0.3200	27	1%
0.3750	136	3%
0.4433	413	10%
0.5000	1,787	45%
0.5600	19	0%
0.6250	157	4%
0.6667	608	15%
0.7200	26	1%
0.7500	109	3%
0.7783	7	0%
0.8000	6	0%
Total	**3,945**	**100%**

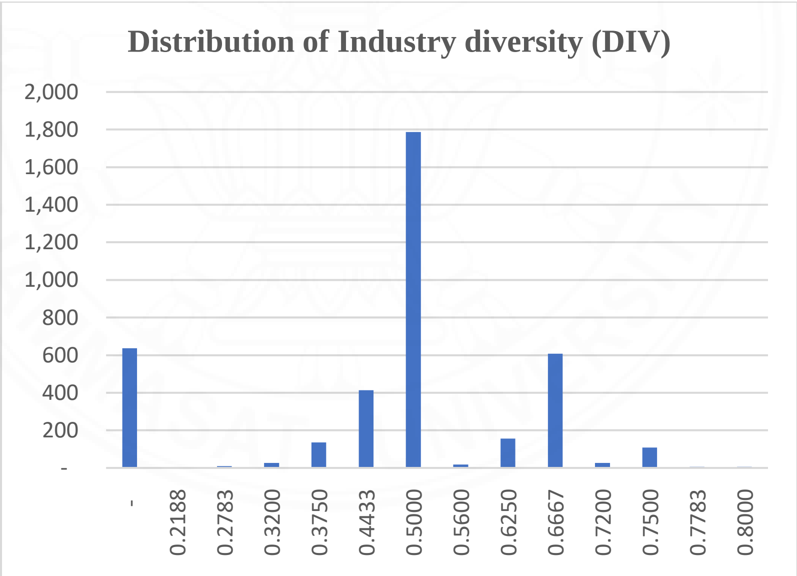


Table 4.5: Proportion of industry-specialist (ISP) partners

Panel A: No. of industry-specialist partners

	Cut-off Thresholds					
	10%	**% of total partners**	**20%**	**% of total partners**	**30%**	**% of total partners**
Specialist (ISP = 1)	680	79%	610	71%	556	65%
Non-specialist (ISP = 0)	180	21%	250	29%	304	35%
Total no. of audit partners	**860**	**100%**	**860**	**100%**	**860**	**100%**

Panel B: No. of firm-year observations that are audited by ISP partners, partitioning by Big 4 vs non-Big 4 and by threshold values

	Cut-off Thresholds					
ISP Partners*	**10%**	**% of total ISP partners**	**20%**	**% of total ISP partners**	**30%**	**% of total ISP partners**
Big 4	1,514	86%	1,396	86%	1,296	86%
Non-Big 4	249	14%	233	14%	207	14%
No. of firm-year obs. audited by ISP partners	**1,763**	**100%**	**1,629**	**100%**	**1,503**	**100%**
% of total sample**	**45%**		**41%**		**38%**	

* The ISP variable based on total assets (TA)
** This ratio is the percentage of no. of firm-year observations audited ISP partners over total no. of firm-year observations in the sample (3,945)

Panel C: No. of firm-year observations that are audited by ISP partners, partitioning by industry diversity (DIV) and by threshold values

DIV*	Cut-off Thresholds					
	10%	**% of total ISP partners**	**20%**	**% of total ISP partners**	**30%**	**% of total ISP partners**
0.0 – 0.2	565	32%	559	34%	558	37%
0.2 – 0.4	100	6%	196	6%	88	6%
0.4 – 0.6	878	50%	791	49%	704	47%
0.6 – 0.8	220	12%	183	11%	153	10%
0.8 – 1.0	0	0%	0	0%	0	0%
Total	**1,763**	**100%**	**1,629**	**100%**	**1,503**	**100%**

* DIV values from Table 5 are categorized into five groups for an ease of presentation

