Auditors as a Vector for Diffusing Forecasting Knowledge

We explore auditors' role in diffusing knowledge about forecasting among their clients. While management forecasts are not audited, prior research suggests that auditors affect management forecasting by serving a governance role that improves companies' internal information environments and the credibility of managerial forecasts. We hypothesize that auditors influence managerial forecasting beyond the governance role by diffusing forecasting process knowledge and best practices across clients. We find that companies whose auditors have greater forecasting knowledge exposure forecast more accurately. However, auditor forecasting knowledge exposure is not associated with audit quality or auditor independence, consistent with auditors affecting management forecasting in a novel manner. Our results persist through a variety of robustness tests, including an extra-industry instrumental variable regression. Our research indicates a novel source of valuable knowledge auditors provide to clients and suggests that auditors improve their clients' unaudited information environment by sharing knowledge across clients.

Keywords: management forecasts; forecast accuracy; auditor forecasting knowledge; knowledge diffusion
JEL Classification: D83; L14; M40; M42

1. Introduction

Management earnings forecasts are common and important voluntary disclosures that have significant implications for company valuation, information asymmetry, the cost of equity and debt capital, and analyst information production.[1] For example, the information in management forecasts is the primary source of over half of all accounting-related information and over 15 percent of *all* information that investors use (Beyer et al. 2010). As such, forecast accuracy is important to ensure corporate stakeholders make well-informed decisions. Forecast accuracy also affects the degree to which corporate stakeholders, such as analysts and investors, rely on company disclosures (Williams 1996; Yang 2012). Because forecast accuracy is so important to corporate stakeholders, managers are also incentivized to forecast accurately. Prior research suggests that managers can develop a form of reputational capital based on their ability to forecast accurately (Graham et al. 2005) and managers' forecasting accuracy affects their careers and compensation (Lee et al. 2012; Hui and Matsunaga 2015).

However, forecasting is a difficult task. Accurate forecasting requires considerable attention, skills, and resources (Clement 1999; Baik et al. 2011), as well as high quality information inputs (Lang and Lundholm 1996; Feng et al. 2009). Accurately forecasting earnings also requires forecasting and planning processes that incorporate many complex factors, including various risks, legal and regulatory changes, and macroeconomic conditions (Duru and Reeb 2002; Plumlee 2003; Hutton et al. 2012; Ittner and Michels 2017). Given the inherent difficulty and dynamism of the forecasting task and the incentives and pressures to forecast accurately, we expect that CEOs seek out external knowledge and advice to help them more accurately forecast earnings (Arendt et al. 2005; McDonald et al. 2008; Ma et al. 2020). This study focuses on an important potential source

[1] See Patell (1976), Waymire (1984), Baginski (1987), Hassell et al. (1988), Coller and Yohn (1997), Wang (2007), Hirst et al. (2008), Cao et al. (2017), and Kitagawa and Shuto (2019).

of external knowledge and advice, the financial statement auditor, and examines whether auditor forecasting knowledge exposure (AFK) helps clients improve their forecasting accuracy.

Auditors are a natural source of external advice and knowledge for managers. Not only must they have detailed knowledge about a client's business to perform an audit competently, but they also develop broad expertise and knowledge through audit experiences across their client portfolio (Ferguson et al. 2003). Prior research suggests that auditors develop industry-specific (Reichelt and Wang 2010; McGuire et al. 2012) and task-specific (Haislip et al. 2016; Ahn et al. 2020; Goldman et al. 2021) expertise that improves audit quality.[2] Auditors disseminate knowledge gained from experiences within the firm by sharing tools, personnel, tasks, and information across client engagements (Argote and Ingram 2000; Cheng et al. 2016). Further, evidence suggests auditors can be a source of client information sharing outside the audit firm, such as with competitors (Aobdia 2015) or investors (Chen et al. 2020). Auditors may have incentives to provide clients general forecasting guidance to encourage consistency among client working papers.[3] In sum, auditors serve as a nexus for knowledge and experience that can be leveraged to enhance audit quality and potentially share information across clients.

However, there are good reasons to predict that auditors may not be vectors for forecasting knowledge, and even that AFK might lead to decreased management forecast accuracy. First, auditors of U.S. listed companies are prohibited from providing consulting services to clients that involve developing forecasts for future earnings.[4] These laws may deter auditors from sharing

[2] Prior research has only examined the effect of industry expertise on client outcomes that are subject to audit, and not on unaudited client outcomes. Further, as we discuss later, the effect of industry expertise on non-audit services is unclear, as is whether these non-audit services affect client operations directly or indirectly by creating knowledge spillovers that improve audit quality, which in turn affects company outcomes that are determined by audit quality.
[3] While management forecasts are not audited, auditors typically review all company disclosures (Lau 2020).
[4] 15 U.S. Code § 78j-1(g). However, these laws do not explicitly address the informal provision of process knowledge or general economic information. There is also guidance for some settings (e.g., derivatives) that permit auditors to provide general guidance to their attest clients in understanding the models, methods, and assumptions of computing estimates, as long as the auditor does not calculate the values themselves (ISB Interpretation 99-1).

even informal forecasting advice to prevent the appearance of providing prohibited services. Second, management earnings forecasts are voluntary disclosures that are not subject to audit (Hirst et al. 2008), so it is not clear that auditors have incentives to develop any significant knowledge or expertise around forecasting.[5] Finally, AFK may decrease managerial forecast accuracy if that knowledge enables auditors to identify and constrain earnings management towards forecast benchmarks (i.e., using earnings management to increase manager's forecast accuracy artificially; see Kasznik 1999).

To examine whether AFK affects clients' management forecasts, we begin by developing a measure of auditor exposure to forecasting process knowledge. Similar to prior measures of auditor expertise (Reichelt and Wang 2010; Ahn et al. 2020), we use the attributes of an auditor's client portfolio to proxy for auditor knowledge. However, different from prior measures, we examine both whether audit clients have a particular attribute (e.g., a management forecast) and the *quality* of the audit client attributes. Specifically, we calculate an audit-office level measure of management forecast accuracy by ranking audit client portfolios by average client forecast accuracy within each metropolitan statistical area (MSA) and year (Francis et al. 2005).

Using this measure, we find that clients of auditors with greater AFK have more accurate management earnings forecasts. These results are robust to a substantial battery of control variables, including measures of audit quality and expertise used in prior research (Reichelt and Wang 2010; Ball et al. 2012). This association between AFK and client forecasting accuracy indicates that auditors serve as (a) vectors for diffusing forecasting process knowledge and (b) valuable external advisors on items outside the scope of the financial statement audit.

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[5] Prior research on auditor expertise focuses on expertise related to audited items or tax services that auditors are permitted to perform.

To further explore this idea, we examine cross-sectional variation in our base result. We find that the association between AFK and management forecast accuracy is greater when forecasting is inherently more difficult, as proxied by greater stock return volatility and analyst forecast dispersion. We also find that this association is weaker among (a) larger companies, which are more sophisticated and have access to greater resources, (b) companies with more talented managers, (c) companies with greater analyst following, and (d) companies with earnings that map more closely to industry competitors and thus may be able to increase forecast accuracy simply by mimicking peers forecasts.[6] Altogether, these cross-sectional findings are consistent with the effects of AFK being greater when forecasting knowledge demand is greatest and when the supply of alternative sources of forecasting knowledge is lowest.

We then perform a variety of robustness tests to provide support for our inferences. First, as an alternative and complementary way of examining our research question, we examine whether AFK improves the predictive ability of valuation allowances. Valuation allowances are unusual in that they are an audited financial statement account that implicitly contains manager forecasts of future taxable income, and as such, can predict future company performance (Dhaliwal et al. 2013; Axelton et al. 2021). We find that both our primary AFK measure and a valuation-allowance-specific measure of auditor expertise are associated with a greater predictive ability of valuation allowances, both separately and incremental to each other. In addition to showing that AFK helps with forecasting in a different setting, this finding suggests that AFK provides benefits beyond the account-specific accounting knowledge examined in prior research (e.g., Ahn et al. 2020).

[6] We expect that weaker results among companies with high analyst following could be due to either (a) analysts acting as an alternative source of macroeconomic and forecasting process knowledge (Hutton et al. 2012; Warren 2021) or (b) analysts demanding greater forecasting effort (Lang and Lundholm 1996; Baginski and Hassell 1997), which could crowd out the effect of auditor advice if managers can forecast more accurately with greater effort.

Next, we consider whether AFK is capturing auditor independence impairments, instead of forecasting knowledge, that allow companies to manage earnings toward forecast benchmarks (Kasznik 1999). We find evidence that our results are stronger when auditor independence impairments are *less* likely, inconsistent with auditor independence driving our results. We also do not find evidence that AFK enables managers to exceed (vs. underperform) forecast benchmarks or that AFK is associated with changes in accruals or discretionary accruals. However, AFK is associated with improved revenue forecast accuracy, suggesting that it improves forecasting of information that is more difficult to manipulate (Ertimur et al. 2003; Koo and Lee 2018).

While we control for audit variables associated with management forecast accuracy by prior research, we perform two further tests to ensure that the AFK measure is not capturing previously-documented auditor effects on management forecasts previously documented. These previous effects include auditors acting as a corporate governance mechanism that constrains managers' ability to bias forecasts or manage earnings towards forecast benchmarks (McConomy 1998; Behn et al. 2008) and the "confirmation" hypothesis, where higher audit quality improves earnings quality and the ability of stakeholders to use earnings realizations to discipline managers who forecast inaccurately (Ball et al. 2012). We find evidence that AFK improves management forecast accuracy even among companies without significant accounts requiring future-oriented estimates and thus enable auditor governance over these accounts to affect the results. We also examine the effect of AFK on earnings quality, proxied by earnings restatements. We do not find an association between AFK and restatements, even when examining restatement types most likely affected by forecasting-related changes in audit quality (e.g., restatements related to tax accruals and intangibles). Similarly, we do not find an association between AFK and internal control weaknesses. Together with the auditor independence analyses, these results are inconsistent with AFK affecting management forecast accuracy through a corporate governance or confirmation mechanism. Instead, we suggest that we are identifying a new effect of auditors on management forecasting outside the scope of the financial statement audit.

Finally, we show that our results are robust to alternative specifications and an instrumental variable design. Our results persist with multiple alternative measures of AFK, company fixed effects to create a quasi-differenced design, and MSA-year fixed effects to address correlated omitted variables at the audit office level. We also develop an instrumental variable that is calculated similarly to our primary AFK measure, but excludes all companies in the same industry as the client. Thus it only captures AFK from outside the client's industry and is free of concerns that can arise when using a same-industry instrument (Larcker and Rusticus 2010). The results when using this instrumental variable in a two-stage least squares regression support our prior findings that AFK benefits management forecast accuracy.

Our study makes several contributions to the research literature. First, we contribute to research on auditor knowledge spillovers (e.g., Simunic 1984; Beck and Wu 2006) by documenting a new type of knowledge spillover (a) that flows from auditors to clients and (b) that results in improved disclosure quality for clients outside of the audit.[7] By examining how auditors serve to diffuse forecasting knowledge, we also document a new form of "non-audit service" that auditors provide. Our findings further support prior research suggesting that the provision of non-audit services by auditors can lead to beneficial increases in disclosure quality (Kinney et al. 2004;

[7] Prior research suggests that auditor quality and industry expertise can help clients increase investment efficiency (Bae et al. 2017) and that auditors also diffuse tax avoidance techniques across professional networks (Bianchi et al. 2019). We differ from Bae et al. (2017) in that (a) management forecasts are not audited, unlike many of the inputs to their measure of investment efficiency, and (b) we show that our results are likely not driven by the governance role of auditors or changes in earnings quality beyond controlling for discretionary accruals. We differ from Bianchi et al. (2019) in that (a) management forecasts are not audited, unlike tax positions, and (b) greater tax avoidance tends to decrease, rather than increase, companies' information quality (Balakrishnan et al. 2019).

Robinson 2008; Gleason and Mills 2011; Knechel and Sharma 2012); however, our evidence suggests these increases *also* occur outside of the scope of the financial statement audit. As non-audit services continue to be controversial (Beardsley et al. 2021; Ahn et al. 2021), our findings can help to inform regulators and policymakers.

Second, we also contribute to the research literature on management forecasts (Hirst et al. 2008) by identifying a new determinant of managerial forecast accuracy. Given the importance of management forecasts to financial markets (Beyer et al. 2010) and managers (Lee et al. 2012; Hui and Matsunaga 2015), understanding how managers can improve their forecasting process knowledge is critical to corporate stakeholders.

Finally, we contribute to management research on executive advice seeking (Ma et al. 2020) by identifying a company's external auditor as a valuable source of knowledge on matters outside the scope of the financial statement audit. Our finding that the benefits of AFK are greatest when the complexity and uncertainty of the forecasting task are highest also provides empirical support to theoretical research on executive-advisor interactions in the presence of environmental dynamism (Arendt et al. 2005).

2. Background and Hypothesis Development

2.1. Management Earnings Forecasts

Management earnings forecasts are unaudited voluntary disclosures that managers make to convey private information about earnings expectations to the market.[8] Given the importance of earnings expectations in valuing companies (Ohlson 1995; Ohlson and Juettner-Nauroth 2005), management forecasts are extremely important to firm stakeholders (Beyer et al. 2010). Prior research shows that equity investors react to the information in management forecasts (Patell 1976;

[8] See Hirst et al. (2008) and Beyer et al. (2010) for reviews of this research.

Waymire 1984; Cao et al. 2017) and adjust their valuations for the information contained in management forecasts of peer companies (Baginski 1987). Management forecasts also reduce information asymmetry and the cost of capital in equity markets (Coller and Yohn 1997; Cao et al. 2017) and reduce the cost of debt financing (Kitagawa and Shuto 2019). Further, analysts adjust their forecasts in response to management forecasts and forecast features, which increases their forecast accuracy (Hassell et al. 1988; Baginski and Hassell 1990; Williams 1996; Cotter et al. 2006).

