Auditing the Fair Values of Investment Securities: An Archival Examination of Auditor Response to Risk Cues

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ABSTRACT: PCAOB inspections and recent field research highlight difficulties faced by auditors when testing fair value estimates. In this study, we exploit a unique dataset with security-level fair value estimates to better understand variation in auditors' performance in this difficult area. Consistent with regulator concerns, we find that more than one-third of the securities in our sample differ from the consensus fair value by greater than five percent, which is an amount large enough to warrant further auditor consideration. Accordingly, we identify cues available to the auditor during the risk assessment and substantive testing phases that are associated with larger fair value differences. We then examine whether auditor expertise is associated with incremental reductions in fair value differences in the presence of these cues. Our findings reveal that auditors with greater expertise respond to low integrative complexity cues related to substantive testing as shown by reductions in security-level fair value differences. However, we fail to find evidence of expert auditors reducing fair value differences in response to high integrative complexity cues related to overall risk assessment. Our study indicates the auditor's ability to effectively identify and respond to risk-related information varies based on the type of cue and auditor expertise.

1. Introduction

The complexity and discretion in fair value estimates results in the potential introduction of error and bias into the financial statements (Beatty and Weber 2006; Vyas 2011; Hanley et al. 2018). Despite extensive feedback from the Public Company Accounting Oversight Board ("PCAOB"), significant audit deficiencies and errors in audited fair value estimates continue to be observed (Hanley et al. 2018; Glover et al. 2019; PCAOB 2014). In this study, we use security-level data to document the prevalence of errors in investment fair values that would likely warrant further auditor consideration and examine the association of these errors with informational cues indicating a greater risk of material misstatement.[1] We then evaluate whether and when auditors are responding to these risk-relevant cues in the audit of investment fair values.

During the PCAOB's tenure, inspection findings consistently reveal deficiencies related to the audit of estimates and fair value measurements (Church and Shefchik 2012; Cohn 2017; PCAOB 2017a). Recent field study research confirms that auditors struggle with testing in this area due to the high degree of subjectivity in assumptions, third parties who are unable or unwilling to provide detail for data used in their models, inadequate management understanding, lack of concise auditing guidance, and gaps between auditors' and regulators' interpretation of the standards (Cannon and Bedard 2017; Glover et al. 2019). Compounding these challenges, auditors tend to rely too much on management's process rather than engaging in critical, independent analysis of the estimate (Griffith et al. 2015a). Auditors face significant *ex post* scrutiny in their testing of estimates as the PCAOB specifically focuses on estimates during the inspection process (e.g., PCAOB 2017b). PCAOB inspectors (or peer/internal reviewers) have the benefit of hindsight

[1] Paragraph 27 of PCAOB AS 2810: *Evaluating Audit Results* refers to bias related to patterns of individually reasonable accounting estimates that achieve a desired outcome such as higher or lower income. Given that the standards mention patterns in either direction, we use the wording "fair value error" throughout the paper to refer to both inflation and deflation of investment fair values.

to gauge the appropriateness of their audit procedures and conclusions, creating incentives for auditors to minimize outliers in fair value estimates that are difficult to justify with evidence gathered from pricing services and other sources.

Despite these incentives, significant and material deviations from "true" fair value exist in individual security level fair value estimates as well as in the aggregate audited investment portfolio