Table 4.6: Correlation analysis

Panel A: Correlation coefficients

	ADACC	ISP	DIV	ISPDIV	BIG4	LOSS	SIZE	LEV	MTB	CFO	ROA	GROWTH	LOG SDSALES	AO	AOIC
ADACC	1.00														
ISP	-0.08*	1.00													
DIV	-0.04*	-0.40*	1.00												
ISPDIV	-0.11*	0.71*	0.13*	1.00											
BIG4	-0.13*	0.07*	-0.12*	-0.03	1.00										
LOSS	0.31*	-0.03*	-0.17*	-0.16*	-0.11*	1.00									
SIZE	-0.31*	0.28*	-0.02	0.31*	0.37*	-0.46*	1.00								
LEV	0.04*	0.04*	0.01	0.05*	0.09*	0.05*	0.03*	1.00							
MTB	-0.13*	0.02	-0.06*	-0.02	0.09*	-0.1*	0.39*	-0.07*	1.00						
CFO	-0.17*	0.01	0.13*	0.11*	0.08*	-0.59*	0.44*	-0.05*	0.25*	1.00					
ROA	-0.27*	-0.01	0.19*	0.13*	0.08*	-0.83*	0.48*	-0.11*	0.23*	0.74*	1.00				
GROWTH	-0.20*	0.07*	-0.05*	0.03	0.04*	-0.09*	0.17*	-0.05*	0.23*	0.11*	0.11*	1.00			
LOGSDSALES	-0.10*	0.23*	0.07*	0.31*	0.31*	-0.34*	0.70*	0.22*	0.03	0.31*	0.35*	0.06*	1.00		
AO	0.05*	0.02	-0.03*	-0.01	-0.02	0.08*	-0.04*	0.11*	-0.02	-0.10*	-0.10*	-0.03*	-0.01	1.00	
AOIC	0.16*	-0.11*	(0.03)	-0.15*	-0.24*	0.28*	-0.46*	-0.00	-0.13*	-0.27*	-0.27*	-0.03*	-0.38*	0.07*	1.00

The asterisk mark (*) denotes the 5% significance level

Panel B: Variance inflation factor (VIF) for testing multicollinearity

Variables	VIF*
ISP	8.44
ISPDIV	7.27
DIV	4.46
ROA	3.07
CFO	2.80
SIZE	2.12
LOSS	1.68
AOIC	1.37
BIG4	1.25
SDSALES	1.12
LEV	1.10
AO	1.03
GROWTH	1.02
MTB	1.01
Mean VIF	**2.70**

* Sorted from the highest to the lowest VIF

Table 4.7: Multivariate panel analysis

Model 1: GLS random-effect panel regression from the panel sample
Model 2: GLS random-effect panel regression from the panel sample with a robust standard error
Model 3: GLS random-effect panel regression from the reduced panel sample (ADACC < 0.5)
Model 4: Tobit panel regression with upper limit of ADACC at 0.5

The equation for estimating coefficients for all models:

$$ADACC_{it} = \alpha_0 + \alpha_1 ISP_{it} + \alpha_2 DIV_{it} + \alpha_3 ISPDIV_{it} + \alpha_4 BIG4_{it} + \alpha_5 LOSS_{it} + \alpha_6 SIZE_{it} + \alpha_7 LEV_{it} + \alpha_8 MTB_{it} + \alpha_9 CFO_{it} + \alpha_{10} ROA_{it} + \alpha_{11} GROWTH_{it} + \alpha_{12} LOGSDSALES_{it} + \alpha_{13} AO_{it} + \alpha_{14} AOIC_{it} + \omega_{it}$$

	Expected signs	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Dependent variable = ADACC					
ISP	-	-0.0585*	-0.0585	-0.0458***	-0.0393**
		(0.01)	(0.19)	0.00	(0.00)
DIV	-	-0.173***	-0.173*	-0.0712***	-0.0787***
		0.00	(0.02)	0.00	0.00
ISPDIV	+	0.0928*	0.0928	0.0588**	0.0500*
		(0.05)	(0.26)	(0.00)	(0.05)
BIG4	-	-0.0592***	-0.0592***	-0.0187**	-0.0394***
		0.00	0.00	(0.00)	0.00
LOSS	+	0.0561***	0.0561*	0.0220***	0.0325***
		0.00	(0.03)	0.00	0.00
SIZE	-	-0.0400***	-0.0400***	-0.0171***	-0.0259***
		0.00	0.00	0.00	0.00
LEV	+	0.0204	0.0204	-0.000667	0.00367
		(0.08)	(0.27)	(0.91)	(0.59)
MTB	+	0.000275	0.000275**	0.00011	0.000169*
		(0.06)	(0.01)	(0.07)	(0.03)

