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Is sophistication always better? Can perceived data analytic tool sophistication lead to biased judgments?

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Running head: Is sophistication always better? The impact of data analytics on complex estimates.

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ABSTRACT

The rise of technology-enabled data analytic tools creates opportunities for firms to improve audit quality related to complex estimates. To combat auditors' resistance to using technology-enabled tools, firms may promote the sophistication of such tools to their audit staff. However, there is a paucity of research that has examined how auditors' perceived sophistication of an analytic tool impacts judgments about audit evidence. We conduct an experiment and find that, holding all other information constant, the preferences of an audit supervisor interact with the perceived sophistication of an analytic tool to jointly impact auditors' anticipated evaluation from a supervisor and, in turn, their evidence assessment decisions when auditing a complex estimate. As such, the promotion of tool sophistication by audit firms can significantly affect the audit of complex estimates to a greater degree than what would be expected. Implications for audit theory and practice are discussed.

Key Words: Complex Estimates, Data Analytics, Supervisor Preference

JEL Classifications: M41, M42

I. INTRODUCTION

Audit firms are increasingly leveraging technology enabled resources, such as data analytic tools, to disseminate centralized knowledge and aid firm professionals in gathering evidence related to audits of complex estimates (Dowling and Leech 2014; Boland, Daugherty, and Dickins 2019; Leech and Sutton 2002).[1] Recent advances in technology have greatly expanded the capabilities of these tools to identify audit relevant information (Jans, Alles, and Vasarhelyi 2014; Moffitt and Vasarhelyi 2013; Jans, Alles, and Vasarhelyi 2013; Brown-Liburd and Vasarhelyi 2015; Appelbaum et al. 2017).[2] However, research suggests that auditors may resist using these tools by engaging in adverse behaviors, such as disengaging from the task and/or working around the technology (Bedard et al. 2003; Dowling and Leech 2014; Cao et al. 2022; Krieger, Drews, and Velte 2021). This can negatively impact audit quality if the tool's usage would otherwise improve the effectiveness of the audit. Additionally, these technology-enabled tools may in fact attenuate previously observed biases in auditors' judgments.

Prior research demonstrates that individual judgments are influenced by the preferences of one's superiors (Tetlock 1983; Lerner and Tetlock 1999; Kaplan and Lord 2001; Bierstaker and Wright 2005). That is, individuals expect more favorable treatment when they make judgments consistent with those of their superiors. Accordingly, audit research shows that this causes auditors to strategically attempt to influence their supervisor's assessment by determining what information is included in the workpapers and how that evidence is presented and

[1] Disseminating this centralized expertise to lower-level staff, including through data analytic tools, can increase audit quality by empowering lower level staff with expert knowledge. While technology-enabled tools represent a variety of tools (not just confined to accounting and auditing), we refer to "data analytic tools" as a subset of technology-enabled tools that are particularly relevant for analysis in an accounting/auditing setting. Data analytic tools are the focus of our current study.

[2] Data analytic tools can be utilized in nearly all areas of the audit. For example, engagement teams may use analytics to assess the reliability of client's estimates in financial statements. Such tools can aggregate data from multiple sources and identify outliers or anomalies in valuation inputs. This can help determine whether the audit team needs to modify key assumptions or record adjustments to estimates (Deloitte 2018).

interpreted (Peecher 1996; Hoffman and Patton 1997; Rich, Solomon, and Trotman 1997; Tan, Jubb, and Houghton 1997; Cohen and Trompeter 1998; Wilks 2002; Peytcheva and Gillett 2011) and these actions can impair audit quality (Tan and Trotman 2003). Although the impact of supervisor's preferences on audit workpaper quality has been shown in the prior literature, we examine whether this effect is also applicable in the emerging setting of auditors' use of technology enabled tools: specifically, when using tools of greater perceived sophistication.[3]

In an effort to reduce resistance and encourage adoption of new technology enabled tools, firms often promote the enhanced sophistication of the tools, relative to traditional methods, to their audit practitioners.[4] The perceived sophistication may be used to induce use of a tool by suggesting to users that the tool can help them achieve more effective outcomes while working more efficiently (via reduced time). While differences in *actual* tool sophistication would undoubtedly impact audit judgments, little is known about whether mere *perceptions* of tool sophistication might impact audit decision making, particularly under varying supervisor preferences. Therefore, the purpose of this study is to examine whether perceptions regarding the sophistication of data analytic tools have the propensity to exacerbate differences in auditors judgments' under varying supervisor preferences. We conduct an experiment to investigate this issue.

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[3] Although prior accounting research has examined "sophistication," there is limited research examining technology sophistication in an audit setting. As a result, no generally accepted definition of "sophistication" from prior research could be adapted for this study. In our study, we use the term "sophistication" to refer to a tool's capability to achieve more effective outcomes for its users.

[4] For example, PwC (2016) describes its data auditing technology, *Halo*, as "revolutionizing our audits, enabling greater assurance and deeper insight" (p. 11). EY (2019) states that the information provided by its analytics software, *Helix*, will allow "auditors' inquisitiveness and skepticism [to be] enhanced." KPMG (2017) describes the potential of data analytic tools in the audit setting as "driving up audit quality, sophistication and depth and, therefore, driving up trust and transparency in the capital markets" (p. 4). Deloitte (2016) describes their *Argus* tool as a "cognitive audit application" that "learns" from every human interaction and leverages advanced machine learning techniques and natural language processing to automatically identify and extract key accounting information from any type of electronic document" (p. 6).

The halo effect is generally defined as the "influence of a global evaluation on evaluations of individual attributes of a person" (Nisbett and Wilson 1977).[5] For example, halo effect theory would suggest that if one likes a person, one is likely to assume that unknown attributes of that person are also favorable. The halo effect undermines a rater's ability to objectively assess the strengths and weaknesses of an object being assessed (Nathan and Lord 1983) as well as its diagnosticity (Murphy, Jako, and Anhalt 1993). Furthermore, accounting research demonstrates that auditors are susceptible to this bias (Tan and Jamal 2001; O'Donnell and Schultz 2005). This suggests that, within the audit setting, halo generated from a more sophisticated tool may cause auditors to perceive evidence generated by that tool as more diagnostic (i.e., more relevant to the audit risk assessment decision), even though its actual diagnosticity would be the same if it were generated using a less sophisticated tool. This overweighting of evidence diagnosticity may cause judgments to be more susceptible to other factors: such as supervisor preferences. Therefore, we expect that using a sophisticated tool will generate a halo, which will cause the auditor to assess evidence less diagnostically and make judgments more in line with their supervisors' preference. Yet, we do not expect this effect to be as pronounced when using a less sophisticated tool.

For example, when a supervisor expresses a concern that past judgments of complex estimates have been overly sensitive to possible impairment, we expect that auditors will overweight their reliance on evidence that suggests a complex estimate is appropriately valued in order to comport with their supervisor's preference. In this scenario, halo theory would predict that data generated from a more sophisticated tool will be overweighed, regardless of its actual

[5] In this study, "global evaluation" refers to a viewpoint in which all different aspects of a target being evaluated are considered.

diagnosticity (Murphy et al. 1993; O'Donnell and Schultz 2005). Yet, we would not expect this overweighting to occur when a less sophisticated tool is used to generate evidence.

However, this effect is unlikely to occur in situations where a superior expresses a concern that past judgments of complex estimates have been insufficiently sensitive to evidence suggesting impairment. This is because auditors have a pervasive and overriding concern for negative outcomes (i.e., conservatism) and are less sensitive to decision biases in situations where negative outcomes are especially salient (Smith and Kida 1991). Therefore, in situations where a supervisor expresses a preference for more conservative complex estimate assessments, we believe that auditors will be less susceptible to halo effects and more likely to accurately judge the diagnosticity of the evidence presented. This will mitigate any impact of perceived tool sophistication on auditor judgments, ceteris paribus. Taken together, we expect to observe a difference in auditors' complex estimate assessments from using a more (versus less) sophisticated tool only when a supervisor has expressed a concern of over sensitivity to impairment indicators.

