Do Audit Teams Affect Audit Production and Quality? Evidence from Audit Teams' Industry Knowledge*

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ABSTRACT

We examine how the extent and distribution of industry knowledge within an audit team affect audit outcomes. While prior research examining the role of auditors' industry knowledge focuses mainly on audit firms, audit offices, and audit partners, audits are conducted by audit teams. Using an audit framework and proprietary data from a Big 4 firm that includes audit hours for each team member, we find that Big 4 audit teams with higher average industry knowledge are associated with more audit effort. In contrast, we find mixed evidence on the relation between the average hourly internal cost rate and team knowledge. Furthermore, we find that balanced teams, which have at least one team member who qualifies as an industry specialist at both the senior rank and junior rank, produce higher-quality audits than teams that have no specialists. In contrast, the audit quality of unbalanced teams, which have a specialist at the senior rank but not the junior rank or vice versa, is not statistically different than teams with no specialists. Overall, our evidence suggests that both the extent and distribution of industry knowledge within a team matter for audit production and that industry knowledge is utilized more effectively when it is spread throughout the team. The findings have useful implications for audit firms and regulators regarding how team composition and industry knowledge affect audit outcomes.

Keywords: audit teams, audit production, audit quality, industry knowledge, team composition, team dynamics

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Les équipes d'audit influencent-elles la production et la qualité des audits? Données probantes relatives à la connaissance du secteur qu'ont les équipes d'audit

RÉSUMÉ

Nous examinons de quelle façon l'ampleur et la distribution de la connaissance du secteur au sein d'une équipe d'audit influencent les résultats des audits. Si la recherche menée jusqu'ici sur le rôle de la connaissance du secteur que possèdent les auditeurs met principalement l'accent sur les cabinets d'audit, les bureaux d'audit et les partenaires d'audit, les audits sont dans les faits menés par des équipes d'audit. À l'aide d'un cadre d'audit et de données exclusives d'un cabinet du Big 4 qui incluent les heures consacrées à l'audit par chaque membre de l'équipe, nous montrons que les équipes d'audit qui possèdent en moyenne une meilleure connaissance du secteur sont associées à un effort d'audit plus soutenu. Par contre, nous dégageons des éléments de preuve mitigés sur la relation entre le coût horaire interne moyen et la connaissance du secteur que possède l'équipe. En outre, nous établissons que les équipes équilibrées, c.-à-d., celles comptant un spécialiste du secteur à l'échelon supérieur et un à l'échelon subalterne, produisent des audits de meilleure qualité que les équipes n'ayant pas de spécialistes. À l'opposé, la qualité des audits effectués par des équipes non équilibrées, qui ont un spécialiste du secteur à l'échelon supérieur ou subalterne n'est pas statistiquement différente de celle des audits des équipes dépourvues de spécialistes. Dans l'ensemble, nos données portent à croire que l'ampleur et la distribution de la connaissance du secteur au sein d'une équipe d'audit sont importantes pour la production d'audits, et que la connaissance du secteur est utilisée plus efficacement lorsqu'elle est partagée par plusieurs membres de l'équipe. Nos résultats ont des répercussions utiles pour les cabinets d'audit et les organismes de réglementation concernant la façon dont est composée l'équipe et la manière dont la connaissance du secteur influence les résultats des audits.

Mots-clés : équipes d'audit, production d'un audit, qualité d'un audit, connaissance du secteur, composition d'une équipe, dynamique d'une équipe

1. Introduction

Prior literature (O'Keefe et al. 1994; Stein et al. 1994; Hackenbrack and Knechel 1997; Blokdijk et al. 2006; Bell et al. 2008; Schelleman and Knechel 2010) focuses on labor as the primary factor input in the audit production process. These studies model labor hours, and sometimes hourly rates, as a function of client attributes. Bell et al. (2008) extend this research by considering the audit firm's technology in terms of business risk auditing, while Dekeyser et al. (2019) document an audit office effect on audit production. Interestingly, although audits are conducted by teams, archival research on how audit team dynamics affect audit production is only starting to emerge (Aobdia, Choudhary, and Newberger 2021; Christensen et al. 2021; Contessotto et al. 2021).[1] In this study, we contribute to this limited line of literature by considering the role of industry-specific knowledge in Big 4 audit teams within a production function model that examines both engagement effort and outcomes.

We focus on industry knowledge among team members because there is ample evidence that auditors can develop expertise in certain industry sectors in order to benefit from efficiency gains or knowledge sharing (Eichenseher and Danos 1981; Craswell et al. 1995; Cahan et al. 2008; Reichelt and Wang 2010; Bills et al. 2015). At an individual auditor level, experimental studies such as Wright and Wright (1997) and Solomon et al. (1999) find that industry specialist auditors have greater non-error knowledge and are better at generating error-related hypotheses when

1. In contrast, the experimental research on audit teams is more developed. For example, see Trotman et al. (2015) for a review of the experimental research on audit teams in relation to the hierarchical review process, brainstorming, and consultation within firms.

balances appear to be out of line with expectations. In another experimental study, Owhoso et al. (2002) find that a sequential review by industry specialist seniors and managers can enhance error detection.[2] Blokdijk et al. (2006) posit that the quality of labor inputs will affect audit production, and the results of these experimental studies suggest that industry knowledge can positively affect labor input quality. As such, the industry knowledge of team members could have an important impact on the audit production process.

Whether, and how, industry knowledge within an audit team affects an engagement is not self-evident as team dynamics can influence how much an audit team utilizes the industry-specific knowledge of team members. For example, prior research indicates that teams often fail to recognize team members with greater expertise (Trotman et al. 1983; Libby et al. 1987; Baumann and Bonner 2004; Hackman 2011) or assign inappropriate weight to an expert's contribution (Hackman and Morris 1975; Bottger and Yetton 1988; Hackman and Wageman 2005). As a result, knowledge sharing among team members may not occur.[3] Furthermore, if a team's industry knowledge does matter, the direction of its impact is unclear. On one hand, teams with greater industry knowledge may conduct more thorough, higher-quality audits (Palmrose 1989; Bae et al. 2019), suggesting a positive relation between team industry knowledge and audit effort. On the other hand, greater team industry knowledge may allow the team to conduct the audit more efficiently (Eichenseher and Danos 1981; Low 2004), implying a negative relation between team expertise and audit effort.

Equally important is how the expertise is distributed within the team. Chi and Chin (2011), Zerni (2012), Goodwin and Wu (2014), and Bell et al. (2015) find that engagements led by specialist partners are associated with fee premiums and higher audit quality. However, it is not clear whether these outcomes are due to the partner's expertise per se or whether these partners are supported by teams with different attributes and levels of expertise than teams headed up by a non-specialist. Within the hierarchical structure of the audit team, partners typically have planning and quality control roles and are responsible for client relations, managers have a supervisory and coordination role, and associates carry out most of the testing and technical tasks necessary to complete the audit (Maister 1982; Hackenbrack and Knechel 1997; Contessotto et al. 2019). If industry-specific knowledge is mainly relevant for the planning and review aspects of the audit, it may be sufficient to have industry knowledge only at the senior ranks. However, if industry knowledge facilitates and enhances audit testing, greater industry knowledge at the junior ranks will be important. Thus, we consider the effects of teams that have members with a high level of industry experience at both the senior and junior ranks (hereafter, *balanced* teams) and teams that have members with a high level of industry experience at only the senior *or* junior rank (hereafter, *unbalanced* teams) separately.

We use proprietary data from a Big 4 firm in Sweden that includes information about the hours and hourly internal cost rates of individual team members for 908 audit engagements.[4] The use of data from a single firm allows us to control for organization-level factors. We adopt a human resources approach that uses the audit firm's workload allocations to construct a measure of industry knowledge at the team member level that is based on the hours a team member spends on audits of clients in industry k relative to all other auditors within the sample who work on audits

2. Although Owhoso et al. (2002) examine "real" teams, their teams are constructed for the purpose of their experiment.
3. In addition, Wittenbaum et al. (2004) and Gardner et al. (2012) find that within-group competition and rivalries can undermine knowledge sharing. Contessotto et al. (2021) find that industry knowledge is not shared among team members in mid-tier firms. Whether such knowledge sharing occurs in a Big 4 setting is an empirical question.
4. In private correspondence with the audit firm, we were informed that the hourly internal rate "impacts more or less everything [the teams] plan to do." One example given was "we cannot use the experienced audit partner too much on this engagement because then the total cost will be too high." We were also informed that while the internal rate is generally consistent within ranks, the internal rate can be different for "experts" at the same rank.

of clients in industry k.[5] This approach is consistent with prior studies that use portfolio-based (i.e., within-firm) measures of auditor industry specialization (Neal and Riley 2004) and assumes that the allocation of individual auditors to clients within an industry reveals the firm's beliefs about their expertise.[6] This approach is also consistent with research that shows professionals learn by doing (Itami 1987; Løwendahl et al. 2001). In an auditing context, Bonner and Lewis (1990) find that industry-specific knowledge is developed through direct industry experience.[7]

Consistent with the research on team composition (Barrick et al. 1998), we use the mean score of relative industry exposure across team members to measure the extent of industry knowledge within a team. To consider the distribution of industry knowledge at the individual auditor level, we classify team members who are in the top quartile of relative industry experience in a client's industry as an industry "specialist auditor." We also compute the average level of industry knowledge across all team members and classify teams that have an average in the top quartile as a "specialist team." We then determine whether each specialist team is balanced or unbalanced based on the distribution of specialist auditors within the team. Specialist teams with at least one specialist auditor at both the senior and junior ranks are balanced teams. Specialist teams with at least one specialist auditor at only the senior rank or only the junior rank are unbalanced teams.

Our main results are as follows. First, teams with greater industry knowledge use more aggregate audit hours, consistent with these teams conducting more thorough audits. Second, we find that the increase in audit hours is similar for balanced and unbalanced specialist teams when compared to audit teams that lack industry specialists. Third, we find inconsistent evidence regarding the relation between a team's industry knowledge and the internal cost rate, as we find a positive and significant association in some models but an insignificant result in others. Fourth, following Francis and Yu (2009) and Aobdia (2019a), we use small positive profits as an output measure of audit quality and find evidence that audit quality increases with a team's industry knowledge.[8] Notably, this effect is driven by balanced specialist teams, suggesting that teams with industry knowledge spread throughout the team are more effective. Collectively, these results indicate that both the extent and distribution of industry knowledge in audit teams affect audit production.

The closest related study is Contessotto et al. (2021). They use team data from two mid-tier firms in Australia and find no evidence that the collective industry experience of an audit team affects audit effort in terms of audit hours. However, our evidence is distinct from theirs as we focus on Big 4 teams instead of mid-tier teams. Indeed, Contessotto et al. (2021, 264) acknowledge that auditors in mid-tier firms are less likely to have industry-focused workloads,[9] and state that "[g]iven that Big 4 auditors spend more time on individual clients and often work within one to two industry sectors, often becoming industry specialists, further research is required to

5. There is scarce work that considers how auditors "see themselves" as experts. Krishnan (2001) uses self-reported specializations from audit firms' websites as indicators of expertise. However, her analysis is at the firm level rather than the team level. Our measure is similar in spirit to Krishnan (2001) as we allow the audit firm to self-identify specialists based on how they allocate staff across clients. Bell et al. (2015) base the classification of specialists on the internal classifications of the firm. We do not rely on the firm classifications but use actual workloads to determine how much expertise an auditor has in an industry. Our measure has the advantage of potentially providing a continuous relative measure of industry expertise. Limitations on our measure are discussed below.
6. We acknowledge that a limitation of our data set is that we do not have the complete workload allocation for each audit team member. This limitation is discussed in more detail when we discuss sample selection and is acknowledged in the concluding section. In the supporting information online Appendix, we discuss how having partial workloads at the individual auditor level might affect our analyses and inferences.
7. Prior studies recognize training (indirect experience) as another source of industry-specific knowledge. We assume that experience and training are correlated.
8. Due to the anonymity of the client information, our analysis is limited to variables provided by the audit firm. Our data are not sufficient to determine abnormal accruals and other traditional audit quality measures.
9. Contessotto et al. (2021, 249) explain that these Australian mid-tier firms are not specialists in any industry sector except for mining.

ascertain the relevance of our findings to Big 4 firms' audit teams." In addition, we examine balanced and unbalanced teams separately.

Our study has several important implications. First, we contribute to an emerging stream of research that uses proprietary data to examine audit team dynamics (Cameran et al. 2018; Contessotto et al. 2019; Aobdia, Choudhary, and Newberger 2021; Christensen et al. 2021; Contessotto et al. 2021) by examining the role of industry knowledge in Big 4 audit teams. In doing so, we answer recent calls for further research on audit teams (Francis 2011; DeFond and Zhang 2014; PCAOB 2015; Christensen et al. 2016). As Aobdia, Choudhary, and Newberger (2021, 1) state, "What remains unknown is whether audit team members beyond the lead partner influence audit effectiveness." Second, we contribute to the literature on audit production (O'Keefe et al. 1994; Stein et al. 1994; Hackenbrack and Knechel 1997; Blokdijk et al. 2006; Bell et al. 2008; Schelleman and Knechel 2010; Dekeyser et al. 2019). In particular, we extend this research by examining the quality of labor inputs at the team level and viewing industry knowledge as an important determinant of this quality. Third, while there is substantial evidence of a positive relation between industry specialization and audit fees (Craswell et al. 1995; Francis et al. 2005; Cahan et al. 2011), the basis for charging a client a specialist premium remains an open question. Taking an audit production perspective, we examine how labor inputs vary as a team's industry knowledge increases. Furthermore, operationalizing industry specialization remains a challenge (Minutti-Meza 2013; DeFond and Zhang 2014; Audousset-Coulier et al. 2016; Eshleman and Guo 2020). We develop a unique measure of industry specialization that is linked to the workloads of audit team members, and we introduce the notion of balanced and unbalanced specialist teams.[10]

2. Theory and hypotheses

Audit team composition

Rich et al. (1997, 90) describe audit teams as "a set of auditors who are assigned collectively to plan and execute the audit." Engagement audit teams are structured during audit planning taking into account different factors such as the characteristics of the client (size, complexity, risk), the level of seniority required for the specific tasks, the level of knowledge (including industry knowledge) needed, and organizational constraints such as timing, availability, and rotation rules (Eilifsen et al. 2013). Within these constraints, the composition of the audit team is based on the set of auditor skills that are available and meet the needs and expectations of the client (Dereli et al. 2007).[11] The various tasks that make up an audit necessitate division of effort across subgroups within the audit team (Cameran et al. 2018).