CFO	-	-0.0717*	-0.0717	0.192***	0.0871***
		(0.05)	(0.65)	0.00	0.00
ROA	+	0.185***	0.185	-0.232***	-0.0982***
		0.00	(0.39)	0.00	0.00
GROWTH	+	0.00580***	0.00580*	-0.00121**	0.00221***
		0.00	(0.03)	(0.01)	0.00
LOGSDSALES	+	0.0294***	0.0294***	0.0154***	0.0223***
		0.00	0.00	0.00	0.00
AO	+	0.0163*	0.0163	0.00429	0.00375
		(0.05)	(0.08)	(0.23)	(0.40)
AOIC	+	0.024	0.024	0.00109	0.0111
		(0.07)	(0.18)	(0.85)	(0.13)
cons		0.402***	0.402***	0.203***	0.269***
		0	0	0	0
N		3462	3462	3297	3462
Wald χ^2		186.6	186.6	522.52	518.26
p-value > Wald χ^2		0.0000	0.0000	0.0000	0.0000
R^2					
- within		0.0418	0.0418	0.0644	
- between		0.1914	0.1914	0.2384	
- overall		0.1207	0.1207	0.1683	
Log likelihood					2033.97
Uncensored obs.					3297
Right-censored obs.					165

- p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001)
- In terms of the sample size (see Section 4.3.1), Models 1 & 2 are estimated based on the ‘panel sample’ (3,462 firm-year observations). Model 3 is estimated based on the reduced panel sample (3,297) by removing items with unusual extreme value of dependent variable (ADACC > 0.5, which is higher than 95th percentile). Model 4 is estimated based on the panel sample (3,462) by using the Tobit technique (I fix data with ADACC > 0.5 to be only 0.5 and do need to remove any extreme items).

Table 4.8: Multivariate panel analysis (without banking and insurance industries)

Model 1: GLS random-effect panel regression from the panel sample
Model 2: GLS random-effect panel regression from the panel sample with a robust standard error
Model 3: GLS random-effect panel regression from the reduced panel sample (ADACC < 0.5)
Model 4: Tobit panel regression with upper limit of ADACC at 0.5

All models are based on the sample without firms in banking and insurance industries (SIC code starting with 6). Therefore, the panel sample is reduced to 3,380 firm-year observations.

The equation for estimating coefficients for all models:

$$ADACC_{it} = \alpha_0 + \alpha_1 ISP_{it} + \alpha_2 DIV_{it} + \alpha_3 ISPDIV_{it} + \alpha_4 BIG4_{it} + \alpha_5 LOSS_{it} + \alpha_6 SIZE_{it} + \alpha_7 LEV_{it} + \alpha_8 MTB_{it} + \alpha_9 CFO_{it} + \alpha_{10} ROA_{it} + \alpha_{11} GROWTH_{it} + \alpha_{12} LOGSDSALES_{it} + \alpha_{13} AO_{it} + \alpha_{14} AOIC_{it} + \omega_{it}$$

	Expected signs	Model 1	Model 2	Model 3	Model 4
Dependent variable = ADACC					
ISP	-	-0.0588*	-0.0588	-0.0437***	-0.0380**
		(0.02)	(0.20)	0.00	(0.00)
DIV	-	-0.175***	-0.175*	-0.0674***	-0.0768***
		0.00	(0.02)	0.00	0.00
ISPDIV	+	0.0968*	0.0968	0.0575**	0.0498
		(0.04)	(0.25)	(0.01)	(0.05)
BIG4	-	-0.0582***	-0.0582***	-0.0178**	-0.0382***
		0.00	(0.00)	(0.01)	0.00
LOSS	+	0.0570***	0.0570*	0.0221***	0.0330***
		0.00	(0.03)	0.00	0.00
SIZE	-	-0.0402***	-0.0402***	-0.0172***	-0.0261***
		0.00	0.00	0.00	0.00
LEV	+	0.0224	0.0224	-0.000589	0.00474
		(0.06)	(0.23)	(0.92)	(0.49)
MTB	+	0.000265	0.000265**	0.0000962	0.000159*
		(0.07)	(0.01)	(0.12)	(0.04)

CFO	-	-0.0772*	-0.0772	0.177***	0.0797***
		(0.03)	(0.63)	0.00	0.00
ROA	+	0.191***	0.191	-0.220***	-0.0930***
		0.00	(0.37)	0.00	0.00
GROWTH	+	0.00579***	0.00579*	-0.00121**	0.00220***
		0.00	(0.03)	(0.01)	0.00
LOGSDSALES	+	0.0291***	0.0291***	0.0156***	0.0222***
		0.00	0.00	0.00	0.00
AO	+	0.0162	0.0162	0.0044	0.00347
		(0.06)	(0.09)	(0.22)	(0.44)
AOIC	+	0.0215	0.0215	0.000324	0.00927
		(0.11)	(0.24)	(0.96)	(0.21)
cons		0.404***	0.404***	0.201***	0.268***
		0.00	0.00	0.00	0.00
N		3380	3380	3218	3380
Wald χ^2		375.84	177.55	485.95	494.74
p-value > Wald χ^2		0.0000	0.0000	0.0000	0.0000
R^2					
- within		0.0425	0.0425	0.0605	
- between		0.1885	0.1885	0.2307	
- overall		0.1195	0.1195	0.1622	
Log likelihood					1975.61
Uncensored obs.					3218
Right-censored obs.					162

p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001)

Table 4.9: Multivariate cross-sectional analysis

Model 1: OLS regression
Model 2: OLS with a robust standard error
Model 3: OLS regression for a reduced sample (ADACC < 0.5)
Model 4: Tobit regression with upper limit of ADACC at 0.5
Model 5: Linear regression with endogenous treatment
Model 6: Linear regression with endogenous treatment for a reduced sample (ADACC < 0.5)

The equation for estimating coefficients for all models:

$$ADACC_i = \alpha_0 + \alpha_1 ISP_i + \alpha_2 DIV_i + \alpha_3 ISPDIV_i + \alpha_4 BIG4_i + \alpha_5 LOSS_i + \alpha_6 SIZE_i + \alpha_7 LEV_i + \alpha_8 MTB_i + \alpha_9 CFO_i + \alpha_{10} ROA_i + \alpha_{11} GROWTH_i + \alpha_{12} LOGSDSALES_i + \alpha_{13} AO_i + \alpha_{14} AOIC_i + \omega_i$$

	Expected signs	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ISP	-	-0.0671**	-0.0671	-0.0443***	-0.0384**	0.278***	-0.0755**
		(0.00)	(0.10)	0.00	(0.00)	0.00	(0.01)
DIV	-	-0.177***	-0.177*	-0.0767***	-0.0857***	-0.154***	-0.0769***
		0.00	(0.01)	0.00	0.00	0.00	0.00
ISPDIV	+	0.0849	0.0849	0.0545**	0.0428	0.0457	0.0550**
		(0.07)	(0.26)	(0.00)	(0.07)	(0.31)	(0.00)
BIG4	-	-0.0576***	-0.0576***	-0.0157**	-0.0321***	-0.0517***	-0.0158**
		0.00	0.00	(0.00)	0.00	0.00	(0.00)
LOSS	+	0.0373***	0.0373*	0.0249***	0.0376***	0.0454***	0.0249***
		0.00	(0.04)	0.00	0.00	0.00	0.00
SIZE	-	-0.0464***	-0.0464***	-0.0195***	-0.0299***	-0.0675***	-0.0174***
		0.00	0.00	0.00	0.00	0.00	0.00
LEV	+	0.0191	0.0191	-0.000217	0.0076	0.0196	-0.000201
		(0.07)	(0.22)	(0.96)	(0.16)	(0.07)	(0.97)
MTB	+	0.000331*	0.000331**	0.0000567	0.000152*	0.000312*	0.0000568
		(0.03)	(0.00)	(0.34)	(0.05)	(0.03)	(0.34)

CFO	-	-0.0961**	-0.0961	0.195***	0.0171	-0.113***	0.194***
		(0.00)	(0.28)	0.00	(0.27)	0.00	0.00
ROA	+	0.0848***	0.0848	-0.223***	-0.0457***	0.128***	-0.222***
		(0.00)	(0.50)	0.00	0.00	0.00	0.00
GROWTH	+	0.00603***	0.00603*	-0.00125**	0.00237***	0.00672***	-0.00125**
		0.00	(0.04)	(0.01)	0.00	0.00	(0.01)
LOGSDSALES	+	0.0403***	0.0403***	0.0163***	0.0250***	0.0365***	0.0164***
		0.00	0.00	0.00	0.00	0.00	0.00
AO	+	0.0131	0.0131	0.00292	0.00339	0.0159	0.00296
		(0.13)	(0.17)	(0.40)	(0.43)	(0.06)	(0.39)
AOIC	+	0.0303*	0.0303	-0.00072	0.00667	0.0174	-0.000566
		(0.01)	(0.06)	(0.89)	(0.28)	(0.15)	(0.91)
cons		0.410***	0.410***	0.216***	0.285***	0.422***	0.214***
		0	0	0	0	0	0
ISP_TA20							
SIZE_MV						-1.366***	-1.513***
						0.00	0.00
_cons						-0.898***	0.196
						0.00	(0.25)
athrho						-0.887***	0.177
_cons						(0.00)	(0.00)
lnsigma						-1.242***	-2.330***
_cons						(0.00)	(0.00)
N		3,945	3,945	3,748	3,945	3,945	3,748
F statistics		37.85	15.21	57.25			
Prob > F		0.0000	0.0000	0.0000			
Likelihood ratio (LR) χ^2					804.6		
Prob > χ^2					0.0000		
Log likelihood					2148.33		
LR test of indep. (rho0 = rho1 = 0)						0.0000	0.4222
Prob > χ^2							
R^2		0.1188	0.1188	0.1768			
Adjusted R^2		0.1157		0.1737			
Pseudo R^2					0.2304		
Uncensored obs.					3,748		
Right-censored ob					197		

p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$)

Table 4.10: Sensitivity analysis for ISP measurement choices

Panel A: Total assets (TA) variable

	Expected signs	Total Assets (TA)		
		10%	20%*	30%
ISP	-	-0.0625**	-0.0519*	-0.0501*
		(0.01)	(0.02)	(0.03)
DIV	-	-0.176***	-0.162***	-0.158***
		0.00	0.00	0.00
ISPDIV	+	0.0959*	0.0835	0.077
		(0.04)	(0.06)	(0.08)
BIG4	-	-0.0596***	-0.0591***	-0.0594***
		0.00	0.00	0.00
LOSS	+	0.0563***	0.0563***	0.0566***
		0.00	0.00	0.00
SIZE	-	-0.0394***	-0.0396***	-0.0395***
		0.00	0.00	0.00
LEV	+	0.0204	0.0201	0.0201
		(0.08)	(0.08)	(0.08)
MTB	+	0.000252	0.000246	0.000243
		(0.06)	(0.07)	(0.07)
CFO	-	-0.0718*	-0.0711*	-0.0711*
		(0.04)	(0.04)	(0.04)
ROA	+	0.188***	0.188***	0.188***
		0.00	0.00	0.00
GROWTH	+	0.00579***	0.00578***	0.00578***
		0.00	0.00	0.00

LOGSDSALES	+	0.0288***	0.0286***	0.0287***
		0.00	0.00	0.00
AO	+	0.0153	0.0152	0.0153
		(0.05)	(0.05)	(0.05)
AOIC	+	0.0243	0.0243	0.0244
		(0.06)	(0.06)	(0.06)
cons		0.405***	0.397***	0.395***
		0.00	0.00	0.00
N		3462	3462	3462

p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001)
This sensitivity analysis is estimated based on the GLS random-effect regression from the panel sample
* This is the baseline model (TA with 20% threshold) from the main multivariate analysis.

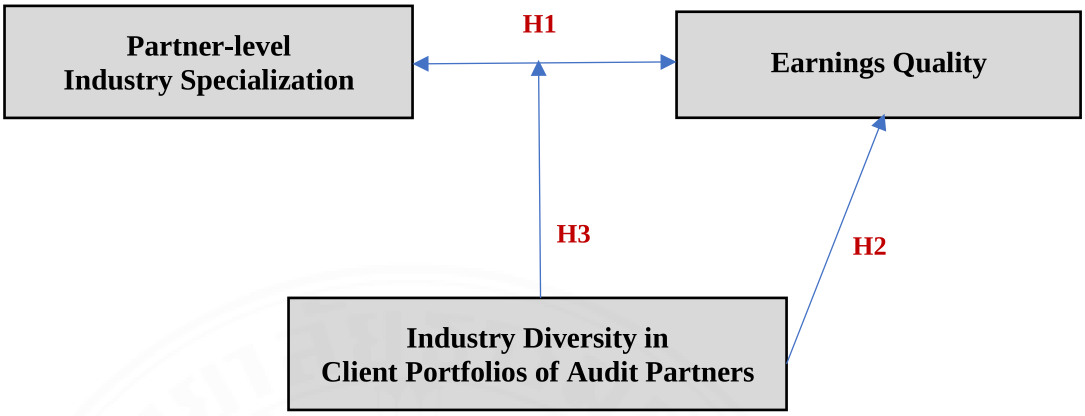
Panel B: square root of Total assets (SqTA) and Total revenues (TR) variables

	Expected signs	Square root of Total assets (SqTA)			Total Revenues (TR)		
		10%	**20%**	**30%**	**10%**	**20%**	**30%**
ISP	-	-0.0504*	-0.0404	-0.0394	-0.0579*	-0.0505*	0.0184
		(0.03)	(0.07)	(0.06)	(0.01)	(0.03)	(0.11)
DIV	-	-0.160***	-0.146***	-0.140***	-0.182***	-0.173***	-0.0697**
		0.00	0.00	0.00	0.00	0.00	(0.00)
ISPDIV	+	0.0815	0.0664	0.0547	0.127**	0.129**	-0.0369
		(0.07)	(0.13)	(0.21)	(0.00)	(0.00)	(0.17)
BIG4	-	-0.0589***	-0.0590***	-0.0593***	-0.0559***	-0.0549***	-0.0584***
		0.00	0.00	0.00	0.00	0.00	0.00
LOSS	+	0.0564***	0.0564***	0.0566***	0.0566***	0.0564***	0.0569***
		0.00	0.00	0.00	0.00	0.00	0.00
SIZE	-	-0.0396***	-0.0398***	-0.0395***	-0.0405***	-0.0409***	-0.0400***
		0.00	0.00	0.00	0.00	0.00	0.00

LEV	+	0.0201	0.0201	0.0201	0.0203	0.02	0.02
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
MTB	+	0.000245	0.00024	0.00024	0.000247	0.000244	0.000216
		(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.11)
CFO	-	-0.0710*	-0.0709*	-0.0721*	-0.0679	-0.067	-0.0717*
		(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
ROA	+	0.188***	0.188***	0.188***	0.190***	0.190***	0.191***
		0.00	0.00	0.00	0.00	0.00	0.00
GROWTH	+	0.00578***	0.00577***	0.00577***	0.00579***	0.00579***	0.00566***
		0.00	0.00	0.00	0.00	0.00	0.00
LOGSDSALES	+	0.0286***	0.0285***	0.0285***	0.0277***	0.0273***	0.0278***
		0.00	0.00	0.00	0.00	0.00	0.00
AO	+	0.0153	0.0152	0.0153	0.0151	0.0152	0.015
		(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
AOIC	+	0.0243	0.0243	0.0242	0.0238	0.024	0.0241
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
cons		0.396***	0.389***	0.384***	0.410***	0.407***	0.348***
		0.00	0.00	0.00	0.00	0.00	0.00
N		3462	3462	3462	3462	3462	3462

p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001)
This sensitivity analysis is estimated based on the GLS random-effect regression from the panel sample

Figure 2.1: Conceptual framework and hypotheses



<u>My expected signs for hypotheses</u>

H1: The *negative* relation between partner-level industry specialization and discretionary accruals*

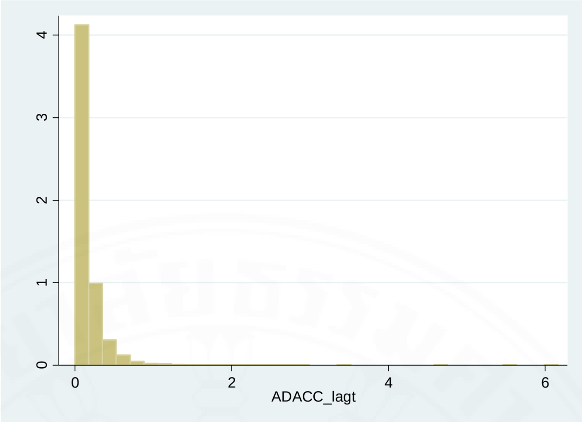
H2: The *negative* relation between industry diversity in client portfolios of audit partners and discretionary accruals (industry diversity is an independent variable on earnings quality).

H3: The *positive* relation between industry diversity in client portfolios of *industry-specialist* partners (the interaction term of ISP and DIV) and discretionary accruals quality (industry diversity is a moderating variable on the effect of industry specialization on discretionary accruals (H1)).

* Discretionary accruals are the proxy of earnings quality

Figure 4.1: Distribution histograms of ADACC variable

All ADACC values*



* This figure clearly shows the outlier items of ADACC variable

Only ADACC values with the value less than 0.5 (after data removal)

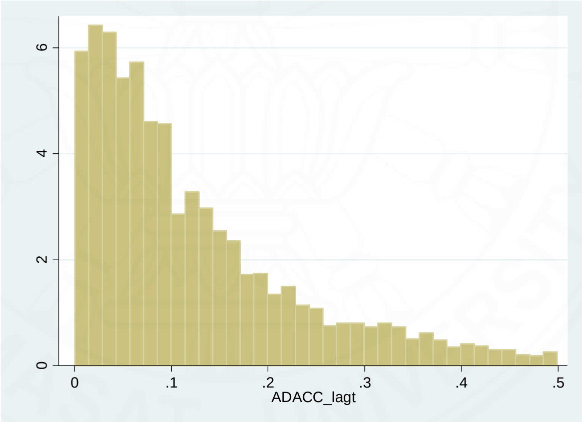
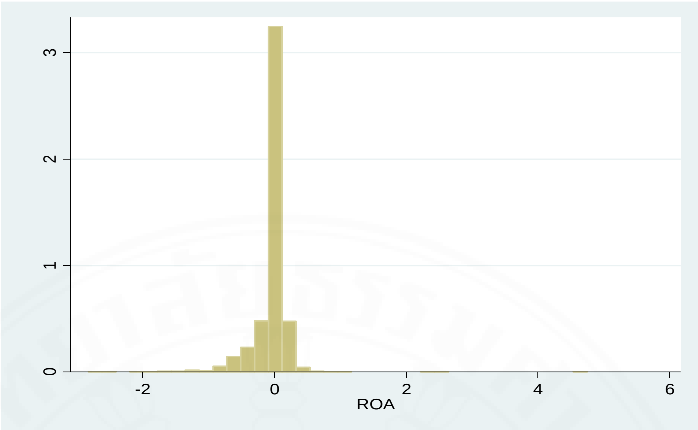
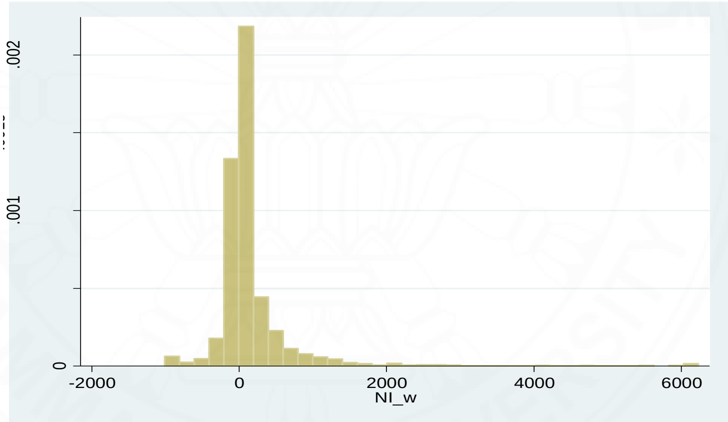


Figure 4.2: Distribution histograms of ROA and NI variables

Return on assets (ROA)



Net income (NI)



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APPENDIX

APPENDIX A

Industry Diversity Calculation

I adopt the measure of industry diversity at an audit office level from Beardsley, Goldman and Omer (2020) and Beardsley, Lassila and Omer (2019). For each partner-year observation, the measure is calculated in the following steps.

- Identify an industry of each client firm based on the two-digit SIC code.
- Compute the industry diversity weight for each client. This weight is the number of clients audited by the same audit partner in a different industry divided by total number of clients audited by that partner. The higher score indicates more industry diversity in which clients in a portfolio are operated in different industries.
- Sum the weights of all clients of the same partner ("Total" in the below tables) to aggregate the industry diversity measure at the partner level.
- Divide by the number of total clients audited by the same partner. This scale makes the industry diversity measure (DIV) between zero and one and mitigates the difference in number of clients for each partner.

Illustrative Example

Given that there are five audit partners. The number of clients for each partner is identical (six clients), but the degrees of industry diversity in the portfolios are different.

More specifically, Partner D and E have six clients from three different industries. To calculate the industry diversity measure of Partner D, the weight of 0.50 (3/6) is assigned to the first three clients in industry #1 because there are other three clients in dissimilar industries (client four, five and six in industry #2 or #3), and Partner D has a total of six clients. Then, the weight of 0.67 (4/6) is given to the fourth and fifth clients because there are four clients (client one, two, three and six) in different industries. Finally, the weight of 0.83 (1/6) is assigned to the sixth client because there are remaining five clients in dissimilar industries. The lower DIV score of Partner D (0.61) indicates less industry diversity in his portfolio than that of Partner E (0.67) due to greater concentration in industry #1 for the Partner D's portfolio.

Note that, for Partner A, all clients are in the same industry. So, the DIV measure equals to zero (no diversity at all). On the other side, the clients of Partner B are totally from different industries. So, the DIV measure equal to 0.83 (most diversity for the case of total six clients[68]). In addition, the industry diversity index of Partner C is 0.5 due to the equal industry distribution in the portfolio.

Partner A		Partner B		Partner C	
Industry	**Weight**	**Industry**	**Weight**	**Industry**	**Weight**
1	0	1	0.83	1	0.50
1	0	2	0.83	1	0.50
1	0	3	0.83	1	0.50
1	0	4	0.83	2	0.50
1	0	5	0.83	2	0.50
1	0	6	0.83	2	0.50
Total	**0**	**Total**	**5.00**	**Total**	**3.00**
DIV	**0**	**DIV**	**0.83**	**DIV**	**0.50**

Partner D		Partner E	
Industry	**Weight**	**Industry**	**Weight**
1	0.50	1	0.67
1	0.50	1	0.67
1	0.50	2	0.67
2	0.67	2	0.67
2	0.67	3	0.67
3	0.83	3	0.67
Total	**3.67**	**Total**	**4.02**
DIV	**0.61**	**DIV**	**0.67**

[68] The maximum score of this industry diversity measure does not equal to one because the weight of each client is never to be one. However, the maximum score approaches to one when the total number of clients in partner's portfolio is extremely high.

BIOGRAPHY

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