We also consider the impact of a supervisor's known preference and perceived data analytic tool sophistication on an auditor's anticipated supervisor evaluation regarding their level of skepticism. We expect auditors' anticipated supervisor evaluation to follow a similar pattern as their complex estimate assessments. Accountability pressures make auditors' evaluations from their supervisors susceptible to the supervisors' biases (Brazel et al. 2016; Brazel et al. 2019). As a result, when a supervisor expresses a concern that auditors have been overly sensitive to evidence suggesting a misstated complex estimate, auditors exposed to evidence generated using a more sophisticated tool will perceive that evidence as more persuasively supporting the preferences of that supervisor. This, in turn, will increase auditors' expectation that they will

receive a favorable evaluation from a supervisor. However, given auditors' aversion to negative outcomes discussed earlier (e.g., Smith and Kida 1991), we do not expect this relationship to hold when a supervisor expresses a concern that auditors have been insufficiently skeptical. In that situation, we expect that auditors will consider the effect of audit evidence on anticipated supervisor evaluation in a more diagnostic manner, regardless of its source. Therefore, we expect to observe a difference in auditors' anticipated supervisor evaluation from using a more (versus less) sophisticated tool only when a supervisor has expressed a concern of over sensitivity to impairment indicators.

To study these issues, we conducted a 2 x 2 between-subjects experiment to examine the effect of supervisor preference and perceived data analytical tool sophistication (our two independent variables). We asked professional auditors to evaluate a client's goodwill impairment analysis (a complex estimate) along with materials documenting that analysis. These materials contained seeded inconsistencies that suggested that the client's assessment was too optimistic. Adapting prior research (Wilks 2002), our participants were also informed that the partner on the engagement had expressed concerns that audit team members had either been either insufficiently or overly skeptical to evidence suggesting goodwill impairment in prior years. Next, we told participants that some of these materials were obtained from the initial use of a data analytic tool that was described as either "more" or "less" sophisticated compared to traditional software tools used in audits, such as Excel. Tool sophistication was described using adapted language from scales used in prior research to measure IT sophistication (Elbashir, Collier, and Sutton 2011; Armstrong and Sambamurthy 1999).[6] Following the exposure to our manipulations and their review of the case materials, participants made a judgment about the

[6] We opted to manipulate *perceived* tool sophistication instead of *actual* tool sophistication to hold the information content provided by the tool constant across conditions.

adequacy of management's fair value analysis (our dependent variable) and the anticipated evaluation of their work from their supervisor.

Our results indicate that, while perceived tool sophistication and preference of a supervisor do not interact in a direct way to impact auditors' judgments regarding estimate assessment, they do jointly impact participants' anticipated evaluation from their supervisor. That is, we told participants that their supervisor was concerned about auditors being overly sensitive to evidence suggesting impairment of a complex estimate, those exposed to the more sophisticated tool were more likely to believe that they would receive a favorable performance evaluation if they agreed with management's assessment. This suggests that auditors using the more sophisticated tool believed they would be more effective in influencing their supervisor's evaluation of their efforts. This finding, combined with the lack of direct support for the joint effect of perceived tool sophistication and supervisor preference on complex estimate assessment, caused us to consider the indirect effect of anticipated supervisor evaluation (as a mediator) on complex estimate assessment. Results of this moderated mediation analysis demonstrate that the effect of tool sophistication and supervisor preference on complex estimate assessment is mediated by anticipated supervisor evaluation. Thus, while perceived data analytic tool sophistication and supervisor preference do not jointly *directly* impact auditors complex estimate assessment, they *indirectly* impact complex estimate assessment through anticipated supervisor evaluation. We believe that this finding is attributable to auditors being cognizant that the engagement partner has more experience and knowledge, and is the individual who is ultimately signing off on the engagement (and can, therefore, override the auditors' assessment). As a result, auditors may be highly focused on their performance evaluation, which impacts the judgments they make related to complex estimate assessment.

The results of our study have implications for the AIS and audit literature. Our study contributes to the early and emerging empirical literature which examines how auditors' judgments are affected by their use of data analytic tools (Rose et al. 2017; Koreff 2022; Commerford et al. 2022). We expand upon prior AIS literature demonstrating adverse consequences of using technology (Koreff et al. 2021; Seow 2011), by showing how touting the sophistication of new analytic tools can undermine the benefits of these tools. We also contribute to the literature by examining the use of technology enabled tools to address a concern expressed by researchers and practitioners alike: the lack of understanding of the challenges encountered during the auditing of complex estimates (Martin, Rich, and Wilks 2006; Bratten et al. 2013; PCAOB 2014; PCAOB 2015). While prior research states that technology enabled tools, such as data analytical tools, can make complex estimates more auditable (Griffith, Hammersley, and Kadous 2015a), this study demonstrates that firms should be cautious in how they promote such tools to audit staff. While firms may tout a new data analytic tool's sophistication in an effort to encourage adoption of the tool, this study shows an unintended negative consequence of this approach, as it may attenuate prior decision biases, such as those attributable to supervisors' preferences.

Finally, we extend the literature on halo effects in the audit setting. Prior accounting research examining the halo effect is largely confined to examining auditors' risk assessments (O'Donnell and Schultz 2005), evaluations of subordinates (Tan and Jamal 2001), and internal control assessments (Gramling, O'Donnell, and Vandervelde 2010). With advancements in technology leading to the development and adoption of advanced data analytical tools by auditors (Brown-Liburd, Issa, and Lombardi 2015; Salijeni, Samsonova-Taddei, and Turley 2019, 2021), examining the implications of halo theory to this setting is increasingly relevant.

II. THEORY AND HYPOTHESES DEVELOPMENT

Audits of complex estimates

Complex accounting estimates, such as fair value estimates, are highly valued by financial statement users (Song, Thomas, and Yi 2010), and are becoming an increasingly important aspect of financial reporting (Barth 2006; Griffith et al. 2015a). Such estimates are often based upon subjective forecasts of future events and these assumptions are typically not verifiable to the same extent as objective facts (Christensen et al., 2012; Griffith et al., 2015a; PCAOB, 2009). Furthermore, this lack of verifiability presents an opportunity for management reporting bias (Lundholm 1999). As such, auditors must exercise significant professional judgment when determining their audit strategy for verifying complex accounting estimates (Glover, Taylor, and Wu 2017).

Engagement team leaders can adopt a number of tactics to improve the quality of audit testing related to complex estimates. For example, they can encourage auditors to incorporate evidence from a variety of sources and from various parts of the audit (Griffith et al. 2015a; Rasso 2015). They can also promote the use of deliberative mindsets (Griffith et al. 2015b), use prompts to promote auditors' intrinsic motivation to promote high-quality cognitive processing (Kadous and Zhou 2019), provide relational cues to highlight aggressive assumptions (Griffith 2018), encourage system level thinking (Bucaro 2019), and provide instructions promoting broad abstract interpretations (Rasso 2015).

Despite these tactics, auditors often have difficulty sufficiently testing complex estimates. PCAOB inspection reports reveal that audit errors surrounding fair value estimates, including impairments, are still prevalent and account for over two thirds of all deficiencies identified (Griffith et al. 2015a), while other types of errors have decreased over time (Church and

Shefchik 2012). Indeed, the audit literature suggests that auditors fail to identify contradictory information and inconsistencies in data underlying complex estimates (Griffith et al., 2015b; PCAOB, 2016; Ricchiute 1999) and tend to make mechanistic decisions when evaluating such estimates (Bucaro 2019).

As a means of addressing these deficiencies, firms can use technology-enabled tools in an effort to disseminate centralized knowledge and assist in the audit of complex estimates (Dowling and Leech 2014; Boland et al. 2019). The increased storage and processing capacity of these tools allow auditors to more thoroughly analyze large data sets from multiple sources and perform expanded analytical capabilities compared to manual techniques (Brown-Liburd et al. 2015). Therefore, effective use of these tools presents a potentially important opportunity to improve audit quality in this area.