The importance of management earnings forecasts makes forecast accuracy vitally important for a variety of stakeholder decisions. For example, prior research suggests that analysts and investors pay close attention to managers' ability to forecast accurately (Williams 1996; Yang 2012). Survey research also suggests managers believe that their forecasting accuracy leads to a visible forecasting reputation that stakeholders use as an indicator of overall managerial ability (Graham et al. 2005). This belief is validated by evidence that management forecast accuracy is associated with proxies for executive ability, executive knowledge of the company, and investment quality (Baik et al. 2011; Goodman et al. 2014; Brockman et al. 2019). Executives' forecasting reputations also appear to have real consequences for executives. Specifically, a reputation as an accurate forecaster can affect executive compensation directly (Hui and Matsunaga 2015) or indirectly by benefitting executive stock and stock option holdings through increases in company value and pricing efficiency (Trueman 1986; Nagar et al. 2003). Forecast reputations can also affect the decision flexibility executives have and result in executive turnover and adverse career outcomes (Graham et al. 2005; Lee et al. 2012).

Because corporate stakeholders and executives care about managerial forecast accuracy, it is important to know the determinants of accuracy and how managers can improve their forecasting ability. Prior research provides several important determinants, suggesting greater managerial forecast accuracy is associated with (a) corporate governance that can effectively discipline managers, (b) better internal information environments, (c) better risk management policies, (d) information exchanges with analysts, and (e) compensation contracts that make managers more risk neutral.[9] Conversely, prior research also provides evidence that managerial overconfidence and strategic reporting incentives are determinants that predict reduced forecast accuracy (Hribar and Yang 2016; Baginski et al. 2018).

2.2. Auditor Knowledge Development and Sharing

Auditing involves performing many unstructured and fundamentally challenging tasks, and as such, requires auditors to develop a substantial knowledge base to audit effectively (Abdolmohammadi and Wright 1987; Libby and Luft 1993). This knowledge base is developed by auditors' exposure to certain tasks (Bonner and Lewis 1990), task domains (Vera-Muñoz et al. 2001), and industry settings (Solomon et al. 1999; Hammersley 2006). These various forms of exposure develop different types of knowledge and expertise, which enhance auditor performance (Libby and Luft 1993).[10] Consistent with this evidence, archival auditing research provides substantial evidence that auditors' experiences produce industry and task expertise at both the audit-firm and audit-office levels, which enhances audit quality.[11]

Aside from experiential learning, auditors also develop knowledge through knowledge

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[9] See Ajinkya et al. (2005), Karamanou and Vafeas (2005), Feng et al. (2009), Ittner and Michels (2017), Baginski et al. (2020), and Warren (2021).

[10] Other factors may affect the link between auditor experience and performance, such as auditors' memory structures (Libby and Frederick 1990; Frederick 1991) and innate ability (Bonner and Lewis 1990; Libby and Luft 1993).

[11] See Balsam et al. (2003), Francis et al. (2005), Gul et al. (2009), Reichelt and Wang (2010), and Gaver and Utke (2019) for evidence on the effects of industry experience. See Haislip et al. (2016), Ahn et al. (2020), Liu (2020), and Goldman et al. (2021) for evidence on the effects of task experience. Additionally, Shepardson (2019) finds evidence that audit committee members can develop task expertise through experience. She further reports that this expertise helps audit committee members in their corporate governance role, but likely does not lead to information transmission across companies.

sharing. Prior research suggests that knowledge transfers can occur between auditors within a firm (Salterio and Denham 1997; Salterio and Koonce 1997), including across different client engagements (Cai et al. 2016; Cheng et al. 2016). Goldman et al. (2021) provide additional detail regarding intra-office knowledge sharing in the context of auditing income tax accounts. Using interview data, they confirm that audit offices share knowledge across engagements via the audit review process, team structures, personnel exchanges, discussions, and formal training. While they summarize how knowledge is transferred among professionals within an audit office, they also emphasize the importance of sharing information. For example, sharing best practices and experiences assists in preventing future errors from occurring and allows auditors to be more efficient. These benefits may not be restricted to audit professionals and may extend to clients when sharing work paper templates or providing guidance in understanding modeling and assumptions used to forecast earnings. Additionally, McGuire et al. (2012) provide evidence that accounting firms develop industry-specific tax expertise through experience providing non-audit services that are associated with tax avoidance.

While prior literature provides evidence for client benefits of auditors sharing knowledge, auditors may also have an incentive to share knowledge of the forecasting process to create a consistent approach among clients that creates efficiencies when reviewing management estimates. Prior research on the provision of non-audit services by audit firms also suggests that knowledge transfers can occur from non-audit service providers and consultants to auditors within a firm (often termed "knowledge spillovers").[12] These knowledge spillovers occur more frequently when the auditor has industry expertise (Lim and Tan 2008), though they can benefit auditors with less industry expertise (Christensen et al. 2015).

[12] See Kinney et al. (2004), Joe and Vandervelde (2007), Gleason and Mills (2011), Krishnan and Visvanathan (2011), Paterson and Valencia (2011), Beardsley et al. (2021), and Axelton et al. (2021).

While intra-firm knowledge transfers appear widespread, it is unclear how much auditors act as sources of knowledge for corporate stakeholders or vectors for transmitting information across clients. Goldman et al. (2021) find auditors do not share tax knowledge among clients if it is confidential or involves proprietary information related to a competitive advantage. However, Aobdia (2015) and Bills et al. (2020) provide evidence to suggest that, when companies chose their auditors, they consider the potential of company information being shared with competitors and that companies are less likely to share an auditor with a rival company when the potential costs of information leaks are greatest. In other words, audit clients and their audit committees make auditor choices as though auditors will share their information with other parties. A recent working paper by Chen et al. (2020) also suggests that mutual fund managers obtain information about companies from social connections to company auditors, and this information aids them in equity trading decisions.

2.3. Auditors and Management Earnings Forecasts

Management earnings forecasts are not subject to audit in the U.S. (Hirst et al. 2008; Ball et al. 2012), and thus it may not seem as though auditors would directly affect management forecast accuracy. However, prior research has examined two potential ways in which auditors could affect forecasts. Behn et al. (2008) show that analysts more accurately forecast earnings when either a Big-N firm or an industry-specialist auditor audits the companies they follow. They theorize that high-quality auditors improve information quality, making it easier to forecast accurately. Ball et al. (2012) show that companies that pay more in audit fees have greater management forecast accuracy. They suggest this result is due to the governance-related "confirmation hypothesis," whereby audit quality affects the credibility of reported earnings, which in turn will affect the degree to which reported earnings could be used to discipline managers whose forecasts are shown to have been inaccurate.[13]

These prior studies suggest that auditors may affect management forecasts by (a) serving as a direct corporate governance mechanism or (b) increasing earnings quality, which enhances the ability of stakeholders to rely on future earnings realizations to evaluate managers' forecasting ability and discipline inaccurate managers. We differ from prior studies by proposing that auditors serve a role outside the formal audit function in a manner that affects management forecast accuracy. Specifically, we explore whether auditors can serve as knowledge vectors to diffuse forecasting knowledge (e.g., forecasting best practices and processes, macroeconomic and industry information) among their clients.

In performing an audit, auditors likely have considerable opportunities to learn about companies' forecasting practices. Prior research suggests that auditors pay attention to management forecasts and incorporate information from management forecasts into audit fees, which are a function of the auditor's assessment of a client's risk (Krishnan et al. 2012). Auditors also are required to review and evaluate the reasonableness of management's accounting estimates that appear in the financial statements (AS 2501; PCAOB 2019), including estimates that incorporate management forecasts, such as valuation allowances (Dhaliwal et al. 2013).[14] Auditors likely develop some degree of expertise around the forecasting task with exposure to a variety of

[13] In addition, Clarkson (2000) shows that companies with Big-N auditors have greater management forecast accuracy. However, Clarkson (2000) examines this question in a setting where management forecasts were subject to audit, which is quite different from the U.S. setting where management forecasts are not audited. Using the same setting, McConomy (1998) shows that requiring audits of management forecasts can affect their forecast accuracy by limiting the degree to which managers are able to add intentional biases to forecasts, supporting that unaudited management forecasts behave differently than those that are audited.

[14] AS 2501 provides guidance on the risk assessment of accounting estimates as well as the substantive procedures necessary to test the account. For example, auditors are required to (1) understand the process in which the client develops the estimate, (2) develop an independent expectation, (3) compare the expectation to the client's estimate, and (4) review subsequent events of transactions.

forecasting practices and knowledge, similar to developing task expertise in other task domains (Haislip et al. 2016; Ahn et al. 2020; Goldman et al. 2021).

We expect this body of forecasting knowledge can be a valuable resource to managers of audit clients seeking to improve their forecasting ability. Management research suggests that managers faced with challenging and dynamic environments will often seek out external advice (Arendt et al. 2005; McDonald et al. 2008; Ma et al. 2020). External advisors are often preferred when seeking out best practices and general market knowledge (Heyden et al. 2013), and obtaining external advice can provide status benefits to managers in settings where perceptions of manager knowledge are important (Menon and Pfeffer 2003), such as management forecasting (Lee et al. 2012). As such, we expect that managers seek out forecasting advice from their auditors, and auditors with forecasting expertise will share their forecasting process knowledge and best practices to differentiate their services from those of other auditors.[15]

However, the idea that auditors might act as a source of knowledge for clients is not new. Bae et al. (2017) suggest that auditors, particularly industry specialists, can serve as a source of knowledge that helps clients improve their investment efficiency, while Bianchi et al. (2019) propose that auditors learn about tax strategies and transmit this knowledge to clients to help them reduce their effective tax rates. We differ from these studies by examining the effect of auditor knowledge exposure on a company outcome that is unaudited, and thus much less likely to be driven by natural outcomes of the audit process rather than knowledge transfers.[16] This distinction is important, as Bae et al.'s (2017) results are also consistent with both a corporate governance and confirmation role of auditors that is distinct from a knowledge source/transfer role. We also differ

[15] Prior research suggests that audit firms have difficulty differentiating their services from those of similarly-sized competitors (Doogar and Easley 1998; Hay et al. 2006; Doogar et al. 2015).
[16] Not only are investments as reported in financial statements subject to audit, but Bae et al. (2017) also measure investment efficiency as the output of a model whose inputs are also audited.

from Bianchi et al. (2019) in that they document auditor knowledge transfers that result in greater tax avoidance that could reduce information quality (Balakrishnan et al. 2019), whereas auditor knowledge sharing that increases management forecast accuracy would increase the quality of companies' information environments.[17]

While we expect that auditors would be a natural source of knowledge and advice, there are good reasons to expect that auditors may not be vectors for forecasting knowledge, and even that AFK might lead to decreased management forecast accuracy. First, auditors of U.S. listed companies are prohibited from providing consulting services to clients that involve developing forecasts for future earnings.[18] While this does not encompass simply providing process knowledge or general information (e.g., regarding industry or macroeconomic trends; Levy 2018; Tysiac 2019), auditors may not be willing to share process knowledge or information if there is a risk of appearing to violate auditor service laws.[19]

Second, management earnings forecasts are voluntary disclosures that are not subject to audit (Hirst et al. 2008; Ball, Jayaraman, and Shivakumar 2012). Thus, it is not clear that auditors will have a vested interest in the management forecasting process at all, let alone enough to develop any significant knowledge or expertise around forecasting. Consistent with this conjecture, Vera-

[17] Additionally, Donohoe and Knechel (2014) suggest that tax service expertise of audit firms may increase audit efficiency and reduce some of the potential costs of tax aggressiveness, which could help auditors gain comfort over the appropriateness of a companies' aggressive tax positions and reduce the general tendency for high-quality auditors to constrain tax aggressiveness (Richardson et al. 2013; Klassen et al. 2016).

[18] Accounting firms are generally prohibited from providing appraisal or valuation services to an audit client (15 U.S. Code § 78j-1(g)). However, the regulations underlying the statute clarify that appraisal and valuation services may not be prohibited if "it is reasonable to conclude that the results of these services will not be subject to audit procedures during an audit of the audit client's financial statements" (17 CFR §210.2-01(c)(4)(iii)). Further guidance allows auditors to provide consulting services in certain scenarios (e.g., calculating derivatives), including general guidance in understanding models, assumptions, inputs, and sources of information as long as auditors do not audit their work or calculations (ISB Interpretation 99-1). It is not explicitly clear from standards whether auditor advice to managers regarding earnings forecasts, which are not directly audited but may be incorporated into auditor judgments, would be considered acceptable or prohibited.

[19] In 2019, the Securities and Exchange Commission sanctioned PwC for multiple instances of performing prohibited services that were characterized as audit services (Barber et al. 2020). The sanctions involved PwC making extensive changes to their quality control and independence systems and paying a fine of almost $8 million.

Muñoz et al. (2001) report evidence that public accounting (i.e., audit firm) experience does not help with forecasting tasks, whereas managerial accounting experience does.

Finally, prior research suggests managers have incentives to forecast accurately, which may lead them to manage earnings up or down to hit their earnings forecast benchmarks (Kasznik 1999; Gramlich and Sørensen 2004). Auditors are aware of management's incentives to manage earnings (Krishnan et al. 2012), and auditors with accumulated forecasting knowledge may be better able to identify and constrain earnings management towards forecast benchmarks. As such, AFK could potentially increase earnings quality while also decreasing managerial forecast accuracy. Given these competing effects, we state our formal hypothesis in the null as:

HYPOTHESIS: *Auditor forecasting knowledge exposure is not associated with client management forecast accuracy.*

3. Empirical Measures, Design, and Sample

3.1. Measuring Management Forecast Accuracy

Following prior research, we define managerial forecast accuracy (*MFA*) as the absolute value of the difference between forecasted earnings per share (EPS) and the actual EPS realized for the period, scaled by the stock price at the beginning of the fiscal year. We multiply this measure by -100 so that *MFA* is increasing in EPS forecast accuracy (Ajinkya et al. 2005; Hui and Matsunaga 2015; Baginski et al. 2020).[20] The Appendix includes detailed descriptions of all variables.