Despite the central role of audit teams in almost every audit (Rudolph and Welker 1998), empirical archival research on audit team composition is sparse because audit team data is difficult to obtain. However, a few recent studies use proprietary data to examine issues such as workloads within teams. For example, Cameran et al. (2018) investigate whether the labor mix within audit teams (i.e., the hours assigned to partners and managers scaled by total team hours) can affect audit quality. Using data from Italy, they find that greater partner and manager hours relative to total hours negatively affects the audit process. Christensen et al. (2021) find that, for a

10. Prior studies use within-industry market shares or within-firm portfolio shares to identify industry specialist auditors. However, other studies raise concerns about these measures. For example, Audousset-Coulier et al. (2016) compare 30 industry specialist measures used in the literature and find they not only yield different classifications of specialists, but also produce inconsistent results when used in models explaining audit pricing and audit quality. Eshleman and Guo (2020) find that Gaver and Utke's (2019) results are sensitive to the way industry specialization is calculated. Minutti-Meza (2013) identifies conceptual and economic problems associated with market share-based measures of auditor industry specialization. In contrast, our measure is more directly linked to the industry experience of individual audit team members that actually conduct the engagement.

11. While firms might like to maximize the fit of the audit team and the client, several constraints make that difficult. Little is known from research about the quality of audit team "fit" but limited empirical results suggest that when there is low fit, clients are likely to change auditors (Brown and Knechel 2016).

sample of audit teams of a global accounting firm in the United States, heavier team workloads during year-end fieldwork is associated with lower audit quality. Furthermore, they find the effect of workload on audit quality is driven by junior audit staff, leading them to conclude that audit firms need to be particularly careful in developing work schedules for staff at these levels.

Recently, researchers have also started to consider the role of knowledge of team members beyond the lead partner. Hossain et al. (2017) examine the importance of an audit team's general auditing knowledge on audit outcomes. Using publicly available data from Japan, they find the number of accounting professionals in a team is positively associated with audit quality, while the number of non-accounting professionals (e.g., actuaries, real estate appraisers, and tax experts) is not, consistent with greater general audit-related knowledge in the audit team being associated with more effective audit outcomes. Aobdia, Choudhary, and Newberger (2021) instead focus on client-specific knowledge. They use proprietary data from PCAOB audit firm inspections, and find that the client-specific experience of audit team members other than the lead partner or engagement quality reviewer is positively associated with audit quality.[12]

Contessotto et al. (2019) use audit team data from two mid-tier Australian audit firms and consider the general, client-specific, and industry knowledge of two types of core role holders in an audit, that is, managers and in-charge auditors. Generally, they find that none of the three aspects of knowledge are related to the way the audit team responds to the client's risk (risk responsiveness) for in-charge auditors. For managers, general and industry knowledge are not related to risk responsiveness while client-specific knowledge is, but only for non-listed clients. When partner industry experience is added to the model with manager and in-charge auditor industry experience, all three variables are insignificant.[13] In a follow-up study, Contessotto et al. (2021) find that the average industry experience of an audit team does not influence audit fees or effort, although teams with more industry experience rely more on junior staff. However, as Contessotto et al. (2021) note, in their mid-tier firm setting, it is unusual for an auditor to become an industry specialist. As a result, how industry-specific knowledge affects audit production in Big 4 audit teams remains largely unexplored.

Auditor industry specialization

Beyond the context of audit teams, there is an extensive literature that considers auditors' industry expertise. Auditors can develop expertise in an industry sector in order to benefit from efficiency gains or knowledge sharing.[14] Prior studies have mainly focused on the relation between industry specialization and audit fees or audit quality. These studies have been conducted at the global, firm, office, and partner levels.[15]

Of these strands of literature, our study is most closely related to the partner-level analyses. The focus on individual partners recognizes that auditing involves judgment, and as a result, audit quality can vary between partners within the same firm. For example, Gul et al. (2013) find considerable variation in audit quality among individual auditors in China, and Knechel et al. (2015) find that aggressive and conservative audit reporting varies systematically among Big 4 partners in Sweden. The research on industry specialist partners builds on the notion that the knowledge and expertise about specific industries can vary across individual partners within an audit firm

12. Aobdia, Choudhary, and Newberger (2021) consider only "experienced" audit team members defined as audit partners, directors, senior managers, and managers involved in the core audit team.
13. As Contessotto et al. (2019) explain, there are various explanations for an insignificant result. For example, managers and in-charge auditors could rely on the audit firm's systems and methodologies, which reduces the need for industry experience; mid-tier auditors may not gain sufficient in-depth industry experience; or the endogenous nature of team assignments that may leave little cross-variation in industry experience.
14. Prior research suggests that concentration, the relative bargaining power of auditors and their clients, investment opportunities, and homogeneity in an industry can affect an audit firm's decision to specialize in an industry (Cahan et al. 2008; Cahan et al. 2011).
15. For a review of these studies, see, for example, Causholli et al. (2010), Habib (2011), and Jeter (2014).

(Chi and Chin 2011; Zerni 2012; Goodwin and Wu 2014; Bae et al. 2019; Aobdia, Siddiqui, and Vinelli 2021). The findings of these studies support the notion that there is a human capital component to industry expertise and that partners can transfer their knowledge between clients in the same industry.

There are several reasons why the industry-specific knowledge of the entire audit team may be important. First, industry knowledge at lower ranks may matter for tasks that are specifically performed by less experienced personnel. For example, junior staff conduct most of the technical tasks necessary to complete the audit (Maister 1982; Cameran et al. 2018). At the same time, partners only account for a relatively small proportion of effort in an engagement.[16]

Second, audit teams consist of multiple members, and most members will be involved in multiple engagements. This suggests that different team members have a different level of exposure to an industry depending on the other clients on which they work. For example, Bianchi et al. (2019) examine the Italian setting where private company audits and the sign off on tax returns are conducted jointly by three appointed auditors. They find that the clients of auditors who are more central in the network created by these joint arrangements have lower tax rates, consistent with more central auditors acquiring greater tax knowledge and expertise. Thus, focusing on a team member's portfolio of engagements can capture industry knowledge in a much broader sense.

Third, in contrast to audit offices (Francis et al. 2005), teams are not constrained by office boundaries. Teams can draw on the human resources of the entire firm or nearby offices (Seavey et al. 2018; Knechel and Williams 2021) and can include individual auditors with the appropriate knowledge set regardless of where the auditors are based (or their level).[17] Thus, team assignments provide a more accurate representation of how an audit firm allocates its human resources to specific clients in its portfolio.

Hypothesis 1: Audit team industry knowledge

In contrast to the multitude of studies that examine audit pricing, only a handful of studies examine the audit production process in detail (O'Keefe et al. 1994; Stein et al. 1994; Hackenbrack and Knechel 1997; Blokdijk et al. 2006; Bell et al. 2008; Schelleman and Knechel 2010; Dekeyser et al. 2019). As labor is the primary factor in producing audits (Causholli et al. 2010), these studies use proprietary data and examine the determinants of labor inputs, in hours and rate per hour, at the engagement level. O'Keefe et al. (1994) view the audit production process as a constrained cost minimization problem for a given level of assurance where the level of assurance is conditional on the audit firm's brand name. Hackenbrack and Knechel (1997) extend this line of research by disaggregating labor hours by the type of audit activity.

While early studies focused on client attributes, as Blokdijk et al. (2006) state, audit production is also affected by the audit firm's technology and expertise of the auditors assigned to an engagement.[18] Consequently, some studies consider aspects of the audit firm's technology, specifically, the use of business risk auditing (Blokdijk et al. 2006; Bell et al. 2008), mix of audit activities (Blokdijk et al. 2006), and intra-office knowledge transfer (Dekeyser et al. 2019). In contrast, labor quality, which "represents the skills, knowledge, and judgement of those that actually perform the audit" (Blokdijk et al. 2006, 28), has not been considered in prior audit

16. In our data set, the proportion of hours performed by all partners in a team (one or more) to total team hours is around 10%.

17. Knechel and Williams (2021) find that specialist knowledge in a market with a high concentration of clients in the same industry (called an agglomeration) have a higher price premium than specialists in smaller markets, for example, the oil and gas industry in Houston. Furthermore, the benefit of being a specialist in a concentrated market can be transferred beyond the local office to nearby offices that are not specialists in the same industry.

18. Sirois and Simunic (2011, 7) define audit technologies as "auditor 'know-how' or competence" which can include "audit programs, training, IT equipment, software, databases and other electronic decision aids, in-house central research and accounting consultation units."

production studies. By focusing on the industry knowledge of the members of the engagement team, we provide evidence on the role of labor quality in audit production. Furthermore, experimental studies indicate that the skills, knowledge, and judgment of industry specialist auditors differ across auditors depending on their level of industry knowledge (Wright and Wright 1997; Solomon et al. 1999; Owhoso et al. 2002). These studies support the notion that relevant industry experience is one dimension that affects the quality of an audit team member's labor inputs in producing an audit.

While industry experience can affect the quality of labor inputs, the implications for audit production are an empirical issue. Although prior studies do not consider industry knowledge of an entire team, Bae et al. (2019) find that engagements led by expert partners use more audit hours. In contrast, in an experimental study, Low (2004) finds evidence that industry knowledge affects audit planning with industry experts budgeting fewer engagement hours. Prior research indicates that team performance is enhanced if team members can recognize members with relevant expertise and utilize that expertise effectively (Libby et al. 1987; Hollenbeck et al. 1995; Bunderson 2003). However, in an audit setting, Trotman et al. (1983) find that groups with varying knowledge did not outperform individuals in making internal control evaluations, which is inconsistent with groups assigning higher weights to the contributions of team members with more expertise. In addition, competition and rivalries among team members (Wittenbaum et al. 2004; Gardner et al. 2012) or status considerations (Knechel and Leiby 2016) could bias communication and undermine collaboration between team members, which can reduce knowledge sharing and marginalize more expert team members.[19] Based on this review of the audit production literature, we state Hypothesis 1 in null form:

HYPOTHESIS 1 (H1). *Audit effort for an engagement is not associated with the industry experience of team members.*

Hypothesis 2: Distribution of within-team industry knowledge

Prior studies on small groups and work teams suggest that how expertise is distributed within a team is also relevant since not all team members will have the same level of expertise (Hollenbeck et al. 1995; Bunderson 2003; Woolley et al. 2008; Gardner et al. 2012). Since the various audit tasks require division of effort across sub-groups (levels) within the audit team, and as audit teams are hierarchical by design, the distribution of expertise at different levels is important. There is some prior research on the audit impact of (individual) team members' expertise or experience on audit work. Low (2004) and Bae et al. (2019) investigate the association between the industry-specific knowledge of partners and audit effort with conflicting results, and Contessotto et al. (2019) consider the association between industry experience of managers and in-charge auditors and risk responsiveness. Contessotto et al. (2021) study the distribution of industry experience across audit team members in mid-tier firms but do not find an effect on audit fees or hours. However, they do not specifically identify specialist auditors at different levels within the team.

Hollenbeck et al. (1995) develop a model for decision-making in hierarchical teams with expertise distributed at each level in the hierarchy. One construct in their model is *staff validity*, which reflects whether the judgment of lower-level members of the team captures the true state of a decision object (i.e., accuracy). Staff validity is a function of the team members' *informedness*. In our setting, junior staff will likely be better informed to perform their immediate tasks when they possess greater industry knowledge. Hollenbeck et al. (1995) also argue that the team leader's (partner's) ability to correctly aggregate and integrate the judgments of subordinates will affect team outcomes. They refer to this as *hierarchical sensitivity*, and argue that this sensitivity can be affected by the relative knowledge of both lower-level members and a team's leader as

19. Audit firms, and by extension audit teams, are subject to agency costs in their operations, which may undermine the effectiveness of the audit (Huddart and Liang 2003, 2005).

they interact. A more informed subordinate is likely to have more impact on a superior's decision than a relatively uninformed subordinate. Thus, in Hollenbeck et al.'s (1995) model, the informedness—or in our case, industry knowledge—of all team members could potentially influence audit outcomes.

Audit work can also be affected by the quality of interaction and communication between team members (Cameran et al. 2018), and informedness is a factor that may facilitate effective communication in audit work as well as learning among team members. Technical knowledge acquisition occurs on the job through the interaction of individual engagement team members (Westermann et al. 2015). One important task of senior-level auditors is to act as a supervisor, to guide and review the work of subordinates to improve their audit judgment and, ultimately, the judgment of the overall team (Gibbins and Trotman 2002; Tan and Tan 2008; Peecher et al. 2010). Subordinates tend to attribute their best review experiences to reciprocal relationships and effective communication with their supervisors (Andiola et al. 2019).

Knowledge sharing among employees (audit team members) increases the effectiveness in which firms can, for example, solve problems and avoid repeating mistakes (Collins and Smith 2006; Robinson et al. 2006) and obtain the desired level of audit assurance (Chow et al. 2008). Most of the interaction to support knowledge sharing between team members of different levels occurs in the review process (Chow et al. 2008). However, systematic differences in knowledge among auditors of different levels have been found to impact the quality of these reviews (Harding and Trotman 1999). Furthermore, knowledge about a client's industry is likely to be unevenly distributed among team members and reviewers (Chow et al. 2008; Harding and Trotman 1999). Insufficient knowledge of the client's industry is one of the characteristics of team members at different levels (e.g., managers, associates) that is referred to by auditors as an obstacle or barrier to completing audit procedures (Chow et al. 2008). In audit teams with relevant industry knowledge at both higher and lower levels, interaction and communication between informed team members are likely to work well, resulting in audit problems being solved and audit procedures being completed more effectively and with fewer mistakes.

Thus, we consider how the distribution of industry knowledge within an audit team affects the quality of labor inputs and team interactions by comparing teams with industry specialists at both the senior and junior rank (*balanced* teams) to teams without industry specialists (*non-specialist* teams) and by comparing teams with specialists at either the senior or junior rank (*unbalanced* teams) to teams without industry specialists. This leads to the following hypotheses (in null form):

HYPOTHESIS 2a (H2a). *Audit effort in an engagement does not differ between balanced specialist teams and non-specialist teams.*

HYPOTHESIS 2b (H2b). *Audit effort in an engagement does not differ between unbalanced specialist teams and non-specialist teams.*

Based on the arguments above, we expect that balanced teams will benefit from having specialists in both senior and junior positions, leading them to produce audits differently from non-specialist teams. In contrast, it is less clear whether teams with specialists at only one rank will conduct audits differently from non-specialist teams.

3. Research design

The Swedish audit market and institutional setting

Auditors of publicly listed companies, and many larger private entities, are required to apply EU directives regarding the audit of Public Interest Entities (EU, No. 537/2014). Only the very smallest entities are currently exempt from the statutory audit requirement (Companies Act,

9:1).[20] The use of International Standards on Auditing (ISA) has been required in Sweden since 2011. Independent oversight of auditors in Sweden is carried out by the Swedish Inspectorate of Auditors (SIA), which is a governmental authority under the Ministry of Justice. SIA performs regular inspections of auditors with publicly listed clients every third year. Auditors without public clients are inspected every sixth year, and SIA has largely delegated these inspections to the accountancy profession in Sweden.[21] Sundgren and Svanström (2017) show that disciplinary sanctions are associated with salary reductions in Big 4 audit firms, suggesting that (Big 4) auditors have incentives to avoid sanctions in Sweden. However, they find no (post) sanction-effect on client losses or auditor reporting behavior for sanctioned auditors. In contrast, research based on PCAOB inspections in the United States supports that both auditors and clients react to the inspection outcomes (Daugherty et al. 2011; DeFond and Lennox 2017), indicating that these inspections are potentially more influential than the inspection by SIA. Litigation risk is relatively low in Sweden as indicated by Wingate's (1997) Litigation Risk Index (Choi et al. 2008). However, there have been a few litigation cases (Kraft & Kulture, Prosolvia, HQ Bank) that have received significant public attention in Sweden during the last 15–20 years.

As of December 31, 2015, there were 642 companies listed on the different stock markets in Sweden (Statistics Sweden 2016, 17). On the main market, NASDAQ OMX Stockholm, there were a total of 283 companies listed. The remaining companies were listed on smaller markets (such as Aktietorget, NGM Equity, and NGM Nordic MTF). Furthermore, approximately 224,000 private companies were audited in 2015 in Sweden.[22] The Swedish audit market is dominated by the Big 4 firms that had a market share of 99.5%, based on total assets, for publicly listed firms in 2015.[23] For unlisted companies, the corresponding figure is 87.7%. In terms of number of clients, Big 4 audit firms audited 75% of listed companies and 33.8% of the unlisted companies. The information about total assets is from the database Serrano, which contains the information from the Swedish Companies Registration Office (Sw. *Bolagsverket*). The SIA provides information about the firm's auditor. The information about whether the firm is listed or not comes from the FinData database. FinData is a provider of financial data worldwide.[24]

Data

Our analysis is based on proprietary data provided by a Big 4 audit firm in Sweden consisting of 908 audit teams/engagements for the period from July 2015 to June 2016.[25] The audit firm originally provided two data files to the lead researcher in December of 2016 under an agreement of confidentiality. One file included the engagement/firm-level data and the other file included the

20. All limited liability companies that exceed two out of the following three size criteria must have an audit: 3 million SEK in total revenue, 1.5 million SEK in balance sheet total assets, and three employees (Companies Act, 9:1).
21. Audit firms that have clients listed on the US stock market are also subject to the inspections of the PCAOB.
22. The Swedish Inspectorate of Auditors (SIA) provides information about the audit firms appointed in these companies.
23. Auditors are assigned to engagements based on competence, relevant professional and *industry experience*, and the characteristics of the engagements (KPMG 2016/2017, 9). EY (2017, 12–13) states that factors considered when assigning people to audit teams include engagement size and complexity, *specialized industry knowledge and experience*, timing of work, continuity, and opportunities for on-the-job training. Also, PwC (2016/2017, 7) indicates audit teams involve *industry specialists* within the organization (emphasis added in all citations).
24. We note that 46 banks and 126 insurance firms, of which 70 are publicly listed, are not conventional limited liability companies and are excluded when calculating these figures.
25. There are 909 clients/teams in the data set, but one client has a missing value for total assets and we therefore use data on 908 clients/teams. As all companies in the sample have a December 31, 2015 fiscal year end, the study period ensures that all hours spent on the engagement are included (from audit planning in the autumn of 2015 until completion of the audit during spring of 2016).

detailed information about the composition of 908 audit teams.[26] Companies in the first file were anonymized by the audit firm with an identifier number. The second file included the ID number of all team members for the 908 audit engagements.[27] All analyses have been done with anonymized company and personnel files. This arrangement was approved by the audit firm. Overall, there are 1,512 individual auditors associated with the 908 audit teams, and 8,282 team-auditor observations.

The data set contains the actual audit hours (i.e., not budgeted hours) incurred by each auditor and the total cost per auditor from which the hourly internal rate is computed. Based on discussions with partners at the firm, this rate reflects the labor input cost plus mark-up and is used for the firm's internal accounting purposes as part of its time scheduling system.[28] The hourly internal rate, together with hours, is used for various key decisions in the audit firm including composition of audit teams, allocation of resources, budgeting, and monitoring.[29]

The 908 teams in the data set audit relatively large clients. All the personnel are classified into one of the following levels: partner, director, senior manager, manager, assistant manager, senior associate, associate, and others.[30] Because we have a unique employee ID for each auditor, we can identify all the team assignments of a particular auditor to the extent that the team has been included in the data set. However, we do not have the complete annual workload allocations for the auditors. Specifically, we acknowledge that a limitation of our data is that we do not have information for smaller, less complex audits but assume that industry expertise plays less of a role in straightforward or routine audits (Contessotto et al. 2021).[31]

Each audit client-team pair is assigned to one of 16 industries based on the industry groupings used by the audit firm. We retain these classifications rather than trying to force clients into a standardized industry classification system (e.g., GICS) because the audit firm is best placed to identify similarities between its clients and to group them accordingly. Put differently, our measure of industry expertise essentially reflects the firm's designation of industry classifications since we observe how the firm has allocated the workload of its auditors to clients in the same industry or in different industries based on its own industry definitions.

Measuring industry knowledge

We construct a measure of industry knowledge or expertise at the individual auditor level that is based on each auditor's industry hours *relative* to all other auditors in the same audit firm who

26. The 908 audit engagements were selected from clients with a December 31, 2015, fiscal year end based on the following selection criteria: three or more levels of auditors in the audit engagement, minimum of 20 hours for the engagement, only limited liability companies, only active companies, and only companies registered in Sweden. A small number of engagements (nine clients) did not satisfy all five criteria listed above. Untabulated results remain when we exclude these nine clients. Also, see footnote 31.
27. Only the lead researcher had access to the original personnel data file. The ID number is a 5-digit number assigned to employees by the audit firm and it is not their Swedish personal identification number.
28. We assume any mark-up is consistent across auditors.
29. We do not have data on the total audit fee. However, as O'Keefe et al. (1994) note, the total audit fee reflects more than a simple mark-up over cost as the audit fee can be "contaminated" by the audit firm's pricing policies. Thus, audit fees reflect more than audit production costs.
30. Directors are experienced auditors and are between the level of partners and senior managers. We exclude "others" from our analyses as individuals in this category are likely to be non-accounting professionals and they usually have very few audit hours and low hourly internal rates.
31. The listed clients in our sample have average total assets that are 1.1 times the average total assets of all listed firms in the Big 4 firm's client portfolio. In contrast, for private firms, the average total assets of private clients in our sample is 14 times the size of the average private client in this Big 4 firm's portfolio. More specifically, while the sample includes less than 5% of the total number of private clients of this Big 4 firm, the private clients included in the sample represent more than 30% of the total assets in the Big 4 firm's private client portfolio. Overall, this is consistent with our data excluding the Big 4 firm's smallest clients.

work on clients in the same industry.[32] As auditors are usually involved in multiple audit teams in an industry, we combine each auditor's hours across all clients of this auditor in that industry to assess the auditor's total industry exposure. For each industry, we rank all senior auditors (i.e., partners, directors, and senior managers) involved in audits of clients in that industry into ventiles (i.e., 20 groups in five percentile increments) based on their total hours spent on clients in that industry. We repeat the calculation for all junior auditors (i.e., managers, assistant managers, senior associates, and associates) involved in audits in an industry.[33] For each audit team, we then compute the mean ventile rank of all team members. For example, consider client *j* in industry *k* that has an audit team consisting of five auditors with ventile ranks with respect to industry *k* of 15, 12, 8, 18, and 16, respectively (higher ventiles indicate greater relative industry exposure). The mean rank for this team is 14. We label this *IKTeam* and interpret the variable as a measure of industry knowledge at the engagement team level. Teams with higher mean ranks have team members who, on average, have greater industry experience relative to their colleagues working in the same industry.[34]

To measure the distribution of industry knowledge within the team, we classify each team member as an industry specialist (*IS*) or non-specialist based on their relative experience with a client's industry.[35] For each industry *k*, we designate individual auditors in the top five ventiles (i.e., top quartile) as an industry specialist in industry *k*. That is, these auditors have the most exposure to industry *k* on a relative basis. We then create two indicator variables: *Bal* (balanced specialist team) is coded one for clients audited by an engagement team that has average industry knowledge among the top quartile and has at least one industry specialist team member at both the senior (partner, director, senior manager) rank and junior (manager, assistant manager, senior associate, associate) rank, and zero otherwise; *Unbal* (unbalanced specialist team) is coded one for clients audited by an engagement team that has average industry knowledge among the top quartile and has at least one industry specialist at the senior rank *or* the junior rank *only*, and zero otherwise. Teams where both *Bal* and *Unbal* equal zero are classified as non-specialist teams. The supporting information in the online Appendix provides an example of the computations for *IKTeam*, *Bal*, and *Unbal*.

Models

Our audit production model draws on O'Keefe et al. (1994), which is also consistent with Bedard and Johnstone (2004). Similar to Hackenbrack and Knechel (1997), we use a reduced version of O'Keefe et al.'s (1994) model due to data limitations to examine H1:

32. Our measure differs from Contessotto et al.'s (2021) measure of team industry experience. They use a survey that asked auditors to estimate their industry experience. As the response rate was 50%, they estimated the industry experience of non-respondents using the audit firm's records of clients the auditor had worked on in the current and three prior years. They do not consider relative workloads between auditors in the same firm as we do.
33. In robustness tests, we also define managers as senior team members instead of junior team members. That is, we classify partners, directors, senior managers, and managers as senior ranked auditors and the other three levels as junior ranked auditors. The findings are reported in Table 7, panel B.
34. We acknowledge that we do not have the complete workload of auditors in our sample. The engagements included in our data set were selected based on five criteria that we gave to the Big 4 audit firm. The purpose of the criteria is to select the audit firm's larger and more complex engagements that were audited by teams involving auditors from different levels (i.e., partners, managers, associates). While data on the complete portfolio of clients would generate the most correct measure of industry experience as discussed by Lennox and Wu (2018), we note that, for practical reasons, using a subsample of larger engagements is the standard practice of most papers on partners' workloads and industry experience (Audousset-Coulier et al. 2016, 148). Overall, while our data set includes many of the audit firm's larger and more complex audits that are likely to require some degree of industry expertise, it is not possible to assess the level of industry expertise required for clients not in our sample.
35. Our focus on individual specialists is consistent with the small group literature on distributed expertise (Hollenbeck et al. 1995; Bunderson 2003; Woolley et al. 2008; Gardner et al. 2012) focusing on the interactions between individual members within a team.

$$Ln(Effort) = b_0 + b_1 IKTeam + b_2 TeamSize + b_3 LnTA + b_4 Leverage + b_5 SalesGrowth + b_6 ROA + b_7 Tenure + b_8 Public + b_9 Loss + b_{10} Stockholm + Industry\ fixed\ effects, \quad (1)$$

where *Effort* refers to *TeamHrs* or *TeamRate*. *TeamHrs* is the aggregate audit hours for the engagement and *TeamRate* is the average hourly internal rate for all team members. *IKTeam* is defined above. We control for team size (*TeamSize*), which is the number of auditors in a team, as well as client characteristics including firm size measured by the natural logarithm of total assets (*LnTA*), debt to total asset ratio (*Leverage*), sales growth (*SalesGrowth*), return on assets (*ROA*), and the number of years the client has been registered in the system of the audit firm (*Tenure*) as control variables. Since we have data for public and private clients, we control for whether the client is publicly listed (*Public*). We also control for whether the client is based in Stockholm, which is Sweden's largest city and business center (*Stockholm*). Finally, we include industry fixed effects in all models. All variables are defined in the Appendix.

To test H2, we use an expanded version of equation (1) as follows:

$$Ln(Effort) = b_0 + b_1 Bal + b_2 Unbal + b_3 TeamSize + b_4 LnTA + b_5 Leverage + b_6 SalesGrowth + b_7 ROA + b_8 Tenure + b_9 Public + b_{10} Loss + b_{11} Stockholm + Industry\ fixed\ effects, \quad (2)$$

where *Effort*, *Bal*, and *Unbal* are as defined above and b_1 (b_2) represents the incremental effect of balanced (unbalanced) specialist teams on effort relative to non-specialist teams.

4. Results

Descriptive statistics and correlations

Table 1 presents the number of audit teams per industry. Based on the last column, Business Consulting, Wholesale, and Manufacturing have the highest number of clients with 176, 143, and 139, respectively. Table 2, panel A, presents the descriptive statistics for the full sample. The mean number of total audit hours (*TeamHrs*) for the 908 engagements is 432. The average

TABLE 1
Industry distribution of audit teams

Industry	Total
Administrative and support services	30
Bank and finance	81
Construction	38
Business consulting (law, business, accounting)	176
Technical consulting	21
Electricity, gas, heating, water, garbage	25
Hotel and restaurant	13
Information and communication	58
Manufacturing	139
Other	34
Public administration	26
Real estate	66
Research and development	9
Retail	30
Transport	19
Wholesale	143
Total	908

Notes: Audit teams are classified into the 16 industry categories used by the Big 4 firm providing us with the data.

TABLE 2
Descriptive statistics and correlation matrix

Panel A: Descriptive statistics for the full sample ($N = 908$)

	Mean	SD	5	25	50	75	95
TeamHrs	432	633	20	207	296	474	1,214
TeamRate	1,438	296	1,045	1,248	1,406	1,591	1,990
LnTeamHrs	5.55	1.15	3.00	5.33	5.69	6.16	7.10
LnTeamRate	7.25	0.20	6.95	7.13	7.25	7.37	7.60
IKTeam	9.97	3.52	3.20	7.88	10.10	12.54	15.33
Bal	0.17	0.38	0	0	0	0	1
Unbal	0.08	0.27	0	0	0	0	1
SPP0-1	0.06	0.24	0	0	0	0	1
TeamSize	9.11	6.87	3	5	8	11	20
LnTA	12.48	2.23	8.09	11.35	12.63	13.85	15.98
Leverage	0.62	0.30	0.07	0.44	0.66	0.82	0.97
SalesGrowth	0.16	1.18	−0.35	−0.02	0.03	0.13	0.60
ROA	0.03	0.45	−0.24	0.00	0.05	0.13	0.33
Tenure	11.11	5.36	3	6	11	17	19
Public	0.1	0.3	0	0	0	0	1
Loss	0.27	0.45	0	0	0	1	1
Stockholm	0.43	0.5	0	0	0	1	1

Panel B: Descriptive statistics for balanced and unbalanced specialist teams

	Bal = 1			*Unbal* = 1			*Bal* = 0 and *Unbal* = 0			*Bal* = 1 vs. *Unbal* = 1
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	*t*-value
TeamHrs	726.49	918.01	438.18	383.89	229.66	315.32	369.70	558.92	266.52	−3.08***
TeamRate	1,580.50	312.72	1,495.89	1,401.36	255.69	1,320.32	1,408.95	286.07	1,383.58	−4.20***
LnTeamHrs	6.24	0.75	6.08	5.83	0.46	5.75	5.36	1.20	5.59	−4.18***
LnTeamRate	7.35	0.18	7.31	7.23	0.17	7.19	7.23	0.20	7.23	−4.57***
IKTeam	14.46	1.46	14.15	13.90	1.00	13.71	8.54	2.76	9.1	−2.92***
SPP0-1	0.04	0.19	0.00	0.06	0.23	0.00	0.06	0.25	0	0.63
TeamSize	11.66	9.16	9.00	6.90	3.23	6.00	8.76	6.37	8	−4.23***
LnTA	13.63	1.97	13.50	12.93	1.67	12.96	12.17	2.24	12.44	−2.59**
Leverage	0.57	0.31	0.60	0.54	0.29	0.59	0.63	0.30	0.67	−0.73

(The table is continued on the next page.)

TABLE 2 (continued)

Panel B: Descriptive statistics for balanced and unbalanced specialist teams

	Bal = 1			*Unbal* = 1			*Bal* = 0 and *Unbal* = 0			*Bal* = 1 vs. *Unbal* = 1
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	*t*-value
SalesGrowth	0.19	1.15	0.03	0.07	0.36	0.06	0.17	1.25	0.03	−0.85
ROA	−0.08	0.93	0.03	0.05	0.16	0.04	0.05	0.27	0.05	1.14
Tenure	11.24	5.04	10.50	10.61	5.15	10.00	11.13	5.45	11	−0.85
Public	0.20	0.40	0.00	0.06	0.23	0.00	0.08	0.28	0	−2.75***
Loss	0.33	0.47	0.00	0.26	0.44	0.00	0.26	0.44	0	−1.14
Stockholm	0.62	0.49	1.00	0.53	0.50	1.00	0.38	0.48	0	−1.23
N		156			70			682		

Panel C: Pearson correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 *LnTeamHrs*														
2 *LnTeamRate*	0.426#													
3 *SPP0-1*	0.069*	0.021												
4 *IKTeam*	0.648#	0.338#	−0.006											
5 *Bal*	0.274#	0.221#	−0.040	0.582#										
6 *Unbal*	0.072*	−0.029	−0.003	0.323#	−0.132#									
7 *TeamSize*	0.619#	0.250#	0.101#	0.206#	0.169#	−0.093#								
8 *LnTA*	0.752#	0.466#	0.036	0.502#	0.236#	0.059*	0.471#							
9 *Leverage*	−0.051	−0.109#	−0.105#	−0.107#	−0.064*	−0.071*	−0.039	−0.053						
10 *SalesGrowth*	0.005	0.012	−0.016	0.007	0.012	−0.022	−0.019	0.003	0.029					
11 *ROA*	−0.052	−0.049	−0.014	−0.066*	−0.105#	0.015	0.009	0.077*	−0.151#	−0.005				
12 *Tenure*	0.127#	0.096#	0.012	0.062*	0.011	−0.027	0.104#	0.173#	−0.005	−0.087#	0.057*			
13 *Public*	0.258#	0.287#	0.008	0.116#	0.147#	−0.042	0.292#	0.192#	−0.201#	0.003	−0.091#	0.004		
14 *Loss*	0.038	0.054	−0.018	0.067*	0.062*	−0.01	−0.019	−0.052	0.125#	−0.005	−0.312#	−0.099#	0.056*	
15 *Stockholm*	0.242#	0.203#	0.046	0.272#	0.172#	0.058*	0.131#	0.112#	−0.123#	−0.017	−0.062*	−0.066*	0.085#	0.109#

Notes: Panel A reports descriptive statistics, mean (Mean), standard deviation (SD), and the 5, 25, 50, 75, and 95 percentile values for the full sample. Panel B reports the descriptive statistics for balanced teams (*Bal* = 1), which consist of teams that have high average team knowledge (top quartile) and industry specialists at both the senior rank and junior rank; unbalanced teams (*Unbal* = 1), which consist of teams that have high average team knowledge (top quartile) and an industry specialist at the senior rank only or junior rank only; and all other teams (*Bal* = 0 and *Unbal* = 0). The last column of Panel B presents the *t*-value of the difference between the mean of balanced teams and unbalanced teams. Panel C presents the Pearson correlation matrix for the dependent variable, test variables, and control variables. * and # indicate significance at the 5% and 1% levels, respectively. All variables are defined in the Appendix.

internal hourly rate at the team level (*TeamRate*) is 1,438 SEK.[36] The next two rows report the natural logarithm of these variables, *LnTeamHrs*, and *LnTeamRate*, which are the dependent variables for equations (1) and (2). The test variable *IKTeam* has a mean of 9.97. Seventeen percent of teams are balanced specialist teams (*Bal*) and 8% are unbalanced teams (*Unbal*), meaning 75% of the teams are non-specialists. The mean for audit team size is 9.11 members, ranging from three members at the 5th percentile to 20 members at the 95th percentile.

For the client characteristics, the mean of clients' total assets is 2,064 million SEK (untabulated). The debt to total asset ratio (*Leverage*) has a mean of 0.62, while the mean return on assets (*ROA*) is 0.03. The mean for sales growth (*SalesGrowth*) is 0.16, and the average number of years the clients have been registered in the system of the audit firm (*Tenure*) is 11. Ten percent of the clients are publicly listed (*Public*), 27% have a loss (*Loss*), and 43% are located in Sweden's capital city (*Stockholm*).

Table 2, panel B, provides the descriptive statistics for clients audited by balanced specialist teams (*Bal* = 1), unbalanced specialist teams (*Unbal* = 1), and non-specialist teams (*Bal* = 0 and *Unbal* = 0), respectively. Based on the results of *t*-tests reported in panel B, the clients audited by balanced specialist teams and clients audited by unbalanced specialist teams differ on only two client attributes, *LnTA* and *Public*. Balanced teams have greater average industry knowledge and more team members compared to unbalanced teams. Balanced teams are also associated with more audit hours and a higher average internal rate than unbalanced teams.

Table 2, panel C, reports the Pearson's correlation matrix. The correlations between *LnTeamHrs* and *LnTA* and between *LnTeamHrs* and *TeamSize* are 0.752 and 0.619, respectively, which is not surprising since audits involving larger clients need larger teams with more audit hours. There is a moderately high correlation between *LnTA* and *LnTeamRate* ($r = 0.466$) and between client size (*LnTA*) and *TeamSize* ($r = 0.471$). The variable of interest, *IKTeam*, is significantly correlated with *LnTeamHrs* ($r = 0.648$) and *LnTeamRate* ($r = 0.338$), providing preliminary evidence of an association between team industry knowledge and audit effort.

Tests of H1 and H2a/H2b

Table 3 presents the results for H1. We use two-tailed tests to assess significance levels. The coefficient on *IKTeam* is 0.142 (*p*-value <0.01) in column (1) when the dependent variable is the natural logarithm of team audit hours (*LnTeamHrs*). This result indicates that more team industry knowledge is associated with greater audit effort (more hours).[37] A one standard deviation in *IKTeam* (3.52) is associated with a 0.5 increase in the dependent variable or 43.5% of a standard deviation in *LnTeamHrs* (1.15), which is economically meaningful.[38]

In addition, *IKTeam* is positive (0.006, *p*-value <0.01) in column (2) when the dependent variable is the average internal hourly charge out rate for the team (*LnTeamRate*). This result

36. 1 USD = 8.46 SEK on January 1, 2016.

37. Untabulated results show that the VIF for *IKTeam* is 2.19 and is less than 2 for all the control variables, which suggest there are no concerns about multicollinearity.

38. There may be alternative explanations for a positive relation between *IKTeam* and *LnTeamHrs*. One possibility is that clients demand more assurance and will pay for more expensive engagements and this is reflected in more audit effort. To address this possibility, we consider whether firms with higher agency costs, as proxied by leverage, demand higher quality and pay higher fees. Specifically, we regress a firm's leverage on *IKTeam* and control variables. The coefficient for *IKTeam* is not significant. This indicates that firms' risk measured by leverage may not explain our results. Another possibility is that as audit service is a credence good (Causholli and Knechel 2012), a team that consists of specialist auditors may be more credible to the client so the client is less fee sensitive. To address this possibility, we follow Aobdia, Choudhary, and Newberger (2021) and regress the realization rate, which we compute as total audit fees divided by the hours worked times the internal rate, on *IKTeam*, audit quality, and control variables. After obtaining permission from the audit firm, we manually collect audit fee data for 50 firms. Based on Aobdia, Choudhary, and Newberger (2021), if auditing is a credence good, industry experience would be positively related to the realization rate. We find no evidence of a positive relation between *IKTeam* and the realization rate (results untabulated). However, this result should be interpreted with caution given the small sample size.