However, research suggests that auditors may be reluctant to rely on such tools (Eilifsen et al. 2020; Cao et al. 2022; Loraas and Wolfe 2006; Diaz and Loraas 2010; Loraas and Diaz 2011), or may misuse the tools due to cognitive processing limitations or not trusting the technology (Lee and See 2004). For example, if the tool used provides too much information, effective use of the information can be impeded by cognitive processing limitations (Iselin 1988; Kleinmuntz 1990; Brown-Liburd et al. 2015).[7] In other words, too much information provided may overwhelm auditors and hinder decision making. Resistance to using new technologies can also be attributable to a status-quo bias toward familiar tools (Schmidt, Church, and Riley 2020; Schmidt, Riley, and Church 2020), as well as concerns regarding whether a specific tool will satisfy inspectors (Austin et al. 2021). Furthermore, auditors may be skeptical of the effectiveness of novel tools which can cause them to engage in dysfunctional behaviors such as

[7] Data analytic tools, which often involve the presentation of significant quantities of data, are an example of an audit technology tool that may be impacted by cognitive processing limitations.

disengaging with audit tasks (Bamber and Snowball 1988), or working around the technology (Bedard et al. 2003; Bedard et al. 2007; Dowling and Leech 2014). Therefore, as a means of encouraging auditors to use these tools in a more effective way, firms often seek to promote the value that these sophisticated technologies can bring to the audit, relative to more traditional audit methods. In this paper, we propose that perceptions regarding the sophistication of data analytical tools have the propensity to impact the judgments that auditors make when auditing complex estimates. We believe that this effect is likely to occur when auditors have an incentive to reach a preferred conclusion regarding the reasonableness of the estimate; that is, when a supervisor makes known his/her preference about the conduct of the audit.

Supervisor preferences and auditor accountability

Auditors' decision making is influenced by a variety of factors that cause motivation to achieve a desired conclusion through achieving directional goals, in other words: motivated reasoning (Kadous et al. 2003; Piercey 2011; Koch and Salterio 2017; Austin et al. 2020; Hobson et al. 2017). Specifically, motivated reasoning causes auditors to exploit ambiguity in reporting standards to justify client-preferred positions (Kadous et al. 2003; Koch and Salterio 2017), and dismiss contradictory evidence (Austin et al. 2020) and fraud cues (Hobson et al. 2017). A setting where we expect auditors to be influenced by motivated reasoning is when they have awareness of the preferences of their supervisors (Wilks 2002).

Within public accounting firms, supervisor review has long represented an important aspect of quality control (Kaplan and Reckers 1985). The hierarchical nature of the public accounting firm leads to a status quo in which auditors are held responsible to their superiors within the organization. Accountability, in this context, refers to expectations that one will suffer negative consequences if a supervisor believes that the decision maker's actions are unjustified.

Conversely, one will expect to receive more favorable consequences if a superior judges one's activities to be appropriate (Lerner and Tetlock 1999).

The consequences individuals face from accountability suggest that there are significant implications for individual decision making in situations where decision makers are aware of their supervisor's opinions. Indeed, prior research indicates that feelings of accountability can cause subordinates to make judgments that are consistent with the preferences of their superiors (Tetlock 1992). This is because, when a supervisor's views are known, confirming one's judgments with those views becomes a coping strategy (Tetlock 1983; Tetlock 1992). In situations where one is required to form an opinion, a decision maker can strategically adopt the position of a superior to ensure a favorable performance evaluation (Lerner and Tetlock 1999). Furthermore, psychology research suggests that these preference adoptions can occur even when they ultimately lead to suboptimal decision outcomes (Adelberg and Batson 1978). Collectively, this evidence suggests that auditors' judgments can be influenced by knowledge regarding the preferences of their superiors. That is, feelings of accountability lead auditors to believe that their evaluations will be more favorable if they reach conclusions that are consistent with those preferences.

Prior research suggests that exposure to the known views of a supervisor can hinder audit evidence assessment and overall audit quality by impairing subordinates' independent assessment of evidence (Fargher, Mayorga and Trotman, 2005; Kim and Harding 2017). For example, auditors may choose to stylize their workpapers to be in line with the expectations of their supervisors (Rich et al. 1997; Gibbins and Trotman 2002; Agoglia, Kida, and Hanno 2003; Fargher et al. 2005). Specifically, the preparer can strategically determine what information is included in the workpapers and how that evidence is presented and interpreted to establish

consistency with the reviewer's views. The aim of such efforts is to influence the reputation of the auditor in the minds of the reviewers (who are often the same individuals who are conducting the auditor's performance evaluations (Rich et al. 1997). Audit quality is accordingly reduced, as the reviewer may be presented with an incomplete picture of the audit work performed, increasing the potential for erroneous conclusions (Tan and Trotman 2003).

Additionally, Wilks (2002) found that auditors' exposure to the accounting preferences of their partners prior to the assessment of audit evidence results in evaluating evidence in a manner more consistent with the partner's view. Relatedly, Peecher (1996) found that reviewer preferences regarding excessive auditor pessimism or optimism impacted the likelihood that auditors accept client explanations for account balance fluctuations, as well as how rigorously they searched for alternate explanations. Similar findings have been demonstrated in several other audit studies (e.g., Hoffman and Patton 1997; Tan et al. 1997; Cohen and Trompeter 1998; Peytcheva and Gillett 2011; Peecher et al. 2010). Thus, we expect auditors will make complex estimate assessments in line with their supervisor's preferences:

> H1: Auditors will make more (less) conservative complex estimate assessments when their supervisor expresses a concern of historical insufficient (excessive) skepticism.

Perceived data analytic tool sophistication

Recent technological innovations combined with wider availability of client data has resulted in an increasing role for data analytic tools as part of the audit process and to identify audit-relevant information (Werner et al. 2021; Salijeni et al. 2019; Salijeni et al. 2021; Jans et al. 2013; Jans 2019; Chiu and Jans 2019; Vasarhelyi et al. 2015). Yet different inputs (Koreff 2022; Brazel et al. 2022) and outputs (Rose et al. 2017) related to these analytic tools do not always result in uniform auditor decision making. Although technology enabled tools may allow for more efficient knowledge dissemination (Dowling and Leech 2014), maintaining a human

element when communicating findings results in auditors being more likely to incorporate the findings of the analytics into their decision making (Commerford et al. 2022). Additionally, data analytic tools may result in users following the guidance of these tools passively (Glover et al. 1997), not identifying risks beyond what was identified (Seow 2011), and even enable auditors' abuse of power (Koreff et al. 2021).

As a means of promoting the widespread use of these tools, firms regularly tout the sophistication of their data analytic tools in promotional materials shared with prospective and current employees (Deloitte 2016; Pwc 2016; KPMG 2017; EY 2019). Psychology research on the halo effect suggests that firms' promotion of the sophistication of these tools can affect unrelated auditor judgments.

The halo effect is generally defined as the "influence of a global evaluation on evaluations of individual attributes of a person" (Nisbett and Wilson 1977). That is, global evaluations of a person have the ability to influence assessments of unknown specific individual attributes (Thorndike 1920; Cooper 1981; Murphy et al. 1993). Halo effect results in broad categorizations, and raters making less differentiation among unique characteristics they are evaluating by assimilating information from few categories into existing (perhaps unrelated) categories (Sinclair 1988), at times making an overall evaluation based on only one measure (Cooper 1981; Murphy 1982). Thus, a rater evaluating a target equally across several dimensions is a result of the halo effect, and often does not represent true inter-category relations (Thorndike 1920; Cooper 1981; Pulakos, Schmitt, and Ostroff 1986). In our setting, we expect that an auditor's perception regarding the sophistication of a data analytic tool will influence judgments about the quality of evidence provided by the tool, regardless of whether the tool is used in a setting where its sophistication is necessary. As such, the halo effect undermines a rater's ability

to objectively assess the strengths and weaknesses of a target under assessment (Nathan and Lord 1983; Murphy and Balzer 1986) and results in less accurate decision making (Cooper 1981; Fisicaro 1988; Sinclair 1988; Lance et al. 1994).

Unfortunately, research demonstrates that auditors are also susceptible to halo effects. For example, the halo effect generated from strategic audit risk assessments influences auditors' tolerance for inconsistent fluctuations in individual accounts (O'Donnell and Schultz 2005). Further, the halo effect generated from a subordinate being perceived as "outstanding" results in more favorable evaluation of the subordinate's work (Tan and Jamal 2001).

To the extent that auditors use data analytic tools to aid in tasks requiring high-level data analysis, information about the tool's sophistication may have relevance to the underlying audit process. Conversely, such tools can also be used to perform tasks that lack complexity (i.e., filtering data to identify observations that contain a specific attribute), wherein overall evaluative judgments about the tool's sophistication are not objectively relevant.[8] However, even in the latter situation, salient global evaluations about the sophistication of the data analytic tool has the potential to generate positive halo and ultimately magnify the effect of supervisor preferences on auditors' complex estimate assessment and anticipated supervisor evaluation.