3.2. Measuring Auditor Forecast Knowledge Exposure

Prior research has developed several measures of auditor expertise based on exposure to clients in a particular industry (Ferguson et al. 2003), experience with specific accounts (Ahn et

[20] Results are robust to scaling by the actual realized EPS, similar to Ball, Jayaraman, and Shivakumar (2012).

al. 2020; Goldman et al. 2021), and experience providing auditor-provided tax services (McGuire et al. 2012). Similarly, we estimate auditor-office forecast knowledge for each company in our sample, using the average *MFA* for each audit-office client portfolio by year, where MSA defines the office level (Francis et al. 2005).[21] The average *MFA* for each client's audit-office is calculated as the average of all the other clients' management forecast accuracy for that audit office, exclusive of the client itself. Each client's respective auditor portfolio rank is then used to measure each auditor's forecast knowledge (*AFK*) for that client.

While our measurement of *AFK* is largely consistent with the measurement of other dimensions of audit expertise, one important distinction is worth highlighting. Prior research defines audit expertise based on the auditor's market share (e.g., Francis et al. 2005; McGuire et al. 2012), the number of clients they serve with a particular risk exposure (e.g., Goldman et al. 2021), or the sum of a particular account across their clients (e.g., Ahn et al. 2020); in other words, the *quantity* of an auditor's market share or account exposure is used to define expertise. We differ by examining the accuracy of management forecasts that an auditor's client makes and defining AFK based on the *quality* of the management forecasts to which auditors are exposed.[22]

3.3. Empirical Design

To test our hypothesis, we estimate the following OLS model for company i at time t:

$$MFA_{it} = \alpha + \beta_1 AFK_{it} + \sum_{j=2}^{27} \beta_j BASE_{jit} + \sum_{j=28}^{34} \beta_j AUDIT_{jit} + Industry_i + Year_t + \epsilon_{it} \quad (1)$$

[21] We focus on the MSA-year client portfolio based on theory and interview evidence provided by Goldman et al. (2021), who show that task-specific knowledge is likely to transfer across audit engagements at the office level, regardless of industry divisions. Our supplemental analyses show that our inferences hold when using alternative client portfolio definitions. We also require at least two clients in each auditor portfolio.

[22] This approach is consistent with evidence that experience alone is not enough to develop expert knowledge, but that task performance should also be considered in evaluating expertise (Bonner and Lewis 1990; Ashton 1991).

where the dependent variable is *MFA*, the primary independent variable is *AFK*, and all variables are defined in the Appendix. The coefficient β_1 represents the effect of auditor forecast knowledge exposure on management forecast accuracy. *AFK* is a rank variable (i.e., the auditor with the greatest knowledge exposure has a rank of 1, the next most knowledgeable has a rank of 2) which has been multiplied by -1 so that it is increasing in AFK. As such, a positive (negative) coefficient would indicate that AFK is associated with more (less) accurate client management EPS forecasts.

Equation (1) also includes two-digit SIC industry and year fixed effects as well as two vectors of control variables, *BASE* and *AUDIT*. *BASE* includes a variety of control variables that could affect either management forecast accuracy or audit quality. Because client risk could make forecasting more difficult and affect client portfolio choices of auditors, we control for earnings volatility (*EVOL*), return volatility (*RETVOL*), litigation risk (*LITRISK*), and exposure to foreign risks (*FORGN*). Companies' investment and financing choices could also impact earnings and manager's forecasting incentives, as well as auditors' client selection, so we control for investments in research and development (*RDE*), capital (*CAPX*), and mergers and acquisitions (*M&A*), as well as client leverage (*LEV*) and stock and equity issuances (*ISSUE*). To address potential correlated governance characteristics, we control for analyst following (*ANALYST*), institutional ownership (*IOR*), board of directors independence (*BODIND*), audit committee size (*ACSIZE*). We also control for company size (*SIZE*), market-to-book (*MTB*), profitability (*ROA*), loss incidence (*LOSS*), segmentation (*BUSSEG*), earnings quality (*DACC*), industry concentration (*HHI*), the average management forecast horizon (*HORIZON*), change in deferred tax valuation allowance (*CVAA),* fair value assets (*FVAT*), intangible assets (*INTAN*), goodwill (*GWILL*), and goodwill impairments (*IMPAIR*).

Finally, to ensure that we are identifying a novel effect of auditors on management forecast accuracy, we control for preexisting measures of audit quality and expertise (Behn et al. 2008; Ball et al. 2012; Bae et al. 2017). Specifically, *AUDIT* is a vector of control variables that includes whether the client is audited during the typical busy season (*BUSY*), the audit report lag (*LAG*), whether the auditor is a "Big-N" auditor (*BIGN*), whether the auditor is an industry expert (*INDEXP*), and the natural log of total audit (*FEES*), non-audit service (*NAS*), and auditor-provided tax service (*APTS*) fees.

3.4. Data and Sample Selection

Table 1 reports detail on how we construct our sample. We start with the intersection of Compustat and Audit Analytics for fiscal years 2004 through 2018.[23] We then eliminate companies incorporated outside the U.S., so that all companies' headquarters will be subject to the same U.S. audit regulatory regime. We also drop companies for which there is only one auditor per MSA-industry-year, to ensure variation in our AFK variable across all specifications, and observations with stock price below $1 to address potential scaling issues. Requiring all observations to have management forecast data from I/B/E/S Guidance and sufficient data for all control variables leaves 7,841 company-year observations for 1,720 unique companies.[24]

4. Empirical results

4.1. Descriptive statistics

Table 2 reports descriptive statistics for all variables in equation (1) and our additional analyses. The average (median) company has an auditor that ranks 2.9 (3) by their exposure to forecasting knowledge in their client portfolio. The median company also has a December fiscal

[23] Our sample begins in 2004 to ensure sufficient time for the effects of the Sarbanes-Oxley Act, which substantially changed the relationships between auditors and clients, to take hold. This ensures our results are not driven by auditor-client interactions that cannot exist in the post-Sarbanes-Oxley era.
[24] We keep financial and utility companies in our sample; however, we drop financial and utility companies in untabulated analyses and find that our results are unaffected.

year-end (*BUSY* = 1), an industry-specialist auditor (*INDEXP* = 1), and a Big-N auditor (*BIGN* = 1).

4.2. Primary Hypothesis Test

Table 3 estimates equation (1) to test our hypothesis. Column 1 omits control variables except for industry and year fixed effects to provide a baseline association between AFK and management forecast accuracy (Swanquist and Whited 2018) and shows a positive association between *AFK* and management forecast accuracy ($p < 0.01$). Because we multiply the *AFK* rank variable by -1, so that greater values of *AFK* indicate greater auditor forecasting knowledge, this positive coefficient indicates that AFK is associated with *greater* managerial forecasting accuracy.

Column 2 includes the *BASE* control variables, and column 3 includes all variables from equation (1), including the *AUDIT* control variables. These results continue to show a positive and significant coefficient on *AFK* ($p < 0.01$), suggesting that companies have more accurate management forecasts when their auditors have greater forecasting knowledge exposure.[25] These results are statistically and economically significant, as moving to the next-best auditor by forecasting knowledge (e.g., from the third to second-best) is associated with an improvement in managerial forecast accuracy equivalent to 48% of the inter-quartile range.[26] Overall, these results reject the null hypothesis that AFK is not associated with client management forecast accuracy and suggest that auditors are a significant source of forecasting knowledge.

4.3. Cross-sectional Analyses

We next explore cross-sectional variation in our primary results to better understand the influence of AFK in helping managers improve their forecast accuracy. Table 4 reports the results

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[25] To minimize the effects of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Results are robust to alternately using robust regression.

[26] $0.418/(-0.16 - (-1.03)) = 0.480$

of these analyses.

Theoretically, the knowledge and advice that auditors can provide are more valuable in dynamic environments due to the uncertainty of future events and increased information-processing needs (Arendt et al. 2005; Heyden et al. 2013). As such, we examine how our results vary across high and low environmental dynamism, where we proxy for high environmental dynamism using median splits of return volatility (*HRV*) and analyst forecast dispersion (*HAFD*). Column 1 (column 2) reports the results of estimating equation (1) after adding *HRV* and the interaction *AFK×HRV (HAFD* and the interaction *AFK×HAFD).* In columns 1 and 2, we find positive and significant coefficients on the interactions *AFK×HRV* ($p < 0.01$) and *AFK×HAFD* ($p < 0.10$), indicating that the effect of AFK on accuracy is stronger for companies with high return volatility and analyst forecast dispersion. These results support the theory that external advice, such as that from well-informed auditors, is most beneficial in dynamic environments (Arendt et al. 2005; Heyden et al. 2013; Ma et al. 2020). However, in columns 1 and 2, the positive and significant coefficients on *AFK* ($p < 0.05$ and $p < 0.01$, respectively) also suggest that AFK improves management forecast accuracy even in environments without high dynamism.

Because managers with more resources and talent may be in less need of forecasting advice, we also examine whether company sophistication and managerial ability affect our primary results. Column 3 supplements equation (1) with an indicator for whether the company is greater than the median sized company, *HSIZE*, as well as the interaction *AFK×HSIZE*. We find a negative and significant coefficient on the interaction *AFK×HSIZE* ($p < 0.05$), which indicates the results are less pronounced among larger companies. This finding is consistent with company resources and sophistication helping managers forecast more accurately without relying on external knowledge and advice. Columns 4 and 5 of Table 4 include indicator variables for whether the company has an above-median managerial ability score (*HMAS*; Demerjian et al. 2012) and return on assets (*HROA*), respectively, as well as the respective interactions with *AFK*. In both columns, we find a negative and significant coefficient on the interaction terms ($p < 0.10$ and $p < 0.01$, respectively), consistent with external forecasting advice being less beneficial to more talented managers.

Finally, we examine the effect of alternative information sources on our primary results. Column 6 uses high analyst following (*HAF*) to proxy for alternative information available, given that analysts may be valuable sources of forecasting knowledge for managers (Warren 2021). We find a negative *AFK×HAF* interaction coefficient ($p < 0.01$), consistent with AFK being more valuable for companies without a significant analyst knowledge base. Lastly, because companies with revenues that map more closely to industry counterparts (*HIRS* = 1) are better able to use the public management forecasts of industry peers to inform their own forecasting decisions without the need for an information intermediary, column 7 considers whether companies with higher industry revenue synchronicity (*HIRS*) have different effects of *AFK*. The negative and significant ($p < 0.10$) coefficient on *AFK×HIRS* provides evidence that companies with revenues that maps more closely to competitors do not benefit as much from AFK. As such, this result confirms that AFK is more valuable when managers have less access to alternative knowledge bases. Additionally, because these results show that the effects of AFK on managerial forecast accuracy are lower when the ability to transfer relevant information between industry competitors (i.e., industry synchronicity) is highest, they also suggest that AFK is substantially independent of industry-specific expertise and are consistent with interview evidence in Goldman et al. (2021) that suggests that task-specific knowledge is often transferrable across industry settings.

5. Supplemental Analyses

5.1. Auditor Forecasting Knowledge and Valuation Allowances

To provide an alternative setting to test our hypothesis, we also examine whether AFK helps managers forecast when evaluating deferred tax asset valuation allowances. Similar to bad debt allowances that estimate accounts receivable that are not expected to be collected, valuation allowances are contra-assets that measure deferred tax assets that are not expected to be realized. The primary reason that a deferred tax asset would not result in tax savings is that future taxable income and the related tax liability is insufficient to offset the deferred tax assets, such as net operating loss and tax credit carryforwards, prior to expiring by tax statute. As such, valuation allowances implicitly contain information regarding manager's forecasts of future taxable income that can be used to infer future GAAP profitability and cash flows (Dhaliwal et al. 2013; Edwards 2018; Axelton et al. 2021).

Following prior research (e.g., Dhaliwal et al. 2013; Axelton et al. 2021), we examine the information content of valuation allowance changes for future changes in profitability as a measure of valuation allowance quality. Here, though, we posit that valuation allowance quality is a function of managers' forecasting quality, and thus examine how AFK moderates the association between changes in earnings and changes in valuation allowances. Table 5 reports the results of regressing earnings changes for one-period-ahead (columns 1 and 3) and two-periods-ahead (columns 2 and 4) on (a) changes in valuation allowances scaled by total assets (*CVAA*), (b) *AFK*, (c) the interaction of *AFK* and *CVAA* (i.e., our variable of interest), and (d) control variables commonly used in examining the predictive information of valuation allowances and deferred tax accounts more generally (Jackson 2015).

Consistent with valuation allowance increases (decreases) providing information about future earnings decreases (increases), we find a significant and negative ($p < 0.01$) coefficient on *CVAA* across all columns (Dhaliwal et al. 2013; Axelton et al. 2021). The negative and significant coefficient on *AFK×CVAA* ($p < 0.01$) in column 1 indicates that AFK is associated with an increase in the ability of valuation allowance changes to predict one-period-ahead earnings changes. This finding continues when examining the effect of AFK on the ability of valuation allowance changes to predict two-period-ahead earnings changes as shown in column 2 ($p < 0.05$).

However, a potential concern with the valuation allowance setting is that valuation allowances are audited, and thus general improvements in audit quality around the valuation allowance or the transmission of task-specific auditing knowledge might improve the quality of valuation allowances, rather than a diffusion of forecasting knowledge that exists outside of the audit process. As such, we take advantage of the focused nature of the valuation allowance setting to construct a measure of auditor task knowledge related to auditing valuation allowances similar to measures developed for other settings by prior research (Haislip et al. 2016; Ahn et al. 2020; Goldman et al. 2021). Specifically, we count the total number of clients within each audit office-year portfolio with material (i.e., greater than 2% of beginning-of-year assets) valuation allowances, scaled by the total number of companies with material valuation allowances within the MSA-year. We then include this valuation allowance expertise (*VAEXP*) variable and its interaction with *CVAA* to control for audit task knowledge and related audit quality.

Columns 3 and 4 of Table 5 show negative and significant coefficients on the interaction *VAEXP×CVAA* ($p < 0.01$ and $p < 0.05$, respectively), which provides support that auditor valuation allowance expertise is associated with greater predictive information in client valuation allowances. These findings are consistent with expectations and results from prior audit-task-expertise research (Ahn et al. 2020; Goldman et al. 2021). However, even after including this control for account-specific auditor expertise, we continue to find that AFK incrementally improves the ability of valuation allowance changes to predict earnings changes one- and two-years-ahead, as evident by the negative and significant coefficients on *AFK×CVAA* in columns 3 and 4 ($p < 0.05$ and < 0.10, respectively). Further, the economic magnitude of the effect of AFK (i.e., size of the coefficients) remains similar between columns 1 and 3, as well as between columns 2 and 4, suggesting that AFK operates independently of the effects of auditor task expertise.