TABLE 3
Results for H1: Team industry knowledge and audit production

	(1) *LnTeamHrs*	(2) *LnTeamRate*
IKTeam	0.142***	0.006**
	(19.13)	(2.43)
TeamSize	0.059***	−0.001
	(18.98)	(−0.97)
LnTA	0.209***	0.035***
	(18.95)	(10.03)
Leverage	0.039	−0.025
	(0.62)	(−1.24)
SalesGrowth	0.007	0.002
	(0.48)	(0.46)
ROA	−0.124***	−0.013
	(−2.93)	(−0.99)
Tenure	0.002	0.002
	(0.47)	(1.39)
Public	0.129**	0.106***
	(1.99)	(5.21)
Loss	0.030	0.016
	(0.71)	(1.18)
Stockholm	0.057	0.049***
	(1.39)	(3.74)
Constant	1.196***	6.701***
	(7.70)	(136.89)
N	908	908
Adj. R^2	0.786	0.303

Notes: This table reports results of regressing the natural logarithm of audit hours (*LnTeamHrs*) and the average internal hourly rate (*LnTeamRate*) on the test variable, *IKTeam*, and control variables. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. ** and *** represent significance levels of 5% and 1%, respectively, based on a two-tailed test.

indicates that a one standard deviation increase in *IKTeam* results in an increase of 0.021 in *LnTeamRate*, which is equivalent to 10.6% of one standard deviation in *LnTeamRate*. This result indicates that teams with high *IKTeam* are associated with higher average cost rates, reflecting the higher cost of more experienced effort. However, consistent with Hackenbrack and Knechel (1997), a higher hourly internal rate could be driven by labor mix (i.e., more senior auditors relative to junior auditors). Later tests allow us to distinguish between these two explanations.

For the control variables, *TeamSize* is positive and significant in column (1), consistent with large teams using more hours. Client size (*LnTA*) is positive and significant in both columns, indicating larger clients are associated with greater audit effort and teams that rely more heavily on senior auditors. We find similar results for *Public*. In addition, *ROA* is negatively related to *LnTeamHours*. Finally, the average hourly internal rate is greater for clients based in Stockholm, Sweden's commercial center.

Next, we consider H2a and H2b that explore how the distribution of industry knowledge among team members affects the audit production process relative to non-specialist teams. Specifically, we estimate equation (2), which includes indicators for balanced specialist teams (i.e., *Bal*) and unbalanced specialist teams (i.e., *Unbal*). Table 4 provides the results. In column (1), the coefficient for *Bal* is positive and significant (0.151, *p*-value <0.05). This indicates that teams

TABLE 4
Results for H2a/H2b: Distribution of industry knowledge within teams and audit production

	(1) *LnTeamHrs*	(2) *LnTeamRate*
Bal	0.151**	0.026
	(2.38)	(1.54)
Unbal	0.272***	−0.040*
	(3.28)	(−1.82)
TeamSize	0.053***	−0.002
	(14.37)	(−1.56)
LnTA	0.298***	0.038***
	(25.41)	(12.26)
Leverage	0.049	−0.027
	(0.66)	(−1.35)
SalesGrowth	0.012	0.002
	(0.65)	(0.43)
ROA	−0.182***	−0.014
	(−3.65)	(−1.06)
Tenure	−0.000	0.001
	(−0.08)	(1.23)
Public	0.110	0.103***
	(1.43)	(5.03)
Loss	0.079	0.017
	(1.57)	(1.28)
Stockholm	0.267***	0.057***
	(5.69)	(4.57)
Constant	1.109***	6.705***
	(5.99)	(135.68)
Observations	908	908
Adjusted R^2	0.701	0.303

Notes: This table reports results of regressing the natural logarithm of audit hours (*LnTeamHrs*) and the average internal hourly rate (*LnTeamRate*) on the test variables, *Bal* and *Unbal*, and control variables. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, based on a two-tailed test.

with balanced expertise have higher audit hours relative to teams that lack industry expertise, rejecting the null for H2a with respect to balanced teams. The coefficient for *Unbal* is also positive and significant (0.272, *p*-value <0.01), which indicates that unbalanced teams also have higher audit hours relative to non-specialist teams, so we reject the null of H2b. Since the coefficients for *Bal* and *Unbal* are both significant, we conduct an *F*-test, but we are unable to reject the null that these coefficients are equal (*F*-statistic = 1.69, *p*-value = 0.19).

In terms of hourly rates, we find that the coefficient for *Bal* is positive (0.026) but is not significant at conventional levels. In contrast, the coefficient for *Unbal* is negative and significant (−0.040, *p*-value <0.10). As 93% of the unbalanced teams have a specialist only at the junior level, this result is likely due to unbalanced specialist teams making greater use of less costly junior staff relative to non-specialist teams (as well as balanced specialist teams). This result is consistent with Cahan et al. (2011) who conclude that some industry specialists are low-cost producers.

We conduct subsample tests to consider whether our results are driven by large clients or large teams. First, we consider client size. Since large clients are associated with greater hours

(Table 3), auditors on those teams may incur more industry hours which can increase their relative ranks in terms of industry knowledge, making it more likely that these teams have a higher level of team expertise. Accordingly, we divide the sample based on the median of client size and estimate our models for large and small clients separately. Table 5, panel A,

TABLE 5
Team industry knowledge and audit production: Subsample analyses

Panel A: Large versus small clients for H1

	Large clients		Small clients	
	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *LnTeamHrs*	(4) *LnTeamRate*
IKTeam	0.058***	0.003	0.172***	0.006*
	(6.89)	(0.78)	(16.78)	(1.85)
TeamSize	0.057***	−0.001	0.076***	0.000
	(20.88)	(−0.86)	(13.02)	(0.16)
LnTA	0.112***	0.033***	0.287***	0.032***
	(6.41)	(4.29)	(14.16)	(5.04)
Leverage	0.165**	−0.072**	0.058	−0.007
	(2.29)	(−2.26)	(0.66)	(−0.25)
SalesGrowth	0.017	−0.001	−0.013	0.005
	(0.91)	(−0.18)	(−0.68)	(0.87)
ROA	−0.136	−0.085**	−0.110**	−0.006
	(−1.45)	(−2.07)	(−2.31)	(−0.39)
Tenure	0.003	0.000	−0.000	0.002
	(0.95)	(0.03)	(−0.06)	(1.54)
Public	0.148***	0.081***	0.365***	0.117***
	(2.59)	(3.25)	(2.97)	(3.09)
Loss	−0.043	0.008	−0.026	0.019
	(−0.96)	(0.43)	(−0.40)	(0.96)
Stockholm	0.048	0.035**	0.042	0.070***
	(1.19)	(1.99)	(0.66)	(3.55)
Constant	3.174***	6.800***	0.070	6.722***
	(12.45)	(60.73)	(0.28)	(88.49)
Observations	454	454	454	454
Adjusted R^2	0.713	0.174	0.792	0.229

Panel B: Large clients versus small clients for H2a/H2b

	Large clients		Small clients	
	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *LnTeamHrs*	(4) *LnTeamRate*
Bal	0.171***	0.016	0.307**	0.034
	(3.46)	(0.75)	(2.57)	(1.15)
Unbal	0.093	−0.061**	0.504***	−0.036
	(1.36)	(−2.14)	(3.57)	(−1.05)
Constant/controls	Yes	Yes	Yes	Yes
Observations	454	454	454	454
Adjusted R^2	0.689	0.183	0.667	0.226

(The table is continued on the next page.)

TABLE 5 (continued)

Panel C: Large versus small audit teams for H1

	Large teams		Small teams	
	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *LnTeamHrs*	(4) *LnTeamRate*
IKTeam	0.077***	0.007	0.150***	0.005*
	(6.94)	(1.57)	(18.57)	(1.68)
TeamSize	0.048***	−0.001	0.205***	0.001
	(17.84)	(−0.62)	(13.90)	(0.16)
LnTA	0.083***	0.039***	0.182***	0.034***
	(5.83)	(7.25)	(13.13)	(6.70)
Leverage	0.101	−0.061**	−0.091	−0.011
	(1.40)	(−2.21)	(−1.06)	(−0.36)
SalesGrowth	−0.063	0.025	0.013	0.000
	(−1.40)	(1.44)	(0.88)	(0.09)
ROA	−0.156	−0.068*	−0.102**	−0.004
	(−1.46)	(−1.67)	(−2.49)	(−0.29)
Tenure	−0.001	0.003	0.002	0.001
	(−0.34)	(1.64)	(0.61)	(0.87)
Public	0.154***	0.079***	0.093	0.141***
	(2.68)	(3.58)	(0.84)	(3.46)
Loss	−0.090*	0.030	0.029	0.004
	(−1.81)	(1.57)	(0.55)	(0.19)
Stockholm	0.040	0.021	0.078	0.076***
	(0.88)	(1.21)	(1.52)	(3.98)
Constant	3.752***	6.611***	0.614***	6.718***
	(17.21)	(79.14)	(3.27)	(96.87)
Observations	368	368	540	540
Adjusted R^2	0.681	0.284	0.812	0.271

Panel D: Large teams versus small teams for H2a/H2b

	Large teams		Small teams	
	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *LnTeamHrs*	(4) *LnTeamRate*
Bal	0.167***	0.017	0.312***	0.037
	(2.80)	(0.81)	(3.53)	(1.41)
Unbal	0.036	−0.045	0.505***	−0.044
	(0.32)	(−1.14)	(5.36)	(−1.60)
Constant/controls	Yes	Yes	Yes	Yes
Observations	368	368	540	540
Adjusted R^2	0.644	0.282	0.705	0.274

Notes: Panel A (B) reports results for H1 (H2a/H2b) for subsamples of large and small client firms where large clients have total assets above the median. Panel C (D) reports results for H1 (H2a/H2b) for subsamples of large and small audit teams where large teams have team members above the median. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, based on a two-tailed test.

contains these results for H1. We find that, when the dependent variable is team hours (*LnTeamHrs*), *IKTeam* has a positive coefficient and is significant (p-value <0.01) for both large and small clients. Furthermore, inconsistent with large clients driving our main results, we find *IKTeam* is significantly related to the average internal rate for small clients only.[39] Table 5, panel B, provides the results for H2a and H2b split by client size. For team hours, in column (1), we find that the coefficient for *Bal* for large clients is significant and positive, consistent with balanced teams exerting greater effort relative to non-specialist teams. In contrast, for large clients, audit hours of unbalanced teams do not differ from non-specialist teams. On the other hand, consistent with Table 4, the coefficients for *Bal* and *Unbal* are both positive and significant in column (3) for small clients. For the internal rate regressions, in column (2), *Bal* (*Unbal*) is not (is) significant for large clients while in column (4), neither coefficient is significant. However, based on F-tests, we find a lower team internal rate for unbalanced teams compared to balanced teams for both large and small clients (p-value for F-statistic = 0.013 in column (2),F-statistic = 0.085 in column (4)), similar to the relative difference between the two team types found in Table 4. Thus, it is unlikely that the main results are driven solely by large clients.

Second, we compare large and small teams. Large teams are teams with the number of team numbers above the median (8) and the other teams are defined as small teams. With more team members, large teams may be more likely to have members with a high level of expertise. Counterbalancing this, they may also have more members with low industry knowledge. Table 5, panel C (panel D), reports the findings for large teams and small teams separately for H1 (H2a/H2b). Similar to panel A, for H1, we find a significant relation between *LnTeamHrs* and *IKTeam* for large and small teams, while *IKTeam* is only significantly related to *LnTeamRate* for small teams. For H2a and H2b, *Bal* (*Unbal*) is not significant in columns (2) and (4) of panel D, indicating no difference between balanced teams (unbalanced teams) and non-specialist teams in terms of the internal rate. For *LnTeamHrs*, however, the coefficients for *Bal* indicate a significant difference between balanced teams and non-specialist teams for both large and small teams, while the coefficient for *Unbal* is only significant in the regressions for small teams (see columns (1) and (3)). Overall, these results do not suggest our main results are due to a large team effect.

Audit quality tests

While audit hours can be viewed as an input measure of audit quality (Aobdia 2019a), we conduct further tests using an output measure of audit quality. Teams that collectively reflect a higher level of industry experience are more likely to be able to integrate that knowledge within the audit process. However, as discussed above, teams may not always utilize within-team expertise effectively, which can counteract the positive effects of a team member's relevant knowledge. Consequently, we examine whether the extent and distribution of industry knowledge within an audit team will affect the likelihood of small positive profits.[40] We create an indicator variable for small positive profit *SPP0-1* that is coded one if the

39. Although we argue that industry knowledge is relatively unimportant for the smallest clients, the clients classified as "small" in Table 5 are relatively large compared to the very small clients not included in our sample as discussed in footnote 31.

40. One concern about the use of small positive profits is, one may argue, that it is less relevant for private firms since they are under less pressure from shareholders to meet such targets. However, Burgstahler et al. (2006), using measures that include small positive profits, find that private firms in Europe engage in more earnings management than public firms. Also, we note that Aobdia's (2019a) support for small positive profits as a measure of audit quality is based on data from PCAOB inspections. As these inspections are risk-based, his conclusions may not generalize beyond his sample.

TABLE 6
Audit quality tests

	(1) *SPP0-1*	(2) *SPP0-2*	(3) *SPP0-3*	(4) *SPP0-1*	(5) *SPP0-2*	(6) *SPP0-3*
IKTeam	−0.089	−0.031	−0.024			
	(−1.48)	(−0.66)	(−0.60)			
Bal				−1.235**	−0.611*	−0.573*
				(−2.38)	(−1.80)	(−1.95)
Unbal				−0.481	−0.182	0.431
				(−0.83)	(−0.42)	(1.29)
TeamSize	0.037**	0.027*	0.009	0.039**	0.028*	0.013
	(2.18)	(1.84)	(0.63)	(2.20)	(1.89)	(0.96)
LnTA	0.058	0.158**	0.209***	0.040	0.134**	0.194***
	(0.70)	(2.39)	(3.55)	(0.52)	(2.01)	(3.30)
Leverage	−1.502***	−0.752*	−0.253	−1.492***	−0.715*	−0.180
	(−2.80)	(−1.79)	(−0.70)	(−2.74)	(−1.70)	(−0.50)
SalesGrowth	−0.037	−0.089	−0.000	−0.046	−0.086	0.007
	(−0.19)	(−0.49)	(−0.00)	(−0.23)	(−0.47)	(0.07)
ROA	−0.260	−0.232	−0.221	−0.337	−0.273	−0.267
	(−1.13)	(−1.16)	(−1.20)	(−1.46)	(−1.36)	(−1.43)
Tenure	0.016	0.022	0.001	0.015	0.022	0.003
	(0.55)	(0.99)	(0.08)	(0.50)	(0.97)	(0.14)
Public	−0.649	−0.852**	−0.760**	−0.579	−0.873**	−0.720*
	(−1.27)	(−2.02)	(−2.09)	(−1.14)	(−2.05)	(−1.96)
Loss	−0.055	0.107	−0.063	−0.118	0.088	−0.063
	(−0.15)	(0.40)	(−0.27)	(−0.32)	(0.33)	(−0.27)
Stockholm	0.214	0.016	−0.163	0.222	0.006	−0.186
	(0.64)	(0.06)	(−0.73)	(0.69)	(0.02)	(−0.85)
Constant	−2.871**	−4.297***	−4.849***	−3.329**	−9.624**	−7.799*
	(−2.05)	(−3.95)	(−4.77)	(−2.31)	(−2.07)	(−1.91)
Observations	837	899	899	837	899	899
Pseudo R^2	0.084	0.085	0.104	0.096	0.091	0.113

Notes: This table provides results for regressions of audit quality on industry knowledge of teams (*IKTeam*) in columns (1)–(3) or distribution of expertise (*Bal* and *Unbal*) in columns (4)–(6) and control variables. Audit quality is measured using small positive profits. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, based on a two-tailed test.

client's ROA is between zero and 1%, and zero otherwise. We use *SPP0-1* as the dependent variable in equations (1) and (2). We also use bin widths of 0–2% (*SPP0-2*) and 0%–3% (*SPP0-3*) as alternative measures.

Table 6 contains the results of the audit quality tests. *IKTeam* is not significantly related to *SPP0-1* in column (1). The results for *SPP0-2* and *SPP0-3* are similar. Thus, team industry knowledge is not associated with our output measure of audit quality. However, columns (4)–(6) provide a more nuanced picture. In column (4), we find that *Bal* has a negative and significant relation with *SPP0-1*, indicating balanced teams have a lower incidence of small positive profits, and therefore higher audit quality, compared to teams with no specialists. On the other hand, the coefficient for *Unbal* is insignificant, indicating no difference from non-specialist teams. The

results in columns (5) and (6) are similar.[41] Thus, our evidence is consistent with team industry knowledge improving audit quality relative to non-specialist teams, but only for balanced teams where specialists are present at both the senior and junior ranks.[42]

Additional tests

Robustness tests

We conduct a series of tests to assess the robustness of our tests. Table 7 reports the results of these tests. First, we drop individual auditors who are in the bottom quartile of total hours. For these auditors, we observe a relatively small percentage of their workload, which increases the possibility that we are misrepresenting their industry experience. We recalculate *IKTeam*, *Bal*, and *Unbal* after omitting these auditors. Panel A provides these results, which are consistent with the main findings. Specifically, *IKTeam* is significantly and positively associated with team hours and team rate, but not *SPP0-1*. Furthermore, *Bal* and *Unbal* are significantly and positively related with team hours, indicating that both types of specialist teams use more hours than non-specialist teams. *Unbal* has a negative and significant coefficient when team internal rate is the dependent variable while the coefficient for *Bal* is not significant. Finally, *Bal* (*Unbal*) is negatively and significantly related (unrelated) to *SPP0-1*, consistent with Table 6.[43]

Second, we reclassify managers as a senior rank as it is possible that these individuals may have a more central role on a day-to-day basis. Table 7, panel B, reports these findings which are similar to panel A except that in column (5), *Unbal* is not significantly related to *LnTeamRate*. Third, we exclude clients in "Other" industries. Since this group includes clients from various industries, our measure of industry knowledge may be noisier for clients in this category. Panel C reports the results for this analysis. These results are consistent with our primary results.

Fourth, we consider whether our results are sensitive to the threshold we use to define an industry specialist auditor. In our main tests, we classify an individual auditor as an industry specialist if the hours this auditor spent in an industry are in the top quartile. In panel D, we use two alternative thresholds, that is, 30% (columns (1)–(3)) and 40% (columns (4)–(6)). It is important to note that these thresholds only affect *Bal* and *Unbal*, and do not change *IKTeam*. The results are very similar to our primary results except in column (2), where the coefficient for *Bal* becomes significant. Overall, these alternative thresholds do not affect our inferences.

Fifth, we reestimate our models while explicitly controlling for labor mix. As discussed above, when team rate is the dependent variable, the coefficients for *IKTeam* or *Bal* and *Unbal* could reflect an experience premium (or discount) or differences in the labor mix between teams. To differentiate between these explanations, we compute the proportion of team hours associated with higher ranked auditors (*ProHighRank*). The results are presented in Table 7, panel E. When we control for *ProHighRank*, the results for team hours and *SPP0-1* are consistent with prior

41. The number of observations in Table 6 varies for each regression. This is because certain industries are perfectly collinear so they are omitted from the analysis. We also conduct a Byzalov and Basu (2019) test for our audit quality analysis. Byzalov and Basu (2019) suggest that the dependent variable should be scaled earnings and we use return on assets (*ROA*) as the dependent variable. We utilize various options, such as different interval width (e.g., 0.0025 and 0.005), both models I and II, and both a third- and a fourth-order polynomial for the probability density function. Using an indicator variable for high team industry knowledge, untabulated results show that the coefficients on the test variable are negative and significant, suggesting that audit teams with higher industry knowledge are associated with less earning management.

42. As audit hours can be viewed as an input measure of audit quality (Caramanis and Lennox 2008; Aobdia 2019a), the results for unbalanced teams appear inconsistent since we find higher audit hours for unbalanced teams relative to non-specialist teams (Table 4), but no difference between unbalanced and non-specialist teams in terms of small positive profits, an output measure of audit quality (Table 6). However, these results suggests that, consistent with credence theory (Causholli and Knechel 2012), unbalanced teams work hours for which they get paid, whether or not those hours actually contribute to audit quality.

43. Our results hold when we remove auditors in the bottom 20% or 30% based on their total hours.

TABLE 7
Robustness tests

Panel A: Results excluding individual auditors with total audit hours in the bottom quartile

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *LnTeamHrs*	(5) *LnTeamRate*	(6) *SPP0-1*
IKTeam	0.114***	0.004*	−0.082			
	(14.76)	(1.71)	(−1.32)			
Bal				0.118*	0.024	−1.748***
				(1.83)	(1.33)	(−2.79)
Unbal				0.276***	−0.043*	−0.382
				(3.40)	(−1.88)	(−0.65)
TeamSize	0.063***	−0.001	0.042**	0.059***	−0.002	0.047**
	(18.48)	(−1.03)	(2.15)	(15.37)	(−1.44)	(2.29)
LnTA	0.199***	0.036***	−0.006	0.263***	0.038***	0.000
	(16.78)	(9.69)	(−0.06)	(21.19)	(10.99)	(0.00)
Leverage	0.054	−0.028	−1.754***	0.055	−0.028	−1.704***
	(0.81)	(−1.32)	(−3.10)	(0.75)	(−1.36)	(−2.97)
SalesGrowth	0.007	0.003	0.025	0.006	0.003	0.038
	(0.46)	(0.66)	(0.16)	(0.34)	(0.54)	(0.25)
ROA	−0.133***	−0.015	−0.208	−0.174***	−0.014	−0.356
	(−3.16)	(−1.10)	(−0.86)	(−3.67)	(−1.07)	(−1.44)
Tenure	0.002	0.001	0.034	0.001	0.001	0.032
	(0.55)	(0.99)	(1.10)	(0.17)	(0.88)	(1.03)
Public	0.124*	0.111***	−0.433	0.120	0.107***	−0.332
	(1.84)	(5.22)	(−0.83)	(1.59)	(5.05)	(−0.63)
Loss	0.008	0.009	0.038	0.025	0.009	−0.032
	(0.17)	(0.62)	(0.10)	(0.49)	(0.62)	(−0.09)
Stockholm	0.092**	0.045***	0.088	0.233***	0.051***	0.109
	(2.19)	(3.38)	(0.25)	(5.05)	(3.91)	(0.32)
Constant	1.548***	6.711***	−2.175	1.541***	6.718***	−2.902*
	(9.35)	(128.20)	(−1.48)	(8.20)	(127.12)	(−1.89)
Observations	803	803	744	803	803	744
Adjusted R^2	0.749	0.275	0.091	0.683	0.278	0.115

Panel B: Results including managers in senior rank

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(3) *LnTeamHrs*	(4) *LnTeamRate*	(6) *SPP0-1*
IKTeam	0.143***	0.005**	−0.086			
	(19.34)	(2.15)	(−1.44)			
Bal				0.203***	0.009	−0.772*
				(3.41)	(0.56)	(−1.79)
Unbal				0.353***	−0.041	−1.159
				(3.30)	(−1.41)	(−1.10)
Constant/controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	908	908	837	908	908	837
Adjusted R^2/Pseudo R^2	0.787	0.302	0.084	0.703	0.299	0.090

(The table is continued on the next page.)

TABLE 7 (continued)

Panel C: Results excluding clients in "Other" industries

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(3) *LnTeamHrs*	(4) *LnTeamRate*	(6) *SPP0-1*
IKTeam	0.135***	0.006**	−0.067			
	(18.10)	(2.38)	(−1.10)			
Bal				0.149**	0.027	−1.438**
				(2.34)	(1.57)	(−2.56)
Unbal				0.310***	−0.047**	−0.380
				(3.76)	(−2.08)	(−0.66)
Constant/controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	874	874	803	874	874	803
Adjusted R^2/Pseudo R^2	0.783	0.306	0.084	0.705	0.307	0.098

Panel D: Results with industry specialist using 30% or 40% threshold

	30% threshold			40% threshold		
	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *LnTeamHrs*	(5) *LnTeamRate*	(6) *SPP0-1*
Bal	0.146**	0.029*	−1.310**	0.143**	0.024	−1.184**
	(2.36)	(1.78)	(−2.53)	(2.38)	(1.49)	(−2.44)
Unbal	0.306***	−0.063***	−0.291	0.369***	−0.073***	−0.324
	(3.49)	(−2.69)	(−0.50)	(3.68)	(−2.74)	(−0.49)
Constant/controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	908	908	837	908	908	837
Adjusted R^2	0.702	0.307	0.098	0.702	0.306	0.096

Panel E: Results controlling for labor mix

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *LnTeamHrs*	(5) *LnTeamRate*	(6) *SPP0-1*
IKTeam	0.140***	0.012***	−0.084			
	(18.70)	(6.57)	(−1.38)			
Bal				0.153**	0.024*	−1.239**
				(2.42)	(1.83)	(−2.38)
Unbal				0.218***	0.034*	−0.405
				(2.61)	(1.94)	(−0.69)
ProHighRank	−0.208**	0.590***	0.324	−0.412***	0.576***	0.503
	(−2.13)	(25.06)	(0.42)	(−3.57)	(23.76)	(0.66)
Constant/controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	908	908	837	908	908	837
Adjusted R^2/Pseudo-R^2	0.787	0.592	0.085	0.705	0.575	0.097

Notes: This table presents further robustness tests for H1, H2a/H2b, and audit quality. Panel A reports the results for tests when individual auditors in the bottom quartile of total hours are excluded from the analysis. Panel B reports the results when managers are reclassified as a senior rank. Panel C reports the results when clients in "Other" industries are excluded from the analysis. Panel D reports results using alternative thresholds, 30% and 40%, to define industry specialist auditors. Panel E reports the results when controlling for labor mix. Labor mix is defined as the proportion of senior-rank auditors' (i.e., partner, director, and senior manager) hours to total team hours (i.e., *ProHighRank*). All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, based on a two-tailed test.

results. However, in column (5), where team internal rate is the dependent variable, we now find that coefficients for both *Bal* and *Unbal* are positive and significant similar to *IKTeam* in Table 3. This indicates that the previous negative coefficients for *Unbal* (e.g., in Table 4) reflect the greater use of junior staff, a labor mix effect. Once we control for labor mix, the positive coefficients for *Bal* and *Unbal* indicate that both team types are associated with higher internal rates, suggesting an experience premium.

Alternative measures for industry knowledge within teams

Our next set of tests considers alternative measures for industry knowledge within teams. The first three relate to the distribution of industry knowledge within teams. First, in our main tests, *Unbal* encompasses two types of unbalanced teams, that is, teams with a specialist at the senior rank only and teams with a specialist at the junior rank only. Consequently, we create two new indicators, *Unbal-Senior* and *Unbal-Junior*, to capture these two types of teams. In our sample, there are five teams where *Unbal-Senior* is equal to one and 65 teams where *Unbal-Junior* is equal to one. Table 8, panel A, reports the results. For team hours, *Unbal-Senior* is not significant while *Unbal-Junior* retains a positive and significant coefficient. The insignificance for *Unbal-Senior* could be driven by the few observations or relatively fewer hours spent by senior auditors. For the team rate, *Unbal-Senior* has a positive and significant coefficient while *Unbal-Junior* continues to have a negative and significant coefficient, consistent with the different labor mixes in the two team types relative to non-specialist teams. Finally, for the audit quality tests, neither *Unbal-Senior* nor *Unbal-Junior* are significantly related to small positive profits; however, *Bal* is negative and significant in all three specifications, consistent with our main findings that only teams with balanced expertise provide higher audit quality relative to non-specialist teams.

Second, we measure the distribution of industry knowledge using the ratio of industry knowledge between senior- and junior-ranked auditors to define balanced and unbalanced teams. Specifically, we compute the total ventile ranks based on audit hours of senior-ranked auditors and junior-ranked auditors within the team separately, and use the ratio of the two averages to define balanced and unbalanced teams. *BalRatio* equals one if the ratio of senior-rank industry knowledge to junior-rank industry knowledge is close to one (between 0.85 and 1.15) and the team's *IKTeam* is among the top quartile, and zero otherwise. *UnbalRatio* equals one if the ratio of average senior-rank industry knowledge to junior-rank industry knowledge is more distant from one (below 0.85 or above 1.15) and the team's *IKTeam* is among the top quartile, and zero otherwise. Table 8, panel B, reports these results. For team hours, the coefficients for *BalRatio* and *UnbalRatio* are consistent with main results. Further, *BalRatio* is significant and negative for *SPP0-1*, *SPP0-2*, and *SPP0-3*, indicating that a more balanced distribution of industry knowledge is associated with better audit quality (for *SPP0-1*, p-value $= 0.101$), although *UnbalRatio* is also negative and significant for *SPP0-1* in column (4). Overall, the tenor of the results for audit hours and audit quality is consistent with the main results.

Table 8, panel C, reports the results where three auditor ranks instead of two ranks are used, that is, partners (*P*), managers (*M*), and associates (*A*), to define teams with industry specialist at different ranks. For example, *PMA* equals one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at each of the partner, manager, and associate ranks, and zero otherwise. *P* equals one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at the partner rank but not at the manager and associate ranks, and zero otherwise. The other test variables are defined in a similar manner. The number of teams for *PMA*, *PM*, *PA*, *MA*, *P*, *M*, and *A* are 112, 8, 20, 59, 2, 6, and 19, respectively. The results show that *PMA*, *PM*, and *MA* teams are associated with higher audit hours and that *PM* (*MA*) teams are associated with higher (lower) internal rates relative to teams with no specialists. The most striking result in panel C is that only *PMA* is associated with small positive profits. Again, industry knowledge is associated with higher audit quality only when it is evenly distributed within a team.

TABLE 8
Alternative measures of industry knowledge

Panel A: Results splitting *Unbal* into *Unbal-Senior* and *Unbal-Junior*

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Bal	0.151**	0.026	−1.238**	−0.594*	−0.562*
	(2.37)	(1.57)	(−2.38)	(−1.75)	(−1.92)
Unbal-Senior	−0.115	0.157**			0.053
	(−0.40)	(2.07)			(0.04)
Unbal-Junior	0.301***	−0.055**	−0.404	−0.147	0.435
	(3.53)	(−2.43)	(−0.70)	(−0.34)	(1.27)
TeamSize	0.052***	−0.001	0.039**	0.026*	0.013
	(14.29)	(−1.43)	(2.18)	(1.80)	(0.91)
LnTA	0.299***	0.038***	0.043	0.164***	0.209***
	(25.45)	(12.20)	(0.56)	(2.63)	(3.79)
Leverage	0.050	−0.028	−1.506***	−0.751*	−0.188
	(0.67)	(−1.39)	(−2.76)	(−1.77)	(−0.52)
SalesGrowth	0.011	0.002	−0.050	−0.095	0.006
	(0.65)	(0.45)	(−0.24)	(−0.51)	(0.07)
ROA	−0.182***	−0.014	−0.340	−0.273	−0.267
	(−3.66)	(−1.05)	(−1.47)	(−1.36)	(−1.43)
Tenure	−0.000	0.001	0.014	0.021	0.002
	(−0.08)	(1.23)	(0.47)	(0.93)	(0.12)
Public	0.120	0.097***	−0.572	−0.790*	−0.671*
	(1.56)	(4.77)	(−1.12)	(−1.87)	(−1.84)
Loss	0.079	0.017	−0.121	0.092	−0.062
	(1.57)	(1.29)	(−0.33)	(0.35)	(−0.26)
Stockholm	0.265***	0.058***	0.209	0.037	−0.167
	(5.64)	(4.67)	(0.65)	(0.15)	(−0.78)
Constant	1.102***	6.708***	−3.342**	−4.609***	−5.156***
	(5.96)	(136.19)	(−2.32)	(−4.15)	(−4.98)
Observations	908	908	832	894	899
Adjusted R^2/Pseudo R^2	0.702	0.308	0.096	0.090	0.113

Panel B: Results using the ratio of industry knowledge between senior and junior-ranked auditors to define balanced (*BalRatio*) and unbalanced (*UnbalRatio*) teams

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
BalRatio	0.169**	0.024	−0.999	−0.754*	−0.685*
	(2.05)	(1.08)	(−1.64)	(−1.70)	(−1.82)
UnbalRatio	0.204***	−0.007	−0.943*	−0.338	0.008
	(3.28)	(−0.45)	(−1.91)	(−1.03)	(0.03)
TeamSize	0.052***	−0.001	0.037**	0.027*	0.012
	(14.28)	(−1.40)	(2.08)	(1.84)	(0.84)
LnTA	0.298***	0.039***	0.039	0.158**	0.204***
	(25.38)	(12.29)	(0.51)	(2.56)	(3.72)
Leverage	0.044	−0.025	−1.520***	−0.745*	−0.238
	(0.59)	(−1.23)	(−2.80)	(−1.77)	(−0.66)

(The table is continued on the next page.)

TABLE 8 (continued)

Panel B: Results using the ratio of industry knowledge between senior and junior-ranked auditors to define balanced (*BalRatio*) and unbalanced (*UnbalRatio*) teams

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
SalesGrowth	0.011	0.002	−0.049	−0.096	−0.005
	(0.62)	(0.51)	(−0.25)	(−0.52)	(−0.05)
ROA	−0.180***	−0.015	−0.307	−0.266	−0.243
	(−3.60)	(−1.14)	(−1.34)	(−1.32)	(−1.31)
Tenure	−0.001	0.001	0.015	0.021	0.000
	(−0.12)	(1.31)	(0.50)	(0.93)	(0.01)
Public	0.105	0.105***	−0.610	−0.813*	−0.738**
	(1.37)	(5.13)	(−1.20)	(−1.93)	(−2.03)
Loss	0.078	0.018	−0.119	0.092	−0.070
	(1.55)	(1.32)	(−0.32)	(0.34)	(−0.30)
Stockholm	0.267***	0.057***	0.227	0.063	−0.141
	(5.67)	(4.51)	(0.70)	(0.26)	(−0.66)
Constant	1.123***	6.697***	−3.253**	−4.562***	−5.005***
	(6.07)	(135.36)	(−2.27)	(−4.12)	(−4.86)
Observations	908	908	837	899	899
Adjusted R^2/Pseudo R^2	0.701	0.299	0.093	0.090	0.109

Panel C: Results using three-way classification for ranks

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
PMA	0.160**	0.019	−1.808***	−0.663*	−0.746**
	(2.17)	(0.96)	(−2.66)	(−1.73)	(−2.22)
PM	0.493**	0.190***		0.516	0.143
	(2.19)	(3.17)		(0.47)	(0.13)
PA	0.127	0.060	−0.064	−0.543	−0.632
	(0.86)	(1.51)	(−0.07)	(−0.68)	(−0.93)
MA	0.303***	−0.055**	−0.115	−0.269	0.303
	(3.39)	(−2.31)	(−0.21)	(−0.59)	(0.84)
P	0.490	0.119			
	(1.09)	(1.00)			
M	0.236	0.002		1.254	1.417
	(0.90)	(0.02)		(1.26)	(1.53)
A	0.214	−0.069*		−0.866	0.388
	(1.44)	(−1.75)		(−0.81)	(0.63)
TeamSize	0.053***	−0.001	0.042**	0.028*	0.014
	(14.39)	(−1.43)	(2.27)	(1.89)	(1.03)
LnTA	0.298***	0.039***	0.050	0.157**	0.211***
	(25.30)	(12.38)	(0.64)	(2.52)	(3.79)
Leverage	0.041	−0.027	−1.502***	−0.717*	−0.195
	(0.54)	(−1.36)	(−2.73)	(−1.69)	(−0.53)
SalesGrowth	0.012	0.002	−0.063	−0.089	0.007
	(0.69)	(0.40)	(−0.31)	(−0.49)	(0.08)
ROA	−0.180***	−0.014	−0.265	−0.161	−0.168
	(−3.52)	(−1.07)	(−1.11)	(−0.69)	(−0.81)

(The table is continued on the next page.)

TABLE 8 (continued)

Panel C: Results using three-way classification for ranks

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Tenure	−0.001	0.001	0.015	0.021	−0.000
	(−0.22)	(1.20)	(0.51)	(0.93)	(−0.02)
Public	0.110	0.098***	−0.471	−0.768*	−0.611*
	(1.42)	(4.77)	(−0.92)	(−1.81)	(−1.67)
Loss	0.086*	0.016	−0.088	0.111	−0.041
	(1.70)	(1.20)	(−0.24)	(0.41)	(−0.17)
Stockholm	0.258***	0.060***	0.232	0.074	−0.151
	(5.48)	(4.77)	(0.71)	(0.30)	(−0.70)
Constant	1.128***	6.702***	−3.479**	−4.597***	−5.188***
	(6.08)	(136.11)	(−2.37)	(−4.10)	(−4.97)
Observations	908	908	802	897	897
Adjusted R^2/Pseudo R^2	0.702	0.312	0.103	0.093	0.118

Panel D: Results for H1 and audit quality using within-auditor measure of industry knowledge

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
IKTeam	1.480***	0.021	−2.959**	−1.629*	−1.464*
	(8.64)	(0.44)	(−2.19)	(−1.70)	(−1.80)
Constant/controls	Yes	Yes	Yes	Yes	Yes
Observations	908	908	837	899	899
Adjusted R^2/Pseudo R^2	0.721	0.298	0.092	0.089	0.108

Panel E: Results for H2a/H2b and audit quality using within-auditor measure of industry knowledge

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Bal	0.159**	0.033**	−1.090**	−0.855**	−0.823***
	(2.56)	(2.02)	(−2.33)	(−2.53)	(−2.89)
Unbal	0.139	−0.060**	−1.067	−0.402	−0.208
	(1.54)	(−2.51)	(−1.37)	(−0.81)	(−0.52)
Constant/controls	Yes	Yes	Yes	Yes	Yes
Observations	908	908	837	899	899
Adjusted R^2/Pseudo R^2	0.699	0.307	0.097	0.095	0.115

Notes: This table presents results using alternative measures for the distribution of industry knowledge within an audit team. Panel A reports the results when unbalanced teams are split into teams that have industry specialists at the senior rank only (*Unbal-Senior*) and at the junior rank only (*Unbal-Junior*). Panel B reports results where the ratio of industry knowledge between senior- and junior-ranked auditors is used to define balanced and unbalanced teams. The other test variables are defined in a similar manner. Panel D (E) reports the results for H1 (H2a/H2b) and audit quality using a within-auditor measure of industry knowledge. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, based on a two-tailed test.

Finally, we compute a within-auditor measure of industry knowledge. First, we compute each team member's exposure (in hours) to the client's industry relative to the total audit hours. As such, this method is less sensitive to differences in the total audit hours included in our data set across team members. Second, we compute the average for all members in the team. Thus, this measure considers

how an auditor's time is divided between different industries rather than considering an auditor's industry-based experience relative to other auditors. Table 8, panel D (panel E), reports the results for H1 (H2a/H2b) and the audit quality tests using the within-auditor measure. In panel D, *IKTeam* is positively related to *LnTeamHrs*, and negatively related to all three measures of small positive profits. In panel E, *Bal* is positively related to team hours and the team rate, while *Unbal* is negatively related to the team rate. Furthermore, *Bal* is negatively related to *SPP0-1*, *SPP0-2*, and *SPP0-3*. These results are consistent with the overall findings using our main measure of industry knowledge.[44]

Functional form misspecification

We acknowledge that endogeneity is a potential issue in our tests. In particular, clients audited by teams with high industry knowledge may be fundamentally different than clients audited by teams with lower industry knowledge. Similarly, balanced teams may be associated with larger and more complex audits. We use entropy balancing and propensity score matching (PSM) to address one aspect of endogeneity, specifically functional form misspecification (Shipman et al. 2017).

Entropy balancing is useful to create balanced samples with a binary treatment where the control group data can be reweighted to match the covariate moments in the treatment group (Hainmueller 2012; McMullin and Schonberger 2021). We define an indicator variable, *IKT*, that equals one for teams in the top quartile of *IKTeam*, and zero otherwise.

As both methods provide similar results, in Table 9, we only report the results based on entropy balancing. Table 9, panel A, reports the results for H1 based on entropy balancing using the first moment condition for audit hours, team rate, and audit quality. Consistent with Table 3, we find *IKT* is positively and significantly related to audit hours. High industry knowledge teams spend 22.7% more audit hours compared to other teams. However, in column (2), we cannot reject the null of no relation between *IKT* and *LnTeamRate*. Furthermore, the coefficients for *IKT* are negative and significant at the 5% level in columns (3) and (4) where the dependent variables are *SPP0-2* and *SPP0-3*, respectively. These findings suggest that, after mitigating differences in client characteristics by entropy balancing or PSM, there is a positive association between audit quality and team's average knowledge.

As we have three groups—balanced team (*Bal*), unbalanced team (*Unbal*), and non-specialist teams—we are not able to compare all three groups at the same time using entropy balancing. Instead, we separately compare (i) balanced teams with non-specialist teams and (ii) unbalanced teams with non-specialist teams. We report the results in Table 9, panels B and C. Panel B shows that the coefficient on *Bal* is positive and significant at the 1% level for audit hours (column (1)), but is insignificant for team internal rate (column (2)). Columns (3)–(5), which contain the audit quality analyses, indicate that balanced teams provide higher audit quality relative to non-specialist teams as the coefficients on *Bal* are negative and significant in all three columns. Panel C presents the results for unbalanced teams and non-specialist teams. In column (1), the coefficient on *Unbal* is positive and significant at the 1% level, indicating that unbalanced teams are associated with greater audit hours than non-specialist teams. The second column shows that unbalanced teams have a lower team rate compared to non-specialist teams, which could reflect the prominence of junior auditors in unbalanced teams. In contrast to panel B, for audit quality analyses in columns (3)–(5), *Unbal* is insignificant in all three columns. Thus, only teams with balanced expertise are associated with higher audit quality after entropy balancing.[45]

44. We find similar results (untabulated) to panels D and E when the within-auditor measure is computed excluding client hours.

45. We use an impact threshold of confounding variable (ITCV) analysis to consider the influence of omitted variables. The ITCV approach estimates the minimum magnitude that an omitted variable would need to have, compared to the most important control variable, to overturn the main result in a regression (Frank 2000; Chapman et al. 2019). For equation (1), we follow Frank (2000) and compute the ITCV when the dependent variable is *LnTeamHrs* or *LnTeamRate*. These computations (untabulated) indicate that a confounding variable would have to be at least 1.956 and 1.895 times larger than the effect of client size in equation (1) for *LnTeamHrs* and *LnTeamRate*, respectively. It is unlikely that there exists a confounding variable that could overturn our main results.

TABLE 9
Entropy balancing

Panel A: Entropy balancing weighted on the first (mean) moment: *IKT*

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
IKT	0.227***	−0.016	−1.202**	−0.692**	−0.427
	(6.22)	(−0.92)	(−2.51)	(−2.13)	(−1.62)
TeamSize	0.054***	−0.002	0.039*	0.024	−0.000
	(7.86)	(−1.35)	(1.74)	(1.12)	(−0.01)
LnTA	0.157***	0.038***	0.107	0.270***	0.288***
	(10.29)	(7.48)	(1.07)	(3.04)	(3.48)
Leverage	0.124*	−0.042	−1.943**	−1.178**	−0.626
	(1.72)	(−1.27)	(−2.27)	(−2.00)	(−1.32)
SalesGrowth	0.004	−0.002	−0.103	−0.031	−0.111
	(0.34)	(−0.38)	(−0.43)	(−0.28)	(−0.93)
ROA	−0.086***	−0.027	−0.090	−0.177	−0.135
	(−2.64)	(−1.04)	(−0.54)	(−1.31)	(−1.03)
Tenure	0.001	−0.000	0.018	0.044	0.012
	(0.18)	(−0.22)	(0.48)	(1.52)	(0.49)
Public	0.119**	0.131***	−1.327**	−1.364**	−1.150**
	(2.35)	(4.25)	(−1.97)	(−2.44)	(−2.52)
Loss	0.013	0.018	0.164	0.167	−0.031
	(0.32)	(1.08)	(0.39)	(0.49)	(−0.11)
Stockholm	0.145***	0.061***	0.459	0.141	−0.222
	(3.94)	(3.34)	(0.99)	(0.40)	(−0.80)
Constant	3.122***	6.723***	−3.722*	−6.167***	−5.767***
	(15.90)	(96.80)	(−1.88)	(−3.94)	(−3.96)
Observations	908	908	837	899	899
Adjusted R^2	0.666	0.256			
Pseudo R^2			0.139	0.128	0.120

Panel B: Entropy balancing weighted on the first (mean) moment: Balanced teams and non-specialist teams

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Bal	0.225***	0.006	−1.103*	−0.666*	−0.627**
	(5.92)	(0.41)	(−1.87)	(−1.79)	(−2.02)
TeamSize	0.046***	−0.002***	0.027	0.020	−0.005
	(22.23)	(−2.80)	(1.49)	(1.00)	(−0.19)
LnTA	0.175***	0.036***	0.074	0.248***	0.285***
	(16.73)	(9.68)	(0.74)	(2.59)	(3.13)
Leverage	0.099*	−0.044**	−2.019**	−0.861	−0.396
	(1.66)	(−2.06)	(−2.28)	(−1.40)	(−0.76)
SalesGrowth	−0.005	0.000	−0.511	−0.070	−0.034
	(−0.42)	(0.02)	(−0.77)	(−0.56)	(−0.49)
ROA	−0.088***	−0.017*	−0.029	−0.054	0.012
	(−3.70)	(−1.95)	(−0.16)	(−0.38)	(0.08)
Tenure	−0.002	−0.000	0.043	0.038	0.019
	(−0.70)	(−0.28)	(1.28)	(1.19)	(0.65)

(The table is continued on the next page.)

TABLE 9 (continued)

Panel B: Entropy balancing weighted on the first (mean) moment: Balanced teams and non-specialist teams

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Public	0.147***	0.098***	−1.187*	−1.154**	−0.809*
	(3.15)	(5.91)	(−1.82)	(−2.15)	(−1.79)
Loss	0.009	0.012	0.018	0.237	0.142
	(0.25)	(0.92)	(0.04)	(0.62)	(0.44)
Stockholm	0.123***	0.059***	0.481	−0.121	−0.168
	(3.27)	(4.36)	(0.94)	(−0.32)	(−0.55)
Constant	3.001***	6.769***	−3.050	−5.671***	−5.972***
	(16.53)	(104.38)	(−1.44)	(−3.26)	(−3.63)
Observations	838	838	767	829	829
Adjusted R^2	0.710	0.234			
Pseudo R^2			0.123	0.112	0.087

Panel C: Entropy balancing weighted on the first (mean) moment: Unbalanced teams and non-specialist teams

	(1) *LnTeamHrs*	(2) *LnTeamRate*	(3) *SPP0-1*	(4) *SPP0-2*	(5) *SPP0-3*
Unbal	0.357***	−0.045***	−0.622	−0.232	0.535
	(8.03)	(−3.19)	(−0.93)	(−0.46)	(1.39)
TeamSize	0.097***	−0.002	0.134*	0.042	0.054
	(13.85)	(−0.74)	(1.95)	(0.70)	(0.91)
LnTA	0.148***	0.035***	0.038	0.316**	0.225**
	(11.31)	(8.65)	(0.35)	(2.46)	(1.98)
Leverage	0.279***	−0.045*	−2.359**	−1.343*	−0.913
	(3.67)	(−1.86)	(−2.21)	(−1.71)	(−1.45)
SalesGrowth	0.113***	−0.004	0.393	0.382	0.181
	(2.80)	(−0.30)	(0.81)	(0.64)	(0.82)
ROA	−0.175*	−0.160***	−1.982**	−2.532***	−2.816***
	(−1.69)	(−4.93)	(−2.24)	(−3.25)	(−3.47)
Tenure	0.008**	0.001	−0.002	0.031	−0.007
	(2.01)	(1.01)	(−0.04)	(0.76)	(−0.19)
Public	0.121	0.102***	−1.475	−2.469**	−1.814*
	(1.33)	(3.57)	(−1.52)	(−2.34)	(−1.83)
Loss	−0.025	−0.037**	0.181	−0.139	−0.474
	(−0.51)	(−2.34)	(0.28)	(−0.25)	(−0.96)
Stockholm	0.241***	0.065***	0.361	0.450	−0.243
	(5.31)	(4.57)	(0.60)	(1.02)	(−0.64)
Constant	2.708***	6.804***	−6.362***	−6.943***	−5.325***
	(13.17)	(105.31)	(−3.36)	(−3.52)	(−3.04)
Observations	752	752	681	743	743
Adjusted R^2	0.529	0.211			
Pseudo R^2			0.212	0.158	0.202

Notes: This table reports the results using entropy balancing weighted on the first moment. Panel A presents the results for tests of H1 and audit quality where *IKT* is an indicator that variable equals one for teams in the top quartile of *IKTeam*, and zero otherwise. Panel B reports the results for H2a/H2b and audit quality using balanced teams and non-specialist teams. Panel C reports the results for H2a/H2b and audit quality using unbalanced teams and non-specialist teams. All variables are defined in the Appendix. Industry fixed effects are included for all analyses. The *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1% level, respectively, based on a two-tailed test.

5. Conclusion

While audit teams are fundamental to the audit process (Rudolph and Welker 1998), little is known about whether and how audit team attributes affect audit production and audit quality. We consider how the extent and distribution of industry knowledge within an audit team affect audit outcomes. We find that Big 4 audit teams with higher average industry knowledge are associated with more audit effort, contradicting Contessotto et al. (2021) who find that team industry experience is unrelated to audit effort for their sample of mid-tier audit firms. In contrast, evidence on the association between the average hourly internal rate and team knowledge is mixed. Furthermore, we find that balanced teams produce higher-quality audits than non-specialist teams while the audit quality of unbalanced teams is not statistically different from the non-specialist teams. Overall, our results extend and confirm some prior evidence of firm, office, and partner expertise to the team dimension and provide new evidence on the consequences of balanced expertise within the team for audit effort and quality.

Finally, we acknowledge that our data have limitations. For example, we only have data for a single year and for a limited number of financial statement items, and our data do not include the entire workload of each auditor. Given that our sample is based on many of the largest clients in the firm, the engagements that are omitted and that comprise the unobserved workload of individual auditors are likely to be small, less complex, and require less specific industry expertise. Furthermore, the unobserved workload information adds noise to our measure of industry knowledge, which likely has the effect of reducing the power of our tests. Finally, we only have data from a single Big 4 firm located in Sweden, which may limit the generalizability of our results (Kinney 2015; Aobdia 2019b). Nevertheless, this study contributes to the audit literature by providing novel evidence on the role of industry knowledge within audit teams.

Appendix: Variable definitions

Variable	Definition
LnTeamHrs	Natural logarithm of aggregated audit hours for all team members in an engagement team
LnTeamRate	Natural logarithm of mean hourly internal rate for all team members in an engagement team computed as team cost/team hours
SPP0-1	Indicator for small positive profits equal to one if a client's ROA is between zero and 1%, and zero otherwise (*SPP0-2*, *SPP0-3* defined similarly)
IKTeam	Mean of ventile rank of all team members in a team where the ventile rank is based on a team member's audit hours in the client's industry relative to all other auditors in the sample of the same rank (senior or junior) who work in the same industry
Bal	Equal to one if a team has average industry knowledge among the top quartile and has at least one industry specialist auditor at the senior rank (partner, director, senior manager) and junior rank (manager, assistant manager, senior associate, and associate), and zero otherwise
Unbal	Equal to one if a team has average industry knowledge among the top quartile and has at least one industry specialist auditor only at the senior rank (partner, director, and senior manager) but not junior rank (manager, assistant manager, senior associate, and associate) or vice versa, and zero otherwise
ProHighRank	Proportion of senior-rank auditors' (i.e., partner, director, and senior manager) hours to total team hours
Unbal-Senior	Equal to one if an unbalanced team has at least one industry specialist auditor only at the senior rank but not junior rank, and zero otherwise
Unbal-Junior	Equal to one if a unbalanced team has at least one industry specialist auditor only at the junior rank but not senior rank, and zero otherwise

(The table is continued on the next page.)

(continued)

Variable	Definition
BalRatio	Equal to one if the ratio of senior-rank industry knowledge to junior-rank industry knowledge (based on ventile ranks) is close to one (between 0.85 and 1.15) and the team's *IKTeam* is among the top quartile, and zero otherwise
UnbalRatio	Equal to one if the ratio of average senior-rank industry knowledge to junior-rank industry knowledge (based on ventile ranks) is more distant from one (below 0.85 or above 1.15) and the team's *IKTeam* is among the top quartile, and zero otherwise
PMA	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at each of the partner, manager, and associate ranks, and zero otherwise
PM	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at each of the partner and manager ranks but not the associate rank, and zero otherwise
PA	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at each of the partner and associate ranks but not the manager rank, and zero otherwise
MA	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at each of the manager and associate ranks but not the partner rank, and zero otherwise
P	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at the partner rank but not at the manager and associate ranks, and zero otherwise
M	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at the manager rank but not at the partner and associate ranks, and zero otherwise
A	Equal to one for teams that are among the top quartile based on team industry knowledge and have at least one industry specialist at the associate rank but not at the partner and manager ranks, and zero otherwise
TeamSize	Number of team members on a team
LnTA	Natural logarithm of total assets (in thousand SEK)
Public	Equal to one if the engagement is for a public firm, and zero otherwise
Leverage	Total debt/total assets
SalesGrowth	Sales growth, i.e., $(Sales_t/Sales_{t-1}) - 1$
ROA	Net income/total assets
Tenure	Number of years since the client was registered in the system of the Big 4 audit firm
Loss	Equal to one if the client encounters a loss, and zero otherwise
Stockholm	Equal to one if the headquarters of the client is located in Stockholm, and zero otherwise

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:
Online Appendix. Supporting information