When halo surrounding audit evidence is present, auditors evaluate this evidence in line with global knowledge (i.e., knowledge derived from beyond the specific evidence being evaluated) rather than the diagnosticity of this information (O'Donnell and Schultz 2005). Further, when halo is present, evidence perceived as inconsistent with global knowledge is viewed as less diagnostic (Murphy et al. 1993). Thus, we expect that when using a more

[8] For example, auditing complex estimates can involve simplistic analyses, such as identifying an increase in revenue accompanied by a decrease in operating expenses, which may be indicative of a potential error. Such analysis would likely not require the use of a sophisticated analytic tool and could be just as accurately performed using a tool that may be perceived as being "less sophisticated", such as Excel.

sophisticated tool, halo surrounding the tool will be generated and audit evidence will be evaluated less diagnostically, resulting in decisions more in line with supervisor's preferences. Yet, we expect this phenomenon to be less pronounced when using a less sophisticated tool.

We predict that when a supervisor expresses a concern that auditors have been overly skeptical of evidence indicating complex estimate impairment in the past (i.e., indicating that auditors have been overly inclined to evaluate a complex estimate as impaired), the perceived sophistication of the data analytic tool will affect the judgments auditors make regarding complex estimates. However, when a supervisor expresses a concern that the auditor has been insufficiently sensitive to evidence suggesting a misstated complex estimate (i.e., indicating a belief that auditors have been reluctant to evaluate a complex estimate as impaired), we expect this response to be more muted. This is because auditors are highly sensitive to salient negative information (Ashton and Ashton 1990) and have a pervasive and overriding concern for negative outcomes (i.e., conservatism) (Smith and Kida 1991). That is, the unique characteristics of the audit environment (i.e., the risks and consequences of incorrect audit judgments) can induce a heuristic to give greater attention to data consistent with negative outcomes, which can override the biases observed in many heuristic studies (e.g., McMillan and White 1993; Braun 2001; Wilks 2002). Applied within our setting, this suggests that, when supervisors express a concern that auditors have been insufficiently sensitive to evidence suggesting impairment of a complex estimate, auditors are likely to consider the impact of data analytic tools in a more diagnostic manner, mitigating the impact of the halo effect on their judgments. The result suggests an interaction between our two factors, where the auditor's response to perceived tool sophistication is weaker (stronger) when the supervisor is (not) concerned that the auditors have been

insufficiently skeptical. We show a graphical depiction of this expectation in Figure 1 and express this prediction with the following hypothesis:

> H2a: The effect of a known supervisor preference will result in less (more) conservative complex estimate assessments when the data analytic tool is perceived as being highly sophisticated (unsophisticated) and the supervisor has expressed concern about over sensitivity to evidence indicating impairment.
>
> H2b: When a supervisor has expressed a concern about historical over-professional skepticism, auditors will make less conservative complex estimate assessments when they perceive the data analytic tool as being highly sophisticated.

[INSERT FIGURE 1 ABOUT HERE]

In addition to complex estimate assessment, we also examine the effects of supervisor preference and perceived sophistication on an auditor's anticipated supervisor evaluation. Accountability pressures lead auditors to believe that they will receive more favorable performance evaluations if they adopt the views of their supervisors. Such beliefs can increase the likelihood that auditors will evaluate evidence and make judgments in line with the preferences of that superior.

Prior research demonstrates that audit supervisors' evaluation of their subordinates can be influenced by a subordinate identifying a misstatement (Brazel et al. 2016; Brazel et al. 2019). We argue that the interplay between perceived tool sophistication and supervisor preferences also impacts anticipated supervisor evaluation. That is, we expect that the positive halo generated by exposure to a more sophisticated tool will make auditors believe that the evidence generated by the tool is of higher quality, and therefore, more persuasively supports their supervisor's preference. This will cause auditors to expect a more favorable supervisor evaluation as opposed to when using a less sophisticated tool.

However, consistent with our expectation for auditors' complex estimate assessments, auditors are highly sensitive to salient negative information (Ashton and Ashton 1990; Smith and

Kida 1991), such as a supervisor expressing a concern of insufficient historical skepticism related to complex estimate impairment indicators. We expect that this salience will mitigate the bias attributable to data analytic tool sophistication, and there will be no difference in auditors' anticipated supervisor evaluation when supervisors express such a concern. Collectively, and consistent with H2 for complex estimate assessment, we predict the following:

> H3a: The effect of a known supervisor preference on expectations of receiving a favorable evaluation will be greater (lower) when the data analytic tool is perceived as being highly sophisticated (unsophisticated) and the supervisor has expressed concern about over sensitivity to evidence indicating complex estimate impairments.

> H3b: When a supervisor has expressed a concern about historical over-professional skepticism, auditors will be more likely to expect to receive a favorable performance evaluation for their complex estimate assessment when the data analytic tool is perceived as being highly sophisticated.

III. METHOD

Our participants were 84 external financial statement auditors recruited through the professional network of one of the authors.[9] Participants reported, on average, 5.77 years of audit experience. Approximately 21.4% and 34.5% of participants reported a job title of staff auditor or senior auditor, respectively, with the remaining participants indicating a title of supervisor or higher.[10] The majority of participants (84.5%) indicated prior experience using data analytics in an audit setting. See Table 1 for the full demographic profile of our sample.

[INSERT TABLE 1 ABOUT HERE]

Using a case adapted from Griffith et al. (2015b), the instrument placed participants in the role of an auditor making a preliminary determination regarding the reasonableness of the

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[9] Participants had the option of receiving a gift card or having the authors make a charitable donation on their behalf in recognition of their completion of the experiment. This study received IRB approval and followed all applicable human subject protocols.

[10] Although we believe that administering our study to participants with a wide range of experience levels provides evidence of the robustness of our findings, we did not identify audit experience as a significant covariate.

fair value of a client's business unit as part of a goodwill impairment test.[11] The case materials contained all of the relevant information needed to make a preliminary judgment, including revenue and expense projections for the business unit. While the case materials indicated that management had determined that the fair value of the business unit supported the valuation of goodwill without impairment, the case contained seeded errors and inconsistencies among certain assumptions that implied that the analysis was not comprehensive, resulting in an overstated fair value. Thus, by carefully attending to the information, participants should have identified items that warranted further attention prior to accepting the reasonableness of management's assertion.

We manipulated the audit engagement partners' preference regarding audit testing *(PREF)*, as well as the perceived sophistication of the data analytic tool *(SOPH*[12] as independent variables, resulting in a 2 x 2 between-subjects design. We adapted our supervisor preference manipulation from Wilks (2002), informing participants that the partner on the engagement had "expressed numerous times his concern that audit teams members had been insufficiently (overly) skeptical to evidence suggesting goodwill impairment" and that this had led to "potentially costly increases in liability exposure (unjustified investigations) and to judgments that were unduly optimistic (pessimistic)."[13] Also, consistent with Wilks (2002), after reading this statement participants were asked to note three reasons why auditors can sometimes be

[11] The case was adapted from Griffith et al., (2015b) with the authors permission. Their case has been adapted for use by other studies, including Griffith (2018) and Kadous and Zhou (2019).
[12] We opted to manipulate our construct of "perceived sophistication" to broadly refer to the "capability of the developed data analytic tool to extract, transform, and analyze data." This design choice was made to enhance the generalizability of our findings.
[13] Auditors should be aware of the need to provide sufficient and appropriate audit evidence. However, once obtaining such evidence, an audit team can make its conclusion without conducting additional procedures. This is necessary to ensure that the audit firm achieves a sufficient profit on the engagement and will not impact audit quality. In other words, over-skepticism is not required or desired and could, in fact, actually hurt audit quality if it results in a valuation assessment that is too conservative.

unduly optimistic (pessimistic) when evaluating a client's goodwill, and then rank these reasons in terms of their importance. This manipulation centered around the engagement partner's preference regarding past skepticism on the engagement, not related to using the data analytic tool.