Overall, these results provide confirmatory evidence that AFK can be beneficial to managerial forecasting quality in a different forecasting setting. Additionally, these results support our theory that AFK benefits managerial forecasting in a manner that is different from the effects of audit quality. As seen in columns 3 and 4, AFK is different from task-specific audit knowledge (Ahn et al. 2020; Goldman et al. 2021), consistent with auditors sharing unaudited forecasting process knowledge across clients in a manner that improves clients' information environments.

5.2. Auditor Forecasting Knowledge and Auditor Independence

A potential concern in this setting is that AFK might be correlated with impairments to auditor independence (i.e., inverse auditor governance). If auditor independence is impaired, auditors may allow clients to manage earnings so that reported earnings align with management forecasts (Paterson and Valencia 2011; Barber et al. 2020). We perform four additional analyses to investigate whether auditor independence impairments drive the effects of AFK.

First, we explore how cross-sectional variation in client importance affects our primary results. We include interactions between *AFK* and measures of client importance, as measured by total fees (*HCIMP_TO*), audit fees (*HCIMP_AU*), non-audit service fees (*HCIMP_NAS*), and the natural logarithm of non-audit services (*HNAS*), in columns 1, 2, 3, and 4, respectively, of Table

6, Panel A. In columns 1 through 3, we do not find an association between the respective measures of client importance and *AFK* and managerial forecasting accuracy. However, when examining the natural logarithm of non-audit services (*HNAS*) in column 4, we find a negative and significant coefficient on the interaction *AFK*x*HNAS* ($p < 0.01$), inconsistent with auditor independence impairments driving improvements in management forecast accuracy. Instead, this finding suggests that non-audit services impair the ability of auditors to provide useful forecasting advice to clients, potentially by distracting auditors (Beardsley et al. 2021).[27]

Second, we explore whether *AFK* is associated with an increase in the likelihood of managers meeting or exceeding (vs. underperforming) their forecast targets by regressing an indicator variable for whether management forecast errors are positive or zero (*BIAS*) on *AFK*. Column 1 of Panel B shows *AFK* has a negative association with *BIAS* ($p < 0.01$), indicating that better AFK reduces the likelihood of exceeding forecast targets. Contrary to impairments to independence, this result suggests AFK is more useful to clients when clients are not managing earnings to meet/beat forecast targets. In columns 2 and 3, we find that adding control variables eliminates the statistical significance of this association, but the insignificant coefficients still do not provide evidence that AFK impairs auditor independence.[28]

Third, we investigate whether *AFK* is associated with greater accuracy of managerial sales/revenue forecasts, given that revenue news is often more difficult to manipulate (Ertimur et al. 2003; Koo and Lee 2018). We estimate equation (1) after replacing *MFA* with management revenue forecast accuracy (*MRFA*) and report the results in Panel C. We find a positive and

[27] In an untabulated analysis, we partition our sample into fourths based on audit fee quartiles and find that our primary results exist within each of the subsamples.
[28] In an untabulated analysis, we also plot management forecast errors by *AFK* rank. Across these graphs, the distribution of management forecast errors appears similar, except that better auditor forecast knowledge ranks appear to have distributions more tightly clustered around zero forecast error (i.e., have higher kurtosis and lower variance).

significant coefficient on *AFK* across all three columns ($p < 0.01$, $p < 0.05$, and $p < 0.05$, respectively), suggesting AFK can improve managerial forecasting for difficult-to-manipulate accounts, which is inconsistent with auditor independence impairments. These findings provide support that *AFK* is capturing the dissemination of forecasting practices and general forecasting knowledge by auditors.

Fourth, we examine whether *AFK* is associated with changes in audit quality that affect accrual realizations or managers' ability to manage earnings towards forecast benchmarks (Kasznik 1999). To do this, we simultaneously estimate equation (1) and a modified equation (1), replacing *MFA* with the change in either total accruals (Sloan 1996; Hribar and Collins 2002) or discretionary accruals (Dechow et al. 1995) for the year.[29] These analyses allow us to determine whether AFK affects total or discretionary accruals and whether its affect on management forecasts is codetermined with choices regarding accrual management. In other words, we seek to determine whether AFK affects total and discretionary accruals in a manner similar to management forecast accuracy. Table 6, Panel D reports these results. While we continue to find an economically and statistically significant effect of *AFK* on management forecast accuracy in columns 1 and 3 ($p < 0.01$), we do not find evidence of an effect of *AFK* on either changes in total accruals (in column 2) or discretionary accruals (in column 4). While it is difficult to draw substantial inferences from null results, these results imply that changes in audit quality and independence, changes in earnings management, and effects of correlated omitted economic fundamentals do not confound our results.[30]

[29] Earnings management can manage earnings both upward and downward (Krishnan et al. 2011; Seidel et al. 2020); however, our use of absolute-valued discretionary accruals should address both directions of earnings management, as should the other analyses in this section and the lack of association between AFK and restatements (which capture both upwards and downwards manipulation; Demeré et al. 2020) documented in Section 5.3.
[30] In untabulated analyses, we test the variance inflation factors of all null results to ensure that multicollinearity is not driving the null result. In all cases, results indicate no evidence of multicollinearity (VIFs < 5).

5.3. Estimate-based Accounts and Audit Quality

We perform two additional analyses to explore further whether changes in audit quality or correlated omitted variables confound our results. First, AFK could be capturing improved audit quality for accounts that require projections of future economic conditions. Panel A of Table 7 examines how our primary results vary with significant estimate-based accounts using indicators for when companies have significant (i.e., above median) balances of these types of accounts, including valuation allowances, fair value assets, intangible assets, and goodwill impairments.

Column 1 shows that the effect of AFK on management forecast accuracy is greater when companies have significant changes in their valuation allowance (*HCVAA*). While this result indicates that auditor monitoring of valuation allowances may influence our results, the significant main effect of *AFK* and results in Section 5.1 suggest that AFK provides forecasting benefits incremental to the effects of auditor governance on valuation allowances. Column 2 shows that clients with above-median fair value assets (*HFVAT*) receive *less* forecasting benefits from AFK. Similarly, column 3 shows that AFK provides less benefit to clients with above-median intangible assets (*HINTAN*). These findings are inconsistent with audit quality or client exposure to fair value estimates confounding *AFK*. Further, column 4 does not provide evidence for the effects of AFK varying between companies with and without goodwill impairments (*IMPAIRB*), suggesting our results are likely not significantly affected by auditor monitoring of goodwill impairments.

Our second test considers whether our audit forecast knowledge measure captures audit task-specific knowledge associated with better audit quality, as examined in prior research (Ball et al. 2012; Ahn et al. 2020). Specifically, we examine whether AFK predicts audit quality, proxied by the occurrence of restatements (DeFond and Zhang 2014; Demeré et al. 2020). Panel B of Table 7 reports our results. In column 1, we do not find a significant association between *AFK* and restatements, consistent with expectations if *AFK* is not a component of improved audit quality. However, because total restatements include non-estimate based accounts, we also examine specific restatement types that are most likely to be affected by auditor knowledge about forecasting and valuation. Columns 2 and 3 in Panel B of Table 7 examine the association between *AFK* and tax-specific restatements (which would include restatements related to valuation allowances) and intangible-asset-related restatements (which would include restatements related to goodwill impairments), respectively. We do not find any evidence of an association between AFK and restatement likelihood, consistent again with *AFK* capturing an effect of auditors outside the attestation role. Column 4 examines whether *AFK* may capture audit quality over internal controls. We do not find evidence that *AFK* is significantly associated with internal control weaknesses, supporting that *AFK* does not proxy for an internal control effect on management forecasting (Feng et al. 2009).[31]

5.4. Alternative AFK Specifications

Table 8 evaluates the effects of alternative specifications of *AFK*. The main analyses measure *AFK* using the concurrent managerial forecast accuracy of companies in an audit office's current client portfolio, consistent with prior measures of auditor specialization and knowledge (Francis et al. 2005; McGuire et al. 2012; Ahn et al. 2020; Goldman et al. 2021). However, because changes to the auditor's knowledge base and best practices may reflect the knowledge gained in the prior period, we address potential simultaneity issues by replacing *AFK* with *AFK* at t-1 (*L1AFK*). Column 1 of Table 8 reports a positive and significant coefficient on *L1AFK* ($p < 0.01$),

[31] We present results in Table 7 using logistic regression given the binary dependent variable. Results are similar when OLS is used. Variance inflation factor analysis on the OLS results indicates that multicollinearity is not a factor in these null results (VIFs < 5).

providing evidence consistent with our primary results that AFK improves management forecast accuracy.

Prior research does not exclude the client when calculating auditor expertise, as we do to prevent a mechanical correlation between a company's management forecast accuracy and their auditor's client-portfolio forecast accuracy. However, to ensure that this design choice does not affect our results and that our results are robust to precedents in prior research, we also build a client-inclusive *AFK* measure (*AFK2*) in column 2 of Table 8 and find that our results are robust to using this measure ($p < 0.01$).

Prior research on task-specific expertise (Goldman, Harris, and Omer 2021) and the results of our cross-sectional analyses suggest that industry specificity is not necessary to consider in evaluating task-specific knowledge. Nevertheless, given that prior research commonly defines auditor knowledge bases by industry, we alternately measure *AFK* using industry-year (*AFK3*) and industry-MSA-year (*AFK4*) client portfolios (McGuire et al. 2012). The positive and significant coefficients on *AFK3* and *AFK4* ($p < 0.01$) in columns 3 and 4, respectively, show that our primary results are robust to using both of these measures.

5.5. Additional Robustness Tests

In our final analyses, we further address the possibility of correlated omitted variables. First, Table 9 repeats our primary hypothesis tests from Table 3 after including either MSA-year fixed effects to control for client and auditor geographic factors or company fixed effects. In columns 1 through 3, we find that controlling for MSA-year fixed effects does not change our results as the coefficients on *AFK* remain negative and significant ($p < 0.01$). In columns 4 through 6, we find that including company fixed effects reduces the economic magnitude of our results by approximately 53 to 58 percent, which is not surprising given that results in Table 8 show that

AFK appears to have multi-period effects on managerial forecast accuracy. Nevertheless, we continue to find economically and statistically significant results even after controlling for company fixed effects, evident by the negative and significant coefficients on *AFK* ($p < 0.01$).[32]

Finally, we use an instrumental variable approach to address a broad range of potential endogeneity concerns. To identify a suitable instrumental variable, we take advantage of the fact that auditors typically have clients from many industries. We argue that auditors can draw on forecasting knowledge gained from clients in one industry to inform clients in a different industry about forecasting techniques and best practices. However, economic factors that might influence one industry are unlikely to carry over to affect an unrelated industry (Kempf et al. 2017). As such, we construct an alternative measure of AFK based on the management forecast accuracy of companies in their client portfolio that are not in the same industry as the client; in other words, a version of *AFK* based only on the forecasting knowledge auditors are exposed to *outside* the client's industry. This extra-industry AFK (*XIAFK*) is strongly associated with *AFK*, with an untabulated first-stage coefficient of 0.987 ($p < 0.001$). Additionally, because *XIAFK* draws only on forecasting knowledge variation from outside the client's industry, it should theoretically meet the exclusion restriction requirement of an instrumental variable. Excluding variation from the client's industry also helps ensure that *XIAFK* is not subject to the issues associated with using industry aggregates as instrumental variables discussed by Larcker and Rusticus (2010).

Table 10 reports the second stage of our two-stage least squares instrumental variable regression. Across all three columns, we continue to find a significant association between AFK

[32] We do not include company fixed effects in our other analyses, given that we find that strict exogeneity is violated, as reported in Table 9 as significant test *t*-statistics. Unlike OLS analyses, which rely on a "contemporaneous exogeneity" assumption, company fixed effect and first difference estimators rely on a stricter "strict exogeneity" assumption that can be explicitly tested (Wooldridge 2010; Grieser and Hadlock 2019). Failure to meet the strict exogeneity assumption can introduce endogeneity bias, resulting in worse identification of causal effects than an OLS regression (Arellano 2003; Grieser and Hadlock 2019).

(Fitted AFK) and management forecasting accuracy (p < 0.01). Further, the fact that the coefficients on *AFK* do not differ substantially between Tables 3 and 8 suggests that endogeneity has little influence on our primary results. Overall, we consistently find that our inferences are robust to endogeneity concerns, and that our results are consistent with a previously undocumented role of auditors in diffusing forecasting knowledge that can provide value to clients and corporate stakeholders.[33]

6. Conclusion

Management forecast accuracy is important to corporate stakeholders and the careers and compensation of managers (Williams 1996; Beyer et al. 2010; Lee et al. 2012; Yang 2012; Hui and Matsunaga 2015), but forecasting is also challenging (Baik et al. 2011; Ittner and Michels 2017). As such, managers are likely to seek out forecasting advice from outside sources (Arendt et al. 2005; Heyden et al. 2013). Prior research shows that auditors develop rich knowledge and expertise around industry settings and audit tasks across their client portfolios (Reichelt and Wang 2010; McGuire et al. 2012; Ahn et al. 2020; Goldman et al. 2021), and thus could serve as a valuable resource to managers in forecasting earnings.

Where prior research shows that auditors, *through the scope of the financial statement audit*, can affect forecasting by improving earnings quality and helping corporate governance mechanisms better discipline poor-forecasting managers (Behn et al. 2008; Ball et al. 2012), we suggest that auditors can also affect management forecasting *outside the audit process* by acting

[33] In small-sample untabulated analyses, we also perform two additional tests to better identify the effects of AFK. First, we examine auditor changes and the effects on management forecast accuracy. We find that almost all companies that change auditors move to an auditor with less forecasting knowledge (higher *AFK*), which may indicate that AFK is not a significant determinant of auditor-client matching decisions. Following a change to a less-knowledgeable auditor, we find that management forecast accuracy declines in an economically significant manner, though the results are only statistically significant (a) without control variables (p < 0.05) or (b) using one-tailed t-tests with all control variables included (p < 0.10). Second, we find that AFK is associated with better managerial forecast accuracy in the initial year that management forecasts are issued.

as a vector that diffuses forecasting knowledge and best practices across clients. Consistent with this hypothesis, we find that AFK is associated with greater management forecast accuracy. The effect of AFK is substantial, with our results suggesting that moving to the next-most knowledgeable auditor in an MSA-year is associated with an improvement in management forecast accuracy equivalent to 48% of the interquartile range of management forecasting accuracy. The effect of AFK on management forecast accuracy is most pronounced in dynamic environments where forecasting is difficult and less pronounced among companies with alternative sources of forecasting resources (i.e., more resources, management talent, access to analysts, and comparable industry competitors). We also provide numerous additional analyses to ensure that AFK is not measuring audit quality, impairments to auditor independence, measurement error, or correlated omitted variable bias, including the use of an extra-industry instrumental variable design.

Overall, our study contributes to the research literature by (a) illustrating a new source of value auditors provide that improves the financial reporting environment, (b) documenting a new and economically important determinant of management forecast accuracy, and (c) providing empirical support for theory about executive advice seeking and identifying the auditor as an important potential source of knowledge and advice for executives. Our results also support arguments that auditors provide services outside the formal attestation function that can increase disclosure quality. We recommend that regulators consider the potential value of auditors' knowledge-sharing role as they consider how to optimally regulate non-audit services and auditor-client interactions.

References

Abbott L, Gunny K, Pollard T (2017) The impact of litigation risk on auditor pricing behavior: Evidence from reverse mergers. *Contemporary Accounting Research.* 34(2): 1103-1127.

Abdolmohammadi M, Wright A (1987) An examination of the effects of experience and task complexity on audit judgments *The Accounting Review.* 62(1): 1-13.

Ahn J, Hoitash R, Hoitash U (2020) Auditor task-specific expertise: The case of fair value accounting *The Accounting Review.* 95(3): 1-32.

Ahn J, Akamah H, Shu SQ (2021) The effect of disclosing audit quality control deficiencies on non-audit tax services: Evidence from Deloitte's 2007 PCAOB Part II Inspection Report *Journal of Accounting and Public Policy*, Forthcoming.

Ajinkya B, Bhojraj S, Sengupta P (2005) The association between outside directors, institutional investors and the properties of management earnings forecasts *Journal of Accounting Research.* 43(3): 343-376.

Aobdia D (2015) Proprietary information spillovers and supplier choice: Evidence from auditors *Review of Accounting Studies.* 20: 1504-1539.

Arellano M (2003) Panel data econometrics: Advanced texts in econometrics. Oxford University Press: Oxford, UK.

Arendt L, Priem R, Ndofor HA (2005) A CEO-Adviser model of strategic decision making. *Journal of Management.* 31(5): 680-699.

Ashton AH (1991) Experience and error frequency knowledge as potential determinants of audit expertise *The Accounting Review.* 66(2): 218-239.

Argote L, Ingram P (2000) Knowledge transfer: A basis for competitive advantage in firms *Organizational Behavior and Human Decision Processes.* 82(1): 150-169.

Axelton Z, Demeré P, Gramlich J, Harris MK (2021) Auditor industry expertise and the predictive power of the deferred tax valuation allowance. Working paper, Washington State University.

Bae GS, Choi SU, Dhaliwal D, Lamoreaux P (2017). Auditors and client investment efficiency *The Accounting Review.* 92(2): 19-40.

Baginski S (1987) Intraindustry information transfers associated with management forecasts of earnings *Journal of Accounting Research.* 25(2): 196-216.

Baginski S, Hassell J (1990) The market interpretation of management earnings forecasts as a predictor of subsequent financial analyst forecast revision *The Accounting Review.* 65(1): 175-190.

Baginski S, Hassell J (1997) Determinants of management forecast precision *The Accounting Review.* 72(2): 303-312.

Baginski S, Campbell J, Ryu P, Warren J (2018) Do managers bias their forecasts in response to their firm's current earnings announcement surprises? Working paper, University of Georgia.

Baginski S, Campbell J, Moon J, Warren J (2020) Towards a risk-neutral disclosure policy: The role of compensation in management forecast quality. Working paper, University of Georgia.

Baik B, Farber D, Lee S (2011) CEO ability and management earnings forecasts *Contemporary Accounting Research.* 28(5): 1645-1668.

Balakrishnan K, Blouin J, Guay W (2019) Tax aggressiveness and corporate transparency *The Accounting Review.* 94(1): 45-69.

Ball R, Jayaraman S, Shivakumar L (2012) Audited financial reporting and voluntary disclosure as complements: A test of the confirmation hypothesis. *Journal of Accounting and Economics.* 53: 136-166.

Balsam S, Krishnan J, Yang J (2003) Auditor industry specialization and earnings quality *Auditing: A Journal of Practice & Theory*. 22(2): 71-97.

Barber R, Dee CC, Gunny K (2020) Does auditor independence matter? Evidence from SEC sanctions against PricewaterhouseCoopers LLP for prohibited non-audit services. Working paper, University of Colorado Denver.

Beardsley E, Imdieke A, Omer T (2021) The distraction effect of non-audit services on audit quality *Journal of Accounting and Economics*. 71(2-3): 101380.

Beck P. Wu M (2006) Learning by doing and audit quality *Contemporary Accounting Research*. 23(1): 1-30.

Behn B, Choi J, Kang T (2008) Audit quality and properties of analyst earnings forecasts *The Accounting Review*. 83(2): 327-349.

Beyer A, Cohen D, Lys T, Walther B (2010) The financial reporting environment: Review of the recent literature *Journal of Accounting and Economics*. 50: 296-343.

Bianchi P, Falsetta D, Minutti-Meza M, Weisbrod E (2019) Joint audit engagements and client tax avoidance: Evidence from the Italian statutory audit regime *Journal of the American Taxation Association*. 41(1): 31-58.

Bills K, Cobabe M, Pittman J, Stein S (2020) To share or not to share: The importance of peer firm similarity to auditor choice *Accounting, Organizations and Society*. 83: 101115.

Bonner S, Lewis B (1990) Determinants of auditor expertise *Journal of Accounting Research*. 28(Supplement): 1-20.

Brockman P, Campbell J, Lee HS, Salas J (2019) CEO internal experience and voluntary disclosure quality: Evidence from management forecasts *Journal of Business Finance & Accounting*. 46: 420-456.

Cai Y, Kim Y, Park JC, White H (2016) Common auditors in M&A transactions *Journal of Accounting and Economics*. 61: 77-99.

Cao Y, Myers L, Tsang A, Yang YG (2017) Management forecasts and the cost of equity capital: International evidence *Review of Accounting Studies*. 22: 791-838.

Chen Y, Huang J, Li T, Pittman J (2020) It's a small world: The importance of social connections with auditors to mutual fund managers' portfolio decisions. Working paper, City University of Hong Kong.

Cheng L, Cheng M, Dhaliwal D, Kaplan S (2016) Bank auditor connection and audit quality. Working paper, University of Arizona.

Christensen B, Olson A, Omer T (2015) The role of audit firm expertise and knowledge spillover in mitigating earnings management through the tax accounts *Journal of the American Taxation Association*. 37(1): 3-36.

Clarkson P (2000) Auditor quality and the accuracy of management earnings forecasts *Contemporary Accounting Research*. 17(4): 595-622.

Clement M (1999) Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*. 27: 285-303.

Coller M, Yohn TL (1997) Management forecasts and information asymmetry: An examination of bid-ask spreads *Journal of Accounting Research*. 35(2): 181-191.

Cotter J, Tuna I, Wysocki P (2006) Expectations management and beatable targets: How do analysts react to explicit earnings guidance? *Contemporary Accounting Research*. 23(3): 593-624.

Dechow P, Sloan R, Sweeney A (1995) Detecting earnings management *The Accounting Review*. 70(2): 193-225.

DeFond M, Zhang J (2014) A review of archival auditing research *Journal of Accounting and Economics.* 58: 275-326.
Demeré P, Lisowsky P, Li LY, Snyder RW (2020) What does GAAP ETR smoothing reveal about financial reporting quality? Working paper, University of Georgia.
Demerjian P, Lev B, McVay S (2012) Quantifying managerial ability: A new measure and validity tests *Management Science.* 58(7): 1229-1248.
Dhaliwal D, Kaplan S, Laux R, Weisbrod E (2013) The information content of tax expense for firms reporting losses *Journal of Accounting Research.* 51(1): 135-164.
Donohoe M, Knechel WE (2014) Does corporate tax aggressiveness influence audit pricing? *Contemporary Accounting Research.* 31(1): 284-308.
Doogar R, Easley R (1998) Concentration without differentiation: A new look at the determinants of audit market concentration *Journal of Accounting and Economics.* 25: 235-253.
Doogar R, Sivadasan P, Solomon I (2015) Audit fee residuals: Costs or rents? *Review of Accounting Studies.* 20: 1247-1286.
Duru A, Reeb D (2002) International diversification and analysts' forecast accuracy and bias *The Accounting Review.* 77(2): 415-433.
Edwards A (2018) The deferred tax asset valuation allowance and firm creditworthiness *Journal of the American Taxation Association.* 40(1): 57-80.
Ertimur Y, Livnat J, Martikainen M (2003) Differential market reactions to revenue and expense surprises *Review of Accounting Studies.* 8: 185-211.
Feng M, Li C, McVay S (2009) Internal control and management guidance *Journal of Accounting and Economics.* 48: 190-209.
Ferguson A, Francis J, Stokes D (2003) The effects of firm-wide and office-level industry expertise on audit pricing *The Accounting Review.* 78(2): 429-448.
Francis J, Philbrick D, Schipper K (1994) Shareholder litigation and corporate disclosures *Journal of Accounting Research.* 32(2): 137-164.
Francis J, Reichelt K, Wang D (2005) The pricing of national and city-specific reputations for industry expertise in the U.S. audit market *The Accounting Review.* 80(1): 113-136.
Frederick D (1991) Auditors' representation and retrieval of internal control knowledge *The Accounting Review.* 66(2): 240-258.
Gaver J, Utke S (2019) Audit quality and specialist tenure *The Accounting Review.* 94(3): 113-147.
Gleason C, Mills L (2011) Do auditor-provided tax services improve the estimate of tax reserves? *Contemporary Accounting Research.* 28(5): 1484-1509.
Goldman N, Harris MK, Omer T (2021) Does task-specific knowledge improve audit quality: Evidence from audits of income tax accounts. Working paper, North Carolina State University.
Goodman T, Neamtiu M, Shroff N, White H (2014) Management forecast quality and capital investment decisions *The Accounting Review.* 89(1): 331-365.
Graham J, Harvey C, Rajgopal S (2005) The economic implications of corporate financial reporting *Journal of Accounting and Economics.* 40: 3-73.
Gramlich J, Sørensen O (2004) Voluntary management earnings forecasts and discretionary accruals: Evidence from Danish IPOs *European Accounting Review.* 13(2): 235-259.
Grieser W, Hadlock C (2019) Panel-Data estimation in finance: Testable assumptions and parameter (In)Consistency *Journal of Financial and Quantitative Analysis.* 54(1): 1-29.
Gul F, Fung SYK, Jaggi B (2009) Earnings quality: Some evidence on the role of auditor tenure and auditors' industry expertise *Journal of Accounting and Economics.* 47: 265-287.

Haislip J, Peters G, Richardson V (2016) The effect of auditor IT expertise on internal controls *International Journal of Accounting Information Systems.* 20: 1-15.
Hammersley J (2006) Pattern identification and industry-specialist auditors *The Accounting Review.* 81(2): 309-336.
Hassell J, Jennings R, Lasser D (1988) Management earnings forecasts: Their usefulness as a source of firm-specific information to security analysts *Journal of Financial Research.* 11(4): 303-319.
Hay D, Knechel WE, Wong N (2006) Audit fees: A meta-analysis of the effect of supply and demand attributes *Contemporary Accounting Research.* 23(1): 141-191.
Heyden M, van Doorn S, Reimer M, Van Den Bosch F, Volberda H (2013) Perceived environmental dynamism, relative competitive performance, and top management team heterogeneity: Examining correlates of upper echelons' advice seeking *Organization Studies.* 34(9): 1327-1356.
Hirst DE, Koonce L, Venkataraman S (2008) Management earnings forecasts: A review and framework *Accounting Horizons.* 22(3): 315-338.
Hribar P, Collins D (2002) Errors in estimating accruals: Implications for empirical research *Journal of Accounting Research.* 40(1): 105-134.
Hribar P, Yang H (2016) CEO overconfidence and management forecasting *Contemporary Accounting Research.* 33(1): 204-227.
Hui KW, Matsunaga S (2015) Are CEOs and CFOs rewarded for disclosure quality? *The Accounting Review.* 90(3): 1013-1047.
Hutton A, Lee LF, Shu S (2012) Do managers always know better? The relative accuracy of management and analyst forecasts *Journal of Accounting Research.* 50(5): 1217-1244.
Independence Standards Board (ISB). 1999. ISB Interpretation 99-1: Impact on Auditor Independence of Assisting Clients in the Implementation of FAS 133. Available at: https://pcaob-assets.azureedge.net/pcaob-dev/docs/default-source/standards/ei/documents/isb_interp_99-1.pdf?sfvrsn=8905afad_0.
Ittner C, Michels J (2017) Risk-Based forecasting and planning and management earnings forecasts *Review of Accounting Studies.* 22: 1005-1047.
Jackson M (2015) Book-Tax differences and future earnings changes *Journal of the American Taxation Association.* 37(2): 49-73.
Joe J, Vandervelde S (2007) Do auditor-provided nonaudit services improve audit quality? *Contemporary Accounting Research.* 24(2): 467-487.
Karamanou I, Vafeas N (2005) The association between corporate boards, audit committees, and management earnings forecasts: An empirical analysis *Journal of Accounting Research.* 43(3): 453-486.
Kasznik R, (1999) On the association between voluntary disclosure and earnings management *Journal of Accounting Research.* 37(1): 57-81.
Kempf E, Manconi A, Spalt O (2017) Distracted shareholders and corporate actions *Review of Financial Studies.* 30(5): 1660-1695.
Kinney W, Palmrose Z, Scholz S (2004) Auditor independence, non-audit services, and restatements: Was the U.S. government right? *Journal of Accounting Research.* 42(3): 561-588.
Kitagawa N, Shuto A (2019) Management earnings forecasts and the cost of debt *Journal of Accounting, Auditing & Finance*, Forthcoming.
Klassen K, Lisowsky P, Mescall D (2016) The role of auditors, non-auditors, and Internal Tax Departments in corporate tax aggressiveness *The Accounting Review.* 91(1): 179-205.

Knechel WR, Sharma D (2012) Auditor-provided nonaudit services and audit effectiveness and efficiency: Evidence from Pre- and Post-SOX audit report lags *Auditing: A Journal of Practice & Theory.* 31(4): 85-114.
Koo D, Lee D (2018) Influential chief marketing officers and management revenue forecasts *The Accounting Review.* 93(4): 253-281.
Kothari SP, Leone A, Wasley C (2005) Performance matched discretionary accrual measures *Journal of Accounting and Economics.* 39: 163-197.
Krishnan J, Su LN, Zhang Y (2011) Nonaudit services and earnings management in the Pre-SOX and Post-SOX eras *Auditing: A Journal of Practice & Theory.* 30(3): 103-123.
Krishnan G, Visvanathan G (2011) Is there an association between earnings management and auditor-provided tax services? *Journal of the American Taxation Association* 33(2): 111-135.
Krishnan G, Pevzner M, Sengupta P (2012) How do auditors view managers' voluntary disclosure strategy? The effect of earnings guidance on audit fees *Journal of Accounting and Public Policy.* 31: 492-515.
Lang M, Lundholm R (1996) Corporate disclosure policy and analyst behavior *The Accounting Review.* 71(4): 467-492.
Larcker D, Rusticus T (2010) On the use of instrumental variables in accounting research *Journal of Accounting and Economics.* 49: 186-205.
Lau D (2020) The effect of audit quality on the quality of management earnings forecasts: Evidence from Japan *Academy of Accounting and Financial Studies Journal.* 24(4): 1-17.
Lee S, Matsunaga S, Park C (2012) Management forecast accuracy and CEO turnover *The Accounting Review.* 87(6): 2095-2122.
Levy H (2018) ICYMI: Maintaining auditor independence when giving accounting assistance and advice *CPA Journal*. October.
Libby R, Frederick D (1990) Experience and the ability to explain audit findings *Journal of Accounting Research.* 28(2): 348-367.
Libby R, Luft J (1993) Determinants of judgment performance in accounting settings: Ability, knowledge, motivation, and environment *Accounting, Organizations and Society.* 18(5): 425-450.
Lim C, Tan H (2008) Non-audit service fees and audit quality: The impact of auditor specialization *Journal of Accounting Research.* 46(1): 199-246.
Liu LY (2020) The value of auditors' cross-client learning in preventing data breaches. Working paper, Columbia University.
Ma S, Kor Y, Seidl D (2020 CEO advice seeking: An integrative framework and future research agenda *Journal of Management.* 46(6): 771-805.
McConomy BJ (1998) Bias and accuracy of management earnings forecasts: An evaluation of the impact of auditing *Contemporary Accounting Research*. 15(2): 167-195.
McDonald M, Khanna P, Westphal J (2008) Getting them to think outside the circle: Corporate governance, CEOs' external advice networks, and firm performance *Academy of Management Journal.* 51(3): 453-475.
McGuire S, Omer T, Wang D (2012) Tax avoidance: Does tax-specific industry expertise make a difference? *The Accounting Review.* 87(3): 975-1003.
Menon T, Pfeffer J (2003) Valuing internal vs. external knowledge: Explaining the preference for outsiders *Management Science.* 49(4): 497-513.
Nagar V, Nanda D, Wysocki P (2003) Discretionary disclosure and stock-based incentives *Journal of Accounting and Economics.* 34: 283-309.

Ohlson J (1995) Earnings, book values, and dividends in equity valuation *Contemporary Accounting Research.* 11(2): 661-687.
Ohlson J, Juettner-Nauroth B (2005) Expected EPS and EPS growth as determinants of value *Review of Accounting Studies.* 10: 349-365.
Patell J (1976) Corporate forecasts of earnings per share and stock price behavior: Empirical tests *Journal of Accounting Research.* 14(2): 246-276.
Paterson J, Valencia A (2011) The effects of recurring and nonrecurring tax, audit-related, and other nonaudit services on auditor independence *Contemporary Accounting Research.* 28(5): 1510-1536.
Plumlee M (2003) The effect of information complexity on analysts' use of that information *The Accounting Review.* 78(1): 275-296.
Public Company Accounting Oversight Board (PCAOB). 2019. Public Company Accounting Oversight Board; Order Granting Approval of Auditing Standard 2501, Auditing Accounting Estimates, Including Fair Value Measurements, and Related Amendments to PCAOB Auditing Standards. PCAOB Release No. 34-86269. Available at: https://www.sec.gov/rules/pcaob/2019/34-86269.pdf
Reichelt K, Wang D (2010) National and office-specific measures of auditor industry expertise and effects on audit quality *Journal of Accounting Research.* 48(3): 647-686.
Richardson G, Taylor G, Lanis R. The impact of board of director oversight characteristics on corporate tax aggressiveness: An empirical analysis *Journal of Accounting and Public Policy.* 32: 68-88.
Robinson D (2008) Auditor independence and auditor-provided tax service: Evidence from going-concern audit opinions prior to bankruptcy filings *Auditing: A Journal of Practice & Theory.* 27(2): 31-54.
Salterio S, Denham R (1997) Accounting consulting units: An organizational memory analysis *Contemporary Accounting Research.* 14(4): 669-691.
Salterio S, Koonce L (1997) The persuasiveness of audit evidence: The case of accounting policy decisions *Accounting, Organizations and Society.* 22(6): 573-587.
Sarbanes-oxley Act of 2002: Conference Report (to Accompany H.r. 3763). Washington, D.C.: U.S. G.P.O., 2002.
Seidel T, Simon C, Stephens N (2020) Management bias across multiple accounting estimates *Review of Accounting Studies.* 25: 1-53.
Shepardson M (2019) Effects of individual task-specific experience in audit committee oversight of financial reporting outcomes *Accounting, Organizations and Society.* 74: 56-74.
Simunic D (1984) Auditing, consulting, and auditor independence *Journal of Accounting Research.* 22(2): 679-702.
Sloan R (1996) Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review.* 71(3): 289-315.
Solomon I, Shields M, Whittington O (1999) What Do Industry-Specialist Auditors Know? *Journal of Accounting Research.* 37(1): 191-208.
Swanquist Q, Whited R (2018) Out of control: The (over)use of controls in accounting research. Working paper, University of Alabama.
Trueman B (1986) Why do managers voluntarily release earnings forecasts? *Journal of Accounting and Economics.* 8: 53-71.
Tysiac K (2019) How auditors can stay independent while advising on revenue recognition *Journal of Accountancy*. December 13.

Vera-Muñoz S, Kinney W, Bonner S (2001) The effects of domain experience and task presentation format on accountants' information relevance assurance *The Accounting Review.* 76(3): 405-429.

Wang IY (2007) Private Earnings Guidance and its Implications for Disclosure Regulation *The Accounting Review.* 82: 1299-1332.

Warren J (2021) Analyst coverage and managers' disclosure of forward-looking information Working paper, University of Connecticut.

Waymire G (1984) Additional evidence on the information content of management earnings forecasts *Journal of Accounting Research.* 22(2): 703-718.

Williams P (1996) The relation between a prior earnings forecast by management and analyst response to a current management forecast *The Accounting Review.* 71(1): 103-115.

Wooldridge J (2010) Econometric Analysis of Cross Section and Panel Data. Second Edition. The MIT Press: Cambridge, MA.

Yang H (2012) Capital market consequences of managers' voluntary disclosure styles *Journal of Accounting and Economics.* 53: 167-184.

Appendix
Variable definitions

MFA	The absolute value of management forecast error (EPS forecast – actual EPS) scaled by stock price at the beginning of the fiscal year (prcc_f) and multiplied by -100. For companies issuing multiple management forecasts, we average the absolute value of management forecast error.
Measures of Auditor Forecasting Knowledge	
AFK	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their other clients (i.e., excluding the client itself) in a given MSA at year t. This measure is then multiplied by -1.
L1AFK	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their clients in a given MSA at year t-1. This measure is then multiplied by -1.
AFK2	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their clients in a given MSA at year t. This measure is then multiplied by -1.
AFK3	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their clients in a given industry (two-digit SICH) at year t. This measure is then multiplied by -1.
AFK4	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their clients in a given MSA and industry (two-digit SICH) at year t. This measure is then multiplied by -1.
XIAFK	The rank of the auditor (equal to 1 for best, 2 for second best, etc.) by the average management forecast accuracy (*MFA*) of their clients in a given MSA at year t, excluding clients in the same industry as the client itself. This measure is then multiplied by -1.
Firm-related Control variables	
SIZE	Company size, defined as the natural log of total assets (at).
RDE	Research and development expense, defined as research and development expense (xrd) divided by total assets (at). Missing values are set equal to 0.
CAPX	Capital expenditure to sales ratio, defined as capital expenditure (capx) divided by total sales (sale).
MTB	Market to book ratio, defined as defined as market value of equity (prcc_f×csho) divided by book value (seq).
ROA	Return on assets, defined as income before extraordinary items (ib) divided by average total assets (at).
EVOL	Earnings volatility, defined as the standard deviation of earnings before extraordinary items (ib) scaled by average total assets (at) over the past three years.
RETVOL	Stock return volatility, defined as the standard deviation of daily stock return (ret) over the past three years. Stock return data obtained from CRSP.
M&A	Indicator variable equal to 1 if cash flow from mergers and acquisitions (aqc) does not equal 0; 0 otherwise.
LITRISK	Indicator variable equal to 1 if the client is in high litigation risk industry (i.e., SICH code 2833-2836, 8731-8734, 3570-3577, 7370-7374, 3600-3674, and 5200-5961); 0 otherwise (Francis, Philbrick and Schipper 1994; Abbott, Gunny, and Pollard 2017).

ISSUE	Indicator variable equal to 1 if the client issues stock or debt in a given year; 0 otherwise.
LOSS	Indicator variable equal to 1 if the client experiences losses (ib<0) in a given year; 0 otherwise.
BUSSEG	Business segments, defined as the natural log of one plus the number of business segments.
FORGN	Foreign sales to total sales ratio, defined as the total sales in foreign countries divided by the total sales.
LEV	Leverage, defined as long-term debt (dltt) divided by beginning year assets (at).
DACC	Absolute value of discretionary accruals, defined as the absolute value of residuals from the performance-matched cross-sectional modified Jones model (Dechow, Sloan, and Sweeney 1995; Kothari et al. 2005).
HHI	Industry concentration (i.e., the Herfindahl-Hirschman Index), calculated by squaring the market share of each company competing in a four-digit SIC code and then summing the resulting numbers. Market share for company *i* is measured as the revenue for company *i* divided by total revenue for all companies in the industry.
HORIZON	Management forecast horizon, defined as the difference in days between the fiscal period end date and the forecast announcement date divided by 365 (i.e., (datadate-announce_date)/365. For companies issuing multiple management forecast, we average the horizons.
ANALYST	Analyst following, defined as the log of one plus the number of analysts covering the company.
IOR	Insitutional ownership percentage (Thomson Reuters Institutional (13f) holdings – stock ownership summary).
BODIND	Board independence, defined as the number of independent directors divided by the total number of board members (Boardex).
ACSIZE	Audit committee size, defined as the total number of audit committee members (Boardex).
FVAT	Fair value assets, defined as defined as total fair value assets (tfva) divided by the total assets at the beginning of the year (at).
IMPAIR	Goodwill impairment, defined as pretax goodwill impairment (gdwlip) divided by total assets at beginning of the year (at).
INTAN	Intangible assets, defined as intangible assets (intan) divided by total assets at beginning of the year (at).
GWILL	Goodwill before impairment, defined as the ending goodwill balance (gdwl) plus any goodwill pretax impairment (gdwlip).
Audit-related Control variables	
BUSY	Indicator variable equal to 1 if the client's fiscal year-end month is December, and zero otherwise.
LAG	Auditor effort, defined as audit report lag for the client at year t. Audit report lag is calculated based on the date between audit report signature date and the client's year-end date.
BIGN	Indicator variable equal to 1 if an audit firm is a Big N auditor, 0 otherwise.
INDEXP	Indicator variable equal to 1 if auditor has industry audit expertise, 0 otherwise. Following McGuire et al. (2012), an auditor has industry audit expertise within the firm's home office city if the auditor receives fees totaling more than 30% of total audit fees paid to all other audit firms within the city and two-digit SIC code.

FEES	Commitment to the independent verification of financial reporting, defined as the natural log of total audit fees a company pays to its auditor at year t.
NAS	The natural log of total non-audit service fees a company pays to its auditor.
APTS	The natural log of total auditor-provided tax service fees a company pays to its auditor.
Cross-sectional variables	
HRV	Indicator variable equal to 1 if the stock return volatility (*RETVOL*) is greater than the median value; and 0 otherwise.
HAFD	Indicator variable equal to 1 if the analyst forecast dispersion is greater than the median value; and 0 otherwise.
HSIZE	Indicator variable equal to 1 if a company has above- median size (i.e., natural log of total assets) in year t; and 0 otherwise.
HMAS	Indicator variable equal to 1 if a company has above-median managerial ability score in year t; and 0 otherwise. Management ability score obtained from Peter Demerjian's website https://peterdemerjian.weebly.com/managerialability.html.
HROA	Indicator variable equal to 1 if a company has above-median return on assets in year t; and 0 otherwise. Return on assets is calculated as earnings before extraordinary items (ib) divided by assets (at).
HAF	Indicator variable equal to 1 if a company has above-median analyst following in year t; and 0 otherwise.
HIRS	Indicator variable equal to 1 if a company has above-median industry revenue synchronicity in year t; and 0 otherwise (Hutton et al. 2012).
HCIMP_TO	Indicator variable equal to 1 if a company has an above-median ratio of total fees to their auditor's total fees in that given MSA in year t; and 0 otherwise.
HCIMP_AU	Indicator variable equal to 1 if a company has an above-median ratio of total audit fees to their auditor's total audit fees in that given MSA in year t; and 0 otherwise.
HCIMP_NAS	Indicator variable equal to 1 if a company has an above-median ratio of total non-audit fees to their auditor's total non-audit fees in that given MSA in year t; and 0 otherwise.
HNAS	Indicator variable equal to 1 if a company has above-median non-audit service fees paid to its auditor in year t; and 0 otherwise.
HCVAA	Indicator variable equal to 1 if a company has above- median changes in deferred tax valuation allowance scaled by total assets in year t; and 0 otherwise.
HFVAT	Indicator variable equal to 1 if a company has above-median fair value assets scaled by total assets in year t; and 0 otherwise.
IMPAIRB	Indicator variable equal to 1 if a company has impairment of goodwill in year t; and 0 otherwise.
HINTAN	Indicator variable equal to 1 if a company has above-median intangible assets scaled by total assets in year t; and 0 otherwise.
Supplemental variables	
VAEXP	Auditor exposure to VA estimates, defined as the number of audit clients within an MSA-year with absolute balances of VAs that exceeds 2% of beginning-of-year assets (at) divided by the number of companies with VAs that exceeds 2% of beginning-of-year assets in that given MSA at year t (S&P Capital).
CVAA	Change in deferred tax valuation allowance (S&P Capital) from year t to t-1 scaled by total assets (at).

CNOLTA	Change in deferred tax assets arising from NOLs (tlcf) from t-1 to t scaled by lag assets (at).
CODTA	Change in deferred tax assets (txndba) arising from sources other than NOLs (tlcf) from year t-1 to t scaled by lagged assets (at).
CDTL	Change in the deferred tax liabilities (txndbl) from year t-1 to t scaled by lag assets.
PIAT	Change in Pretax income (pi) divided by total assets (at) from t-1 to t.
PIAT2	Change in Pretax income (pi) divided by total assets (at) from t-2 to t-1.
HEPS	Average of pretax income (pi) divided by total assets (at) for year t-1 and year t-2.
CMTB	Change in market to book value (prcc_f×csho/ceq) from t-1 to t.
ΔACCR	Change in the accrual component of earnings from t-1 to t, defined as the change in accrual income (ib - oancf) scaled by market value at the beginning of the year (prcc_f×csho).
ΔDACC	Change in discretionary accruals from t-1 to t, defined as the absolute value of residuals from the performance-matched cross-sectional modified Jones model (Kothari et al. 2005).
BIAS	Indicator variable equal to 1 if the average management forecast of EPS exceeds or is equal to actual EPS at year t; and 0 otherwise.
MRFA	Management revenue forecast accuracy, defined as the absolute value of revenue forecast error (revenue forecast – actual revenue) scaled by actual revenue multiplied by -1. For companies issuing multiple management forecasts, we average the absolute value of revenue forecast error.
ALLR	Indicator variable equal to 1 if the financial statements for a company in year t were subsequently restated; and 0 otherwise.
TAXR	Indicator variable equal to 1 if the financial statements for a company in year t were subsequently restated due to tax-related issues; and 0 otherwise.
INTR	Indicator variable equal to 1 if the financial statements for a company in year t were subsequently restated due to intangible-asset related issues; and 0 otherwise.
ICW	Indicator variable equal to 1 a SOX 404 material weakness in internal controls is reported in the audit report; and 0 otherwise.

Note: Compustat mnemonics or variable data source in parentheses.

Table 1. Sample Selection

	Observations	
	Company-Years	Companies
Intersection of Compustat and Audit Analytics (2004-2018)	75,528	10,400
Less: Companies incorporated outside the U.S.	(2,080)	(366)
Less: Observations with only one auditor within an MSA-Industry-Year	(14,420)	(999)
Less: Observations without management forecast data in I/B/E/S Guidance	(48,545)	(6,806)
Less: Observations with stock price below $1	(30)	(6)
Less: Observations with missing data to compute control variables	(2,612)	(503)
Primary Sample	7,841	1,720

Table 2. Descriptive statistics

	N	Mean	Std. Dev.	Q1	Median	Q3
MFA	7,841	-1.62	5.01	-1.03	-0.40	-0.16
AFK	7,841	-2.93	1.52	-2.00	-3.00	-4.00
L1AFK	5,739	-2.92	1.51	-2.00	-3.00	-4.00
AFK2	7,841	-2.89	1.52	-2.00	-3.00	-4.00
AFK3	7,841	-3.38	1.75	-2.00	-3.00	-4.00
AFK4	7,841	-1.73	0.99	-1.00	-1.00	-2.00
XIAFK	7,841	-2.92	1.52	-2.00	-3.00	-4.00
SIZE	7,841	7.53	1.78	6.21	7.45	8.69
RDE	7,841	0.03	0.05	0.00	0.01	0.05
CAPX	7,841	0.05	0.07	0.02	0.03	0.06
MTB	7,841	2.07	1.19	1.25	1.70	2.44
ROA	7,841	0.05	0.09	0.02	0.05	0.09
EVOL	7,841	0.04	0.05	0.01	0.02	0.04
RETVOL	7,841	0.02	0.01	0.02	0.02	0.03
M&A	7,841	0.56	0.50	0.00	1.00	1.00
LITRISK	7,841	0.32	0.47	0.00	0.00	1.00
ISSUE	7,841	0.97	0.16	1.00	1.00	1.00
LOSS	7,841	0.14	0.34	0.00	0.00	0.00
BUSSEG	7,841	0.81	0.81	0.00	1.10	1.61
FORGN	7,841	0.24	0.24	0.00	0.18	0.43
LEV	7,841	0.21	0.20	0.02	0.18	0.32
DACC	7,841	0.11	0.18	0.00	0.04	0.12
HHI	7,841	0.29	0.21	0.14	0.23	0.37
HORIZON	7,841	-0.57	0.18	-0.64	-0.55	-0.51
ANALYST	7,841	2.46	0.67	2.08	2.56	2.94
CVAA	7,841	0.00	0.02	0.00	0.00	0.00
FVAT	7,841	0.07	0.17	0.00	0.00	0.04
IMPAIR	7,841	0.00	0.02	0.00	0.00	0.00
INTAN	7,841	0.30	0.27	0.08	0.24	0.46
IOR	7,841	0.58	0.35	0.35	0.70	0.85
BODIND	7,841	0.71	0.11	0.67	0.73	0.80
GWILL	7,841	0.02	0.09	0.00	0.00	0.00
ACSIZE	7,841	4.20	1.20	3.00	4.00	5.00
BUSY	7,841	0.72	0.45	0.00	1.00	1.00
LAG	7,841	42.79	13.93	32.00	41.00	53.00
BIGN	7,841	0.93	0.26	1.00	1.00	1.00
INDEXP	7,841	0.60	0.49	0.00	1.00	1.00
FEES	7,841	14.55	1.03	13.83	14.50	15.25
NAS	7,841	12.04	3.26	11.50	12.68	13.77
APTS	7,841	9.94	4.99	9.85	11.79	13.13
HRV	7,841	0.50	0.50	0.00	0.00	1.00

Table 2 (continued)

HAFD	7,657	0.50	0.50	0.00	0.00	1.00
HSIZE	7,841	0.50	0.50	0.00	0.00	1.00
HMAS	6,584	0.50	0.50	0.00	0.50	1.00
HROA	7,841	0.50	0.50	0.00	0.00	1.00
HAF	7,841	0.46	0.50	0.00	0.00	1.00
HIRS	7,403	0.50	0.50	0.00	0.00	1.00
HCIMP_TO	7,841	0.50	0.50	0.00	0.00	1.00
HCIMP_AU	7,841	0.50	0.50	0.00	0.00	1.00
HCIMP_NAS	7,841	0.50	0.50	0.00	0.00	1.00
HNAS	7,841	0.50	0.50	0.00	0.00	1.00
BIAS	7,841	0.42	0.49	0.00	0.00	1.00
MRFA	5,568	-0.06	0.19	-0.06	-0.03	-0.01
HCVAA	7,841	0.45	0.50	0.00	0.00	1.00
HFVAT	7,841	0.48	0.50	0.00	0.00	1.00
IMPAIRB	7,841	0.10	0.29	0.00	0.00	0.00
HINTAN	7,841	0.50	0.50	0.00	0.00	1.00
ALLR	7,841	0.14	0.35	0.00	0.00	0.00
TAXR	7,841	0.03	0.18	0.00	0.00	0.00
INTR	7,841	0.01	0.08	0.00	0.00	0.00
FVR	7,841	0.01	0.10	0.00	0.00	0.00
ICW	7,841	0.05	0.22	0.00	0.00	0.00
Δ*ACCR*	7,037	-0.01	0.14	-0.03	0.00	0.02
Δ*DACC*	7,037	-0.01	0.34	-0.04	0.00	0.04

Note: This table reports descriptive statistics for all variables included in our analyses. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Variables are defined in the Appendix.

Table 3. Primary Hypothesis Test – The Effect of Auditor Forecasting Knowledge on Management Forecast Accuracy

	(1) *MFA*	(2) *MFA*	(3) *MFA*
AFK	**0.599*****	**0.444*****	**0.418*****
	(8.653)	**(7.349)**	**(7.104)**
SIZE		-0.276***	-0.435***
		(-3.129)	(-3.255)
RDE		0.860	-0.777
		(0.281)	(-0.253)
CAPX		2.535**	2.944**
		(2.013)	(2.241)
MTB		0.275***	0.225***
		(3.484)	(2.842)
ROA		2.844*	2.779*
		(1.821)	(1.784)
EVOL		-15.09***	-14.83***
		(-5.463)	(-5.404)
RETVOL		-72.01***	-66.53***
		(-4.853)	(-4.538)
M&A		0.0565	0.0504
		(0.413)	(0.365)
LITRISK		0.139	0.198
		(0.516)	(0.732)
ISSUE		0.983*	0.990*
		(1.722)	(1.739)
LOSS		-1.552***	-1.494***
		(-4.551)	(-4.412)
BUSSEG		0.0748	0.0626
		(0.671)	(0.574)
FORGN		-0.115	-0.237
		(-0.307)	(-0.572)
LEV		-0.458	-0.479
		(-1.029)	(-1.056)
DACC		-0.490	-0.445
		(-1.103)	(-1.015)
HHI		0.513	0.665
		(1.104)	(1.473)
HORIZON		2.511***	2.535***
		(6.644)	(6.708)
ANALYST		0.748***	0.636***
		(4.033)	(3.526)

Table 3 (continued)

CVAA		-12.91**	-12.94**
		(-2.479)	(-2.487)
FVAT		0.947**	0.854**
		(2.275)	(2.030)
IMPAIR		-16.67**	-16.73**
		(-2.198)	(-2.229)
INTAN		0.751*	0.873**
		(1.764)	(2.068)
IOR		0.716***	0.714**
		(2.589)	(2.217)
BODIND		-0.552	-0.832
		(-0.678)	(-1.022)
GWILL		1.703*	1.831**
		(1.919)	(2.092)
ACSIZE		0.0671	0.0597
		(1.263)	(1.117)
BUSY			-0.0531
			(-0.278)
LAG			-0.0274***
			(-4.011)
BIGN			1.220***
			(2.709)
INDEXP			0.0538
			(0.401)
FEES			0.0216
			(0.120)
NAS			0.0212
			(0.617)
APTS			0.00260
			(0.165)
Intercept	-7.945***	-7.995***	-7.020***
	(-23.62)	(-6.924)	(-3.206)
Industry FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R^2	0.091	0.242	0.250
Obs.	7,841	7,841	7,841

Note: This table reports the results of estimating equation (1), where *MFA* is the dependent variable. Column (1) presents a baseline result without the *BASE* and *AUDIT* vectors of controls. Column (2) presents the results after controlling for company-specific characteristics. Column (3) presents the results after controlling for company-specific characteristics and auditor characteristics. *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix.

Table 4. Cross-Sectional Analyses

	(1) *MFA*	(2) *MFA*	(3) *MFA*	(4) *MFA*	(5) *MFA*	(6) *MFA*	(7) *MFA*
AFK	0.130^{**}	0.296^{***}	0.555^{***}	0.523^{***}	0.679^{***}	0.561^{***}	0.496^{***}
	(2.155)	(3.670)	(7.285)	(6.017)	(7.532)	(7.116)	(5.700)
HRV	1.984^{***}						
	(6.359)						
AFK×HRV	**0.565*****						
	(6.057)						
HAFD		-0.175					
		(-0.740)					
AFK×HAFD		**0.189***					
		(1.813)					
HSIZE			-1.381^{***}				
			(-4.465)				
AFK×HSIZE			**-0.284****				
			(-2.339)				
MASCORE				-0.545^{**}			
				(-1.977)			
AFK×HMAS				**-0.203***			
				(-1.844)			
HROA					-1.796^{***}		
					(-6.053)		
AFK×HROA					**-0.508*****		
					(-5.266)		
HAF						-1.379^{***}	
						(-4.475)	
AFK×HAF						**-0.331*****	
						(-3.088)	
HIRS							-0.469^{**}
							(-2.043)
AFK×HIRS							**-0.180***
							(-1.908)
Intercept	-8.025^{***}	-7.570^{***}	-7.104^{***}	-6.197^{**}	-6.360^{***}	-7.184^{***}	-6.212^{***}
	(-3.646)	(-3.511)	(-3.538)	(-2.320)	(-2.939)	(-3.327)	(-2.791)
BASE	Included	Included	Included	Included	Included	Included	Included
AUDIT	Included	Included	Included	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included
Adj. R^2	0.257	0.239	0.253	0.247	0.256	0.253	0.256
Obs.	7,841	7,657	7,841	6,584	7,841	7,841	7,403

Note: This table reports cross-sectional analyses based on equation (1), where *MFA* is the dependent variable. *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix. The number of observations in columns 2, 4, and 7 vary due to the data availability.

Table 5. Auditor Forecasting Knowledge and the Predictive Value of Tax Valuation Allowance Changes

	(1)	(2)	(3)	(4)
	ΔPTI1	*ΔPTI2*	*ΔPTI1*	*ΔPTI2*
AFK	-0.001	0.000	-0.001	0.000
	(-1.229)	(0.101)	(-1.278)	(0.075)
CVAA	-0.438***	-0.404***	-0.317***	-0.313***
	(5.729)	(5.696)	(3.407)	(3.655)
AFK×CVAA	-0.059***	-0.041**	-0.051**	-0.035*
	(-2.676)	(-2.098)	(-2.284)	(-1.756)
VAEXP			-0.004	-0.004
			(0.934)	(0.854)
VAEXP×CVAA			-0.322***	-0.239**
			(2.664)	(2.187)
CNOLDTA	0.211***	0.202***	0.209***	0.201***
	(2.905)	(2.877)	(2.911)	(2.884)
CODTA	0.204***	0.185***	0.202***	0.183***
	(3.361)	(3.087)	(3.387)	(3.079)
CDTL	-0.326***	-0.345***	-0.326***	-0.345***
	(2.908)	(3.446)	(2.925)	(3.438)
PIAT	-0.362***	-0.398***	-0.364***	-0.400***
	(8.459)	(9.667)	(8.527)	(9.701)
PIAT2	-0.153***	-0.157***	-0.155***	-0.158***
	(5.686)	(6.180)	(5.770)	(6.242)
HEPS	-0.296***	-0.297***	-0.298***	-0.299***
	(7.957)	(7.855)	(8.058)	(7.913)
CMTB	0.016***	0.014***	0.017***	0.014***
	(6.226)	(5.525)	(6.262)	(5.519)
RDE	-0.090***	-0.103***	-0.090***	-0.103***
	(3.049)	(3.215)	(3.050)	(3.205)
CAPX	-0.042	-0.038	-0.040	-0.036
	(1.269)	(1.056)	(1.203)	(1.009)
EP	-0.140***	-0.141***	-0.145***	-0.145***
	(7.247)	(6.963)	(7.452)	(7.059)
DVC	-0.061	-0.022	-0.057	-0.019
	(0.990)	(0.318)	(0.930)	(0.282)
OANCF	0.281***	0.212***	0.283***	0.214***
	(5.646)	(4.314)	(5.728)	(4.365)
BTM	-0.021***	-0.023***	-0.021***	-0.023***
	(8.169)	(8.170)	(8.157)	(8.143)
ACCRUAL	0.251***	0.163***	0.253***	0.166***
	(4.788)	(3.167)	(4.878)	(3.219)
SIZE	0.002**	0.003***	0.002**	0.003***
	(2.296)	(3.754)	(2.192)	(3.689)

Table 5 (continued)

MERGER	-0.002	-0.004	-0.002	-0.004
	(0.833)	(1.483)	(0.828)	(1.488)
CROA	-0.002	-0.000	-0.000	0.001
	(0.052)	(0.010)	(0.011)	(0.036)
CROA3	-0.039**	-0.035**	-0.037**	-0.033**
	(2.278)	(2.131)	(2.152)	(2.021)
CROA5	-0.065***	-0.073***	-0.065***	-0.073***
	(4.873)	(4.909)	(4.915)	(4.966)
Intercept	-0.005	-0.001	-0.004	-0.001
	(0.383)	(0.087)	(0.355)	(0.068)
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Adj. R^2	0.275	0.344	0.276	0.345
Obs.	5,174	4,920	5,174	4,920

Note: This table reports the results regressing the one- and two-period ahead earnings changes ($\Delta PTI1$ and $\Delta PTI2$, respectively) on *AFK*, the change in the deferred tax valuation allowance (*CVAA*), their interaction, and controls from prior deferred tax accounting research (e.g., Jackson 2015; Axelton et al. 2021). *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix. The number of observations correspond with the data availability of using $\Delta PTI1$ (columns 1 and 3) and $\Delta PTI2$ (columns 2 and 4).

Table 6. Auditor independence

Panel A: Cross-sectional analyses – based on client importance and NAS fees

	(1)	(2)	(3)	(4)
	MFA	*MFA*	*MFA*	*MFA*
AFK	0.465***	0.457***	0.513***	0.636***
	(5.316)	(5.251)	(5.689)	(7.782)
HCIMP_TO	-0.470*			
	(-1.784)			
AFK×HCIMP_TO	-0.0688			
	(-0.608)			
HCIMP_AU		-0.419		
		(-1.631)		
AFK×HCIMP_AU		-0.0490		
		(-0.440)		
HCIMP_NAS			-0.842***	
			(-3.008)	
AFK×HCIMP_NAS			-0.175	
			(-1.553)	
HNAS				-1.462***
				(-4.950)
AFK×HNAS				-0.448***
				(-3.912)
Intercept	-7.369***	-7.438***	-6.905***	-6.019***
	(-3.153)	(-3.203)	(-3.033)	(-2.945)
BASE	Included	Included	Included	Included
AUDIT	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Adj. R^2	0.250	0.250	0.251	0.254
Obs.	7,841	7,841	7,841	7,841

Table 6 (continued)

Panel B: Auditor knowledge exposure on management forecast bias – logistic regression

	(1)	(2)	(3)
	BIAS	*BIAS*	*BIAS*
AFK	**-0.0585*****	**-0.0207**	**-0.0128**
	(-3.375)	**(-1.145)**	**(-0.701)**
Intercept	0.728***	3.000***	1.520*
	(7.914)	(6.934)	(1.922)
BASE	No	Included	Included
AUDIT	No	No	Included
Industry FE	Included	Included	Included
Year FE	Included	Included	Included
Pseudo R^2	0.073	0.075	0.323
Area under ROC	0.620	0.727	0.728
Obs.	7,812	7,812	7,812

Panel C: Auditor forecasting knowledge exposure on revenue forecast accuracy

	(1)	(2)	(3)
	MRFA	*MRFA*	*MRFA*
AFK	**0.00585*****	**0.00347****	**0.00318****
	(3.402)	**(2.151)**	**(1.977)**
Intercept	-0.0552***	0.0903	0.0740
	(-5.514)	(1.459)	(0.758)
BASE	No	Included	Included
AUDIT	No	No	Included
Industry FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R^2	0.046	0.078	0.080
Obs.	5,568	5,568	5,568

Panel D: Comparison of management forecast accuracy and naïve random walk forecast accuracy

	(1)	(2)	(3)	(4)
	MFA	ΔACCR	MFA	ΔDACC
AFK	**0.404*****	**-0.000**	**0.404*****	**-0.001**
	(11.85)	**(-0.413)**	**(11.85)**	**(-0.568)**
Intercept	-11.21***	-0.046	-11.21***	0.030
	(-4.088)	(-0.640)	(-4.088)	(0.158)
BASE	Included		Included	
AUDIT	Included		Included	
Industry FE	Included		Included	
Year FE	Included		Included	
Obs.	7,037		7,037	

Note: Panel A reports cross-sectional analyses based on equation (1), where *MFA* is the dependent variable. Panel B reports logistic regressions where the dependent variable is equal to one for companies that meet/beat their management forecast targets. Panel C reports the results of estimating equation (1) with management revenue forecast accuracy (*MRFA*) as the dependent variable. Panel D reports the results of simultaneously estimating equation (1) with management forecast accuracy (*MFA*) as the dependent variable and a version of equation (1) with *MFA* replaced with either the concurrent change in accrual component of earnings ($\Delta ACCR$ in Panel A), or the concurrent change in the discretionary accrual of earnings ($\Delta DACC$ in Panel B). *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported *t*-statistics or *z*-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix. The number of observations correspond with the data availability of each model and omits observations in which the industry perfectly predicts the outcome.

Table 7. Auditor Governance

Panel A: Cross-sectional tests conditional on estimate-based accounts

	(1)	(2)	(3)	(4)
	MFA	*MFA*	*MFA*	*MFA*
AFK	0.339***	0.542***	0.609***	0.387***
	(5.200)	(7.333)	(7.278)	(6.650)
HCVAA	0.623**			
	(2.393)			
AFK×HCVAA	0.192**			
	(1.999)			
HFVAT		-0.460		
		(-1.556)		
AFK×HFVAT		-0.290***		
		(-2.815)		
HINTAN			-1.081***	
			(-3.785)	
AFK×HINTAN			-0.383***	
			(-3.696)	
IMPAIR				-0.887
				(-1.255)
AFK×IMPAIRB				0.299
				(1.333)
Intercept	-7.107***	-6.119***	-6.563***	-7.189***
	(-3.261)	(-2.849)	(-3.035)	(-3.299)
BASE	Included	Included	Included	Included
AUDIT	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Adj. R^2	0.250	0.250	0.254	0.251
Obs.	7,841	7,841	7,841	7,841

Table 7 (continued)

Panel B: Auditor forecasting knowledge and future restatements of clients

	(1) *ALLR*	(2) *TAXR*	(3) *INTR*	(4) *ICW*
AFK	**-0.002**	**0.017**	**-0.146**	**0.055**
	(-0.085)	**(0.296)**	**(-1.240)**	**(1.351)**
Intercept	-5.680***	-15.268***	-12.29***	-18.49***
	(3.308)	(6.126)	(2.867)	(9.057)
BASE	Included	Included	Included	Included
AUDIT	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Pseudo R^2	0.079	0.107	0.318	0.205
Area under ROC	0.697	0.760	0.905	0.808
Obs.	7,760	7,352	4,370	7,624

Note: Panel A reports cross-sectional analyses based on equation (1), where *MFA* is the dependent variable . Panel B reports logistic regressions where the dependent variable is the occurance of (1) any financial statement restatement, (2) a tax-related restatement, (3) an intangible-asset-related restatement, or (4) an internal control weakness. *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported *t*-statistics or z-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix. The number of observations correspond with the data availability of each model and omit observations in which the industry perfectly predicts the outcome.

Table 8. Alternative Proxies of Auditor Forecasting Knowledge

	(1) *MFA*	(2) *MFA*	(3) *MFA*	(4) *MFA*
L1AFK	0.154***			
	(3.030)			
AFK2		0.449***		
		(7.072)		
AFK3			0.434***	
			(9.068)	
AFK4				0.458***
				(5.072)
Intercept	-10.830***	-6.897***	-7.265***	-7.831***
	(-4.568)	(-3.170)	(-3.381)	(-3.589)
BASE	Included	Included	Included	Included
AUDIT	Included	Included	Included	Included
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Adj. R2	0.254	0.252	0.253	0.241
Obs.	5,739	7,841	7,841	7,841

Note: This table reports the results of estimating equation (1), where *MFA* is the dependent variable and *AFK* has been replaced by alternative proxies of auditor forecasting knowledge. *, **, and *** denote statistical significance levels of $p < 0.10$, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix. The number of observations in column 1 reflect data attrition related to lagging *AFK* by one year.

Table 9. MSA-Year Industry Fixed Effects and Company Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	MFA	*MFA*	*MFA*	*MFA*	*MFA*	*MFA*
AFK	**0.702*****	**0.508*****	**0.507*****	**0.254*****	**0.194*****	**0.193*****
	(9.437)	**(7.960)**	**(8.013)**	**(5.516)**	**(4.571)**	**(4.588)**
BUSY			-0.0324			1.385
			(-0.157)			-1.47
LAG			-0.0243***			-0.0237**
			(-3.250)			(-2.367)
BIGN			1.278**			-0.605
			-2.565			(-1.024)
INDEXP			0.201			0.0797
			-1.39			-0.719
FEES			-0.0304			-0.456*
			(-0.157)			(-1.934)
NAS			0.0132			0.018
			-0.359			-0.482
APTS			0.007			0.00933
			-0.412			-0.571
Intercept	-6.930***	-7.486***	-6.235**	-0.00512	4.040***	10.67***
	(-4.611)	(-4.593)	(-2.546)	(-0.0166)	-2.864	-3.653
BASE	No	Included	Included	No	Included	Included
Company FE	No	No	No	Included	Included	Included
Year FE	No	No	No	Included	Included	Included
MSA-YEAR FE	Included	Included	Included	No	No	No
Industry FE	Included	Included	Included	No	No	No
Strict Exogeneity *t*-stat	N/A	N/A	N/A	3.787***	3.149***	3.049***
Adj. R^2	0.143	0.284	0.291	0.747	0.779	0.780
Obs.	7,841	7,841	7,841	7,841	7,841	7,841

Note: This table reports the results of estimating equation (1), where *MFA* is the dependent variable and fixed effects have been replaced with MSA-year fixed effects in Column (1) – (3) and company fixed effects in Column (4) – (6). Column (1) and (4) present a univariate result. Column (2) and (5) presents the results after controlling for company-specific characteristics. Column (3) and (6) present the results after controlling for company-specific characteristics and auditor characteristics. The Strict Exogeneity *t*-statistic presented in column (4) – (6) is derived from the strict exogeneity assumption test in Wooldridge (2010). *, **, and *** denote statistical significance levels of p < 0.10, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix.

Table 10. Two-Stage Least Square Regression Using an Extra-Industry Instrumental Variable

	(1)	(2)	(3)
	MFA	*MFA*	*MFA*
Fitted AFK	**0.605*** **	**0.451*** **	**0.424*** **
	(8.637)	**(7.389)**	**(7.123)**
BUSY			-0.053
			(0.278)
LAG			-0.027***
			(4.008)
BIGN			1.218***
			(2.702)
INDEXP			0.052
			(0.389)
FEES			0.023
			(0.125)
NAS			0.021
			(0.617)
APTS			0.003
			(0.171)
Intercept	-7.924***	-7.968***	-7.008***
	(23.451)	(6.900)	(3.200)
BASE	No	Included	Included
Industry FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R^2	0.083	0.232	0.239
Obs.	7,841	7,841	7,841

Note: This table reports the second stage of two-stage least squares regression. The untabulated first stage regresses *AFK* on all control variables and our extra-industry instrumental variable *XIAFK*. *Fitted AFK* is the predicted value from the first stage regression. *, **, and *** denote statistical significance levels of p<0.10, 0.05, and 0.01, respectively (two-tailed). Reported t-statistics (in parentheses below the coefficients) are based on robust standard errors clustered by company. Variables are defined in the Appendix.