After their exposure to the supervisor's preference manipulation, we informed participants that their firm developed a data analytic tool to aid in the auditor's assessment of goodwill. We informed participants that this tool was used for the first time and was either "very sophisticated" or "less sophisticated" compared to traditional software tools used in audits, such as Excel. We adapted language from scales in prior research measuring IT sophistication (Armstrong and Sambamurthy 1999; Elbashir et al. 2011) to describe the data analytic tool. For example, we stated: "*This data analytic software is considered to be [very sophisticated / unsophisticated] and due to this [sophistication / lack of sophistication] is based on a program [more sophisticated / less sophisticated] than Excel*" and "*Despite the software's [sophistication / lack of sophistication], there may be opportunities to improve the performance of the software going forward. ... When evaluating the output of this [sophisticated / unsophisticated] software tool…"*.[14] As a halo effect is particularly prevalent when a decision maker acquires general information before detailed information (Murphy et al. 1993), we provide a general discussion of the data analytic tool before providing the detailed output from the tool (which consisted of a simple discounted cash flow analysis for the current year and future year's projections, similar to what would be calculated using an Excel spreadsheet) with background information related to some of the assumptions that went into management's assessment. The information content did

[14] In our instrument, we note that the sophistication of the tool is based upon its capabilities to "extract, transform, and analyze data."

not vary across the tool sophistication conditions; thus, participants should have identified the same risk factors had they carefully attended to the case materials within each condition.

Our first dependent measure is the participants' assessed likelihood that the fair value *(FV)* of the client's reporting unit is reasonable.[15] We assessed this measure using a 7-point Likert scale with endpoints 1 = "Very unlikely" and 7 = "Very likely." For our second dependent variable, we asked participants to indicate their belief about how a supervisor would evaluate their judgments *(EVAL)* in the case if goodwill was found to be appropriately stated (measured using a 7-point Likert scale with endpoints 1 = "Well below expectations" and 7 = "Well above expectations). To identify potential covariates, we asked several questions designed to assess their experience, trust, and self-confidence using data analytic tools during the audit. Finally, participants responded to demographic measures.

IV. RESULTS

As a check of the supervisor preference manipulation *(PREF),* we asked participants to recall whether the engagement partner described in the case believed that the audit team had made overly optimistic or overly pessimistic judgments in prior years. We note that 96.55% of participants answered this question correctly, indicating a successful manipulation.[16] As a check of the sophistication manipulation *(SOPH)*, we asked participants to express their perceptions regarding the sophistication of the data analytic tool mentioned in the case. We measured this variable using a 7-point Likert scale with endpoints labeled 1 = "Very unsophisticated" and 7 =

[15] For additional analysis, consistent with Griffith et al., (2015b), we also asked participants to express the likelihood that management would achieve their revenue *(REV)* and operating expense *(EXP)* projections (the key inputs in the discounted cash flow analysis used to prepare management's assessment).

[16] We removed participants from the analysis that incorrectly answered this manipulation check question. Consistent with prior research (Brown and Popova 2016), we excluded participants who provided either of the two responses at the wrong ends of the manipulation check scale in our analysis. We excluded participants in the "sophisticated" condition that responded with a 1 or 2 on the 7-point scale and participants in the "unsophisticated" condition that responded with a 6 or 7 on the 7-point scale.

"Very Sophisticated." Responses to this measure indicate that when participants were told that the tool was more sophisticated, they perceived higher sophistication, indicating successful manipulation (6.186 vs 2.146; $t = 15.86$; $p < 0.001$). Examination of demographic variables for potential covariates identified participants' prior data analytics experience as a covariate for the *FV* variable, and the difference between participants' trust in technology and self confidence in using technology (Lewandowsky et al. 2000), as a covariate for the *EVAL* variable. We considered these variables when performing our hypothesis tests.

Hypothesis Tests

Table 2 Panel A provides descriptive statistics for the *FV* dependent variable. The ANCOVA results presented in Table 2 Panel B show that, in support of H1 and consistent with prior literature (Peecher 1996; Wilks 2002), supervisor's preference impacts decision making ($F = 7.91$, $p = 0.006$). However, the effect of supervisor preference does not differ when using tools of varying sophistication ($F = 0.24$, $p = 0.622$), thus H2a was not supported, and therefore, we did not test H2b. The lack of a direct interaction between the two factors suggests that the other key characteristics of our setting, the anticipated evaluation from an auditor's supervisor, may play an indirect role in explaining auditor behavior. To investigate this issue further, we next consider the relationship between supervisor preferences, perceived tool sophistication, and anticipated supervisor evaluation.

Table 3 Panel A provides descriptive statistics for the *EVAL* dependent variable. The ANCOVA results presented in Table 3 Panel B show that knowledge of a supervisor's preference impacts anticipated supervisor evaluation ($F = 15.13$, $p < 0.001$). To test H3a, we examine the interaction between supervisor preference and sophistication. The results demonstrate that the effect of a known supervisor preference has a stronger (weaker) impact

when using data analytic tool perceived as being more (less) sophisticated and the supervisor has expressed concern about historical over sensitivity ($F = 8.28$, $p = 0.005$). Thus, H3a is supported.[17] See Figure 2 for a graphical depiction of the results.

[INSERT FIGURE 2 ABOUT HERE]

Next, we analyzed simple effects (while continuing to control for the difference between trust in technology and self-confidence using technology) to test H3b. Although it is not appropriate to use simple effects as the only test of an interaction, they can be used as a supplement test of theory (Guggenmos et al. 2018). The results presented in Table 3 Panel C show that when a sophisticated tool is used, the concern of historical skepticism (e.g., over versus insufficient) expressed by the partner impacts anticipated supervisor evaluation ($F = 23.79$, $p < 0.001$), which supports H3b. However, this does not occur when an unsophisticated tool is used ($F = 0.54$, $p = 0.466$). Additionally, when a partner expressed concern of historical over skepticism, tool sophistication impacts anticipated supervisor evaluation ($F = 8.00$, $p = 0.006$), however this does not occur when a partner expressed concern of historical insufficient skepticism ($F = 1.86$, $p = 0.177$). These results provide support for H3a and H3b.

These findings demonstrate the implications of firms' promotion of sophisticated data analytic tools among their auditors. While the joint effect of supervisor preference and sophistication of a data analytic tool used does not impact complex estimate assessment, it does impact anticipated supervisor evaluation. As predicted by our second hypothesis, when a supervisor expresses a concern that the auditor has been overly sensitive to evidence suggesting a

[17] As a supplementary analysis, we administered our instrument (absent the supervisor preference manipulation) to 25 students enrolled in a graduate level accounting course. These participants had average public accounting work experience of 3.6 months. We find that participants assigned to the sophisticated tool condition reported that the tool would be more diagnostic in auditing management's fair value estimated compared to those assigned to the unsophisticated tool condition (5.91 vs 4.29, $t = 2.74$, $p < .006$), which is consistent with our theory.

misstated complex estimate, the positive halo associated with a more sophisticated tool is expected to make auditors more likely to believe that they will receive a favorable evaluation from a supervisor if they reach a conclusion that is consistent with that preference.

Since we did not find support for H2a but did find support for H3a, we subsequently considered whether supervisor evaluation expectations may play a role in determining how tool sophistication and supervisor preferences impact auditor fair value assessments. That led us to speculate that evaluation expectations may indirectly impact a potential relationship between these variables. Accordingly, we conduct a mediation analysis to examine this potential indirect effect.

Consistent with prior research and the results in Table 2, we continue to expect a direct impact of supervisor preference on audit judgments (Peecher 1996; Wilks 2002). In line with H3a, we also expect that the effect of supervisor preferences on auditors' anticipated supervisor evaluation will be moderated by the sophistication of the data analytic tool. As the initial ANCOVA analysis did not support H2a, we do not include a moderation path on complex estimate assessment and the predicted interaction for H2a is not included the model.

Next, we considered whether auditors would consider their supervisor evaluation before or after making their complex estimate assessment. We expect auditors to be cognizant that the partner has the final determination of the complex estimate assessment and can override the auditor's initial assessment.[18] Accordingly, we expect auditors to perceive a greater ability to influence their performance evaluation relative to the partner's final assessment of the complex estimate. Consistent with prior supervisor preference literature, we expect auditors to enter the complex estimate evaluation with a strategic mindset to achieve the highest supervisor evaluation

[18] At times, the partner may even be privy to confidential information not shared with the audit team that may cause the audit partner to express a desire for a certain audit outcome.

(Rich et al. 1997), and then make a complex estimate assessment accordingly. Further, auditors stylizing workpapers to be in line with supervisors' expectations (Rich et al. 1997; Gibbins and Trotman 2002; Agoglia et al. 2003; Fargher et al. 2005), can include selecting workpaper templates, which occurs before auditors make final assessments. Therefore, we expect that auditors will first be cognizant of their anticipated supervisor's evaluation, then subsequently assess the complex estimate. This predicted model is shown in Figure 3.

[INSERT FIGURE 3 ABOUT HERE]

We test this model by estimating a moderated mediation model of the main effect of supervisor preference *(PREF)* on auditors' assessed fair value of the complex estimate *(FV)* using *SOPH* as the moderating variable and *EVAL* as the mediating variable (model 7, see Hayes 2017).[19] Prior experience using analytics (consistent with Table 2 Panel B) and differences in trust in technology and self-confidence using technology (consistent with Table 3 Panel B) were controlled for in the analysis.

The results of this analysis indicate that the sophistication of a data analytical tool used *(SOPH)* moderates the effect of a known supervisor preference *(PREF)* on participants' anticipated evaluation *(FV)* (p=0.006). This provides additional support for H3a. Furthermore, an expectation of a favorable performance evaluation *(EVAL)* mediates the relationship between supervisor preference *(PREF)* and fair value assessment *(FV)*; however, this relationship is dependent on the perceived sophistication *(SOPH)* of the data analytic tool (90% confidence interval of -0.894 to -0.047). Specifically, we note that the indirect effect of *EVAL* on the relationship between *PREF* and *FV* is only significant in the presence of the moderating variable *SOPH,* such that the relationship is significant when the tool is perceived as being more

[19] We also conducted further analysis (untabulated) using model 7 with *SUPVR* as the outcome variable and *FV* as the mediator. These models were not significant, as demonstrated by confidence intervals containing zero.

sophisticated (90% confidence interval of -0.931 to -0.078) but insignificant when it is not (90% confidence interval of -0.331 to 0.128). Full results are reported in Figure 4.[20]

[INSERT FIGURE 4 ABOUT HERE]

5. CONCLUSION

Technological advances as well as increases in data storage and processing power have resulted in auditors more regularly using data analytic tools to facilitate the audits of complex estimates. As a means of encouraging widespread use of such tools, firms often promote the tools' relative sophistication, compared to existing audit methods, to their staff and to their clients. However, despite the fact that auditors often experience difficulty implementing these tools (CAQ 2019), limited research has examined the role that specific attributes of data analytic tools play in affecting auditor judgments. We address this limitation by examining whether perceptions of tool sophistication attenuate prior biases, specifically attributable to a supervisor's preference, to impact the judgments auditors make when auditing complex estimates.

Drawing upon psychology research related to the halo effect (e.g., Nisbett and Wilson 1977; O'Donnell and Schultz 2005), we show that the impact of knowledge of the preferences on auditor's judgments regarding complex estimates is amplified by perceived tool sophistication. That is, when a supervisor expresses a concern that auditors have been overly sensitive to evidence suggesting impairment of a complex estimate, the availability of a more sophisticated tool will lead auditors to believe that the supervisor will evaluate them more favorably if they reach a client preferred conclusion. This, in turn, biases auditors' evidence assessment and

[20] We conduct additional analysis to examine whether this relationship persists using participants' perceptions of the reasonableness of the client's revenue projections as a dependent variable (untabulated). Since revenue projections are an input into the overall fair value assessment, we conduct this analysis as a robustness check of our model. Accordingly, we run the same moderated mediation analysis described earlier, using revenue as a dependent measure. We find a similar relationship for the moderated impact on supervisor evaluation (p=0.006) and the overall model (90% confidence intervals of -1.045 to -0.136), providing further support for our hypotheses.

subsequent reporting judgments. However, when a supervisor expresses concern that auditors have been insufficiently sensitive to evidence suggesting that a misstatement exists, auditors' sensitivity to loss (e.g., Smith and Kida 1991) will dominate, resulting in no impact of perceived tool sophistication on auditor judgments.

The results of this study have several implications for audit theory and practice. First, while sophisticated data analytic tools have the potential to improve audit quality, our results suggest that perceptions of sophistication may also unintentionally bias auditor judgments, which may undermine the benefits of these tools. Thus, firms should carefully consider how they promote the sophistication of their new technology tools, as well as provide additional training to their auditors to help them distinguish characteristics of a tool that are relevant to audit judgments versus those that are not. Our study also contributes to the literature on the audit of complex estimates, identifying a potential source of bias that may contribute to the deficiencies in auditing such estimates that have been identified by regulators (e.g., PCAOB 2014). Finally, we contribute to the audit literature on halo effect and supervisor preferences, demonstrating that in the modern audit setting, perceived sophistication of a data analytic tool may interact with the effects of supervisor preferences identified in prior audit research.

As with all empirical research, our study is subject to certain limitations. First, while we designed our experimental materials to manipulate the perceived sophistication of the data analytic tool, we intentionally omitted overwhelming our participants with other details about the nature or features of the tool. This to increases the generalizability of our results to several analytic tools used in practice. The perceived sophistication of a tool could interact with other information about the tool (e.g., its accuracy, its cost, etc.) in a way that might have affected our results had we included this other information in our study. Other researchers may wish to

replicate our results using these other pieces of information of analytic tools as a means of addressing this issue. Additionally, future research could seek to examine which specific features of emerging audit technologies are most likely to influence auditor evidence assessments. Increased sophistication may give rise to ethical concerns as technology enabled tools can increasingly operate independently, potentially attenuating prior biases (Munoko et al. 2020). Ethical concerns may also arise due to lack of transparency of analyses conducted by sophisticated tools, prohibiting auditors from fully understanding the process used by the tool. This may lead to auditors making decisions without sufficient understanding of the data.

In addition, we examine the impact of tool sophistication in a single setting: the audit of a complex fair value estimate. While this setting is of interest to researchers and regulators due to identified deficiencies in the audit of such estimates, it is possible that the nature of the task itself could impact the effect of tool sophistication on auditor judgments. For example, our results could be mitigated (or exacerbated) when sophisticated tools are used when completing other audit tasks, such as routine assessments of internal control. Further research will be needed to identify whether our results are also applicable in these other settings. While practitioners anecdotally report that the primary users of data analytic tools are auditors working in the field (e.g., staff or senior level), other researchers may wish to examine whether auditor experience affects the results obtained in our study, and whether such a finding has additional implications for audit practice. Finally, there is limited research that empirically examines how auditors consider sophistication when evaluating their use of data analytic tools. While our results are consistent with halo effects causing overreliance on tools in certain settings, future research may wish to consider possible intervening mechanisms that shed further theoretical light on this

finding. This research would help shed light on perceived sophistication as an important factor to consider when conducting future research on the efficacy of data analytic tools.

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Figure 1
Graphical depiction of hypothesized results

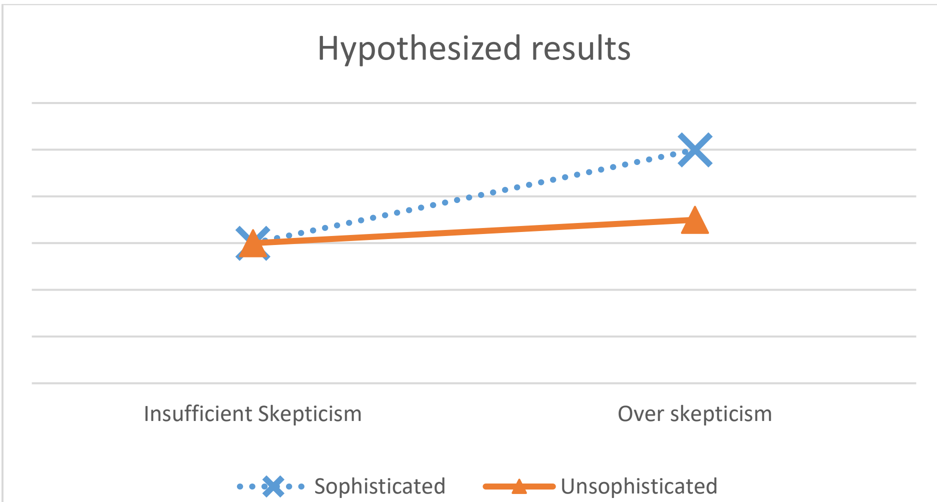
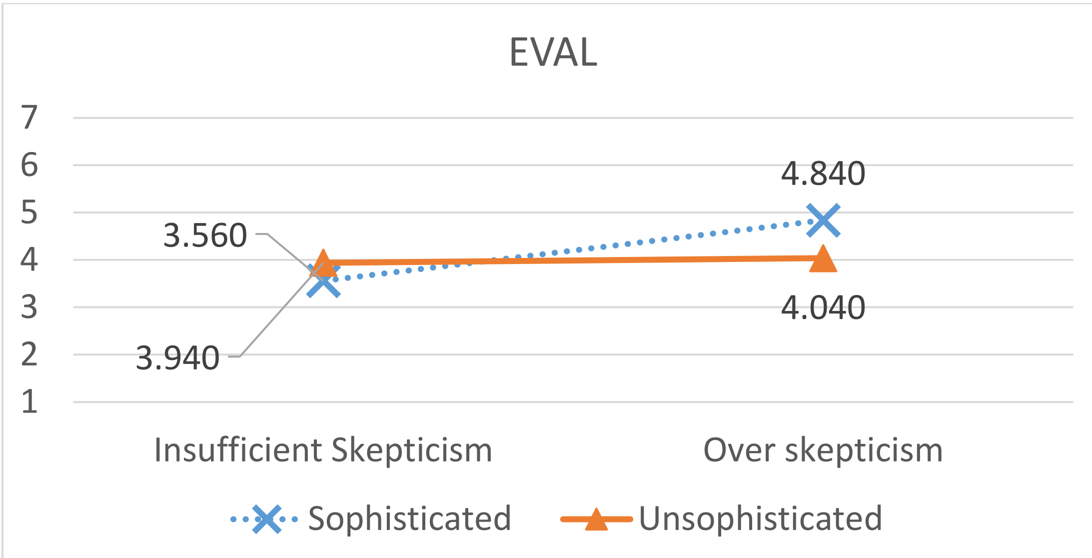


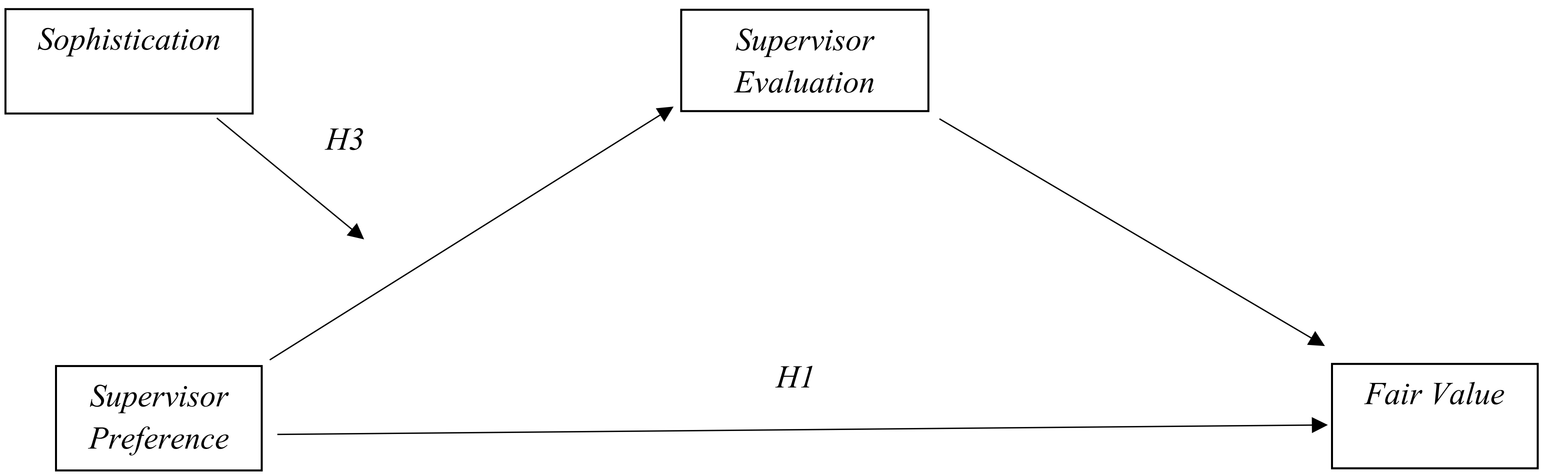
Figure 2
Graphical depiction of *EVAL* results [H3]



Supervisor Preference was manipulated using the language used by Wilks (2002) by describing the engagement partner as expressing a concern that, during prior audits, the audit team was overly (insufficiently) sensitive to evidence suggesting goodwill impairment and caused unjustified investigations (liability exposure).

Sophistication was manipulated by describing the data analytical tool used as very sophisticated or not very sophisticated, using language adapted from prior measures used by Armstrong and Sambamurthy (1999) and Elbashir et al. (2011) to measure IT sophistication.

Figure 1
Theoretical Model



Note: This figure shows the predicted moderated-mediation relationship between our variables.

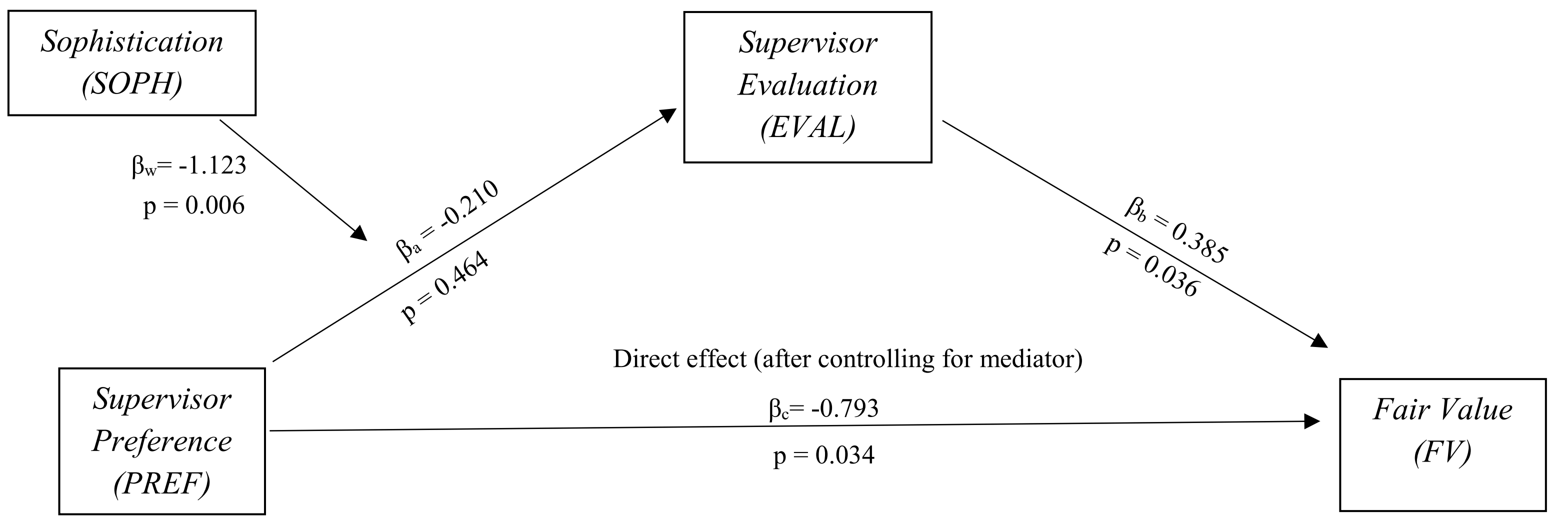
Supervisor Preference was manipulated using the language used by Wilks (2002) by describing the engagement partner as expressing a concern that during prior audits the audit team was overly (insufficiently) sensitive to evidence suggesting goodwill impairment and caused unjustified investigations (liability exposure).

Sophistication was manipulated by describing the data analytical tool used as very sophisticated or not very sophisticated, using language adapted from prior measures used by Armstrong and Sambamurthy (1999) and Elbashir et al. (2011) to measure IT sophistication.

Supervisor evaluation measures participants' perception of how a supervisor would evaluate their decisions if no misstatement was identified (despite the case presenting evidence of a misstatement) on a 7-point Likert scale with endpoints of "Well below expectations" (1) and "Well above expectations" (7)

Fair Value measures participants' assessment of how likely the fair value of the reporting unit was reasonable on a 7-point Likert scale with endpoints of "Very unlikely" (1) and "Very likely" (7).

Figure 2
Moderated-Mediation Analysis



Indirect Effect by *SOPH*	**Test of model**	**Test Result**
SOPH= Low -0.081: (Bootstrapped CI: -0.331 to 0.128) SOPH= High -0.514 (Bootstrapped CI: -0.931 to -0.078)	Path Estimate: -0.433 (Bootstrapped CI: -0.894 to -0.047)	Significant Entire CI < 0

Note: This figure shows the results of a moderated-mediation analysis of participants' fair value assessments. The model shows a one-mediator moderated-mediation of the main effect of supervisor preference on auditors' fair value assessment using tool sophistication as the moderating variable (coefficient weights and p-values are provided).We utilized bootstrapped estimates of confidence intervals to test the individual paths and relative direct and indirect effects of the variables in the model using the Process macro (model 7) (Hayes 2017). The model was tested using 10,000 bootstrapped samples and all reported p-values are

two-tailed. The results presented control for participants' self-reported experience using data analytics tools in the audit and the difference in participants' reported trust in technology less self-confidence in using technology.

Supervisor Preference (PREF) was manipulated using the language used by Wilks (2002) by describing the engagement partner as expressing a concern that during prior audits the audit team was overly (insufficiently) sensitive to evidence suggesting goodwill impairment and caused unjustified investigations (liability exposure). This variable was coded as 1 for participants in the condition where past goodwill impairment assessments were believed to be "overly optimistic / insufficiently sensitive / creating liability exposure" and 0 for participants in the condition where past goodwill impairment assessments were believed to be "overly pessimistic / overly sensitive / creating unjustified investigations".

Sophistication (SOPH) was manipulated by describing the data analytical tool used as very sophisticated or not very sophisticated, using language adapted from prior measures used by Armstrong and Sambamurthy (1999) and Elbashir et al. (2011) to measure IT sophistication.

Supervisor evaluation (EVAL) measures participants' perception of how a supervisor would evaluate their decisions if no misstatement was identified (despite the case presenting evidence of a misstatement) on a 7-point Likert scale with endpoints of "Well below expectations" and "Well above expectations"

Fair Value measures participants' assessment of how likely the fair value of the reporting unit was reasonable on a 7-point Likert scale with endpoints of "Very unlikely" (1) and "Very likely" (7).

Table 1
Demographic Profiles of Participants (n=84)

		n	%
Gender			
	Male	43	51.1%
	Female	40	47.6%
	Not specified	1	1.2%
Title			
	Staff	18	21.4%
	Senior	29	34.5%
	Supervisor	6	7.1%
	Manager	22	26.2%
	Senior Manager	6	7.1%
	Director	3	3.6%
Firm size			
	Local	22	26.2%
	Regional	38	45.2%
	National	19	22.6%
	International	5	6.0%

Table 2 – Results for *FV* dependent variable

Panel A: Descriptive Statistics – mean [SD] of reasonableness of FV of reporting unit

	Partners concern of historical:		
Sophistication	**Insufficient skepticism**	**Over skepticism**	**Combined**
Very sophisticated	4.39 [1.72] n=18	5.16 [1.65] n=25	4.84 [1.70] n=43
Not sophisticated	3.82 [1.85] n=17	5.08 [1.41] n=24	4.56 [1.70] n=41
Combined	4.11 [1.78] n=35	5.12 [1.52] n=49	

Panel B: ANCOVA Results

Source	SS	df	MSE	F-Statistic	p-value
Preference **(H1)**	19.70	1	19.70	7.91	0.006
Sophistication	1.87	1	1.87	0.75	0.389
Preference x Sophistication **(H2a)**	0.61	1	0.61	0.24	0.622
Analytics Experience	19.12	1	19.12	7.67	0.007
Error	196.83	79	2.49		

Supervisor Preference was manipulated using the language used by Wilks (2002) by describing the engagement partner as expressing a concern that during prior audits the audit team was overly (insufficiently) sensitive to evidence suggesting goodwill impairment and caused unjustified investigations (liability exposure). This variable was coded as 1 for participants in the condition where past goodwill impairment assessments were believed to be "overly optimistic / insufficiently sensitive / creating liability exposure" and 0 for participants in the condition where past goodwill impairment assessments were believed to be "overly pessimistic / overly sensitive / creating unjustified investigations".

Sophistication was manipulated by describing the data analytical tool used as very sophisticated or not very sophisticated, using measures from Armstrong and Sambamurthy (1999) and Elbashir et al. (2011) used to measure IT sophistication. This variable was coded as 1 for participants in the "very sophisticated condition" and 0 for participants in the "not sophisticated condition".

Fair Value measures participants' assessment of how likely the fair value of the reporting unit was reasonable on a 7-point Likert scale with endpoints of "Very unlikely" (1) and "Very likely" (7).

Analytics Experience measures participants' experience using data analytic software as part of the audit process on a 7-point Likert scale with endpoints of "Very inexperienced" (1) and "Very experienced" (7)

Table 3 – Results for *EVAL* dependent variable

Panel A: Descriptive Statistics – mean [SD] of anticipated supervisor evaluation

	Partners concern of historical:		
Sophistication	**Insufficient skepticism**	**Over skepticism**	**Combined**
Very sophisticated	3.56 [0.78] n=18	4.84 [0.94] n=25	4.30 [1.08] n=43
Not sophisticated	3.94 [1.20] n=17	4.04 [0.69] n=24	4.00 [0.92] n=41
Combined	3.74 [1.01] n=35	4.45 [0.91] n=49	

Panel B: ANCOVA Results

Source	**SS**	**df**	**MSE**	**F-Statistic**	**p-value**
Preference	11.78	1	11.78	15.13	<0.001
Sophistication	0.49	1	0.49	0.63	0.429
Preference x Sophistication **(H3a)**	6.45	1	6.45	8.28	0.005
TISC	4.19	1	4.19	5.38	0.023
Error	61.51	79	0.78		

Panel C: Simple Main Effects

Source	**SS**	**df**	**MSE**	**F-Statistic**	**p-value**
Effect of Supervisor preference given use of a sophisticated tool **(H3b)**	18.52	1	18.52	23.79	<0.001
Effect of Supervisor preference given use of an unsophisticated tool	0.42	1	0.42	0.54	0.466
Effect of tool sophistication given a partner's concern of historical over skepticism	6.23	1	6.23	8.00	0.006
Effect of tool sophistication given a partner's concern of historical insufficient skepticism	1.45	1	1.45	1.86	0.177

Supervisor Preference was manipulated using the language used by Wilks (2002) by describing the engagement partner as expressing a concern that during prior audits the audit team was overly (insufficiently) sensitive to evidence suggesting goodwill impairment and caused unjustified investigations (liability exposure). This variable was coded as 1 for participants in the condition where past goodwill impairment assessments were believed to be "overly optimistic / insufficiently sensitive / creating liability exposure" and 0 for participants in the condition where past goodwill impairment assessments were believed to be "overly pessimistic / overly sensitive / creating unjustified investigations".

Sophistication was manipulated by describing the data analytical tool used as very sophisticated or not very sophisticated, using measures from Armstrong and Sambamurthy (1999) and Elbashir et al. (2011) used to measure IT sophistication. This variable was coded as 1 for participants in the "very sophisticated condition" and 0 for participants in the "not sophisticated condition".

Supervisor evaluation measures participants' perception of how a supervisor would evaluate their decisions if no misstatement was identified (despite the case presenting evidence of a misstatement) on a 7-point Likert scale with endpoints of "Well below expectations" (1) and "Well above expectations" (7).

TlSC measures participants' difference in their trust in using technology as part of the audit process, measured on a 7-point Likert scale with endpoints of "Very low" (1) and "Very high", (7) and self-confidence in using technology as part of the audit process with endpoints of "Very low" (1) and "Very high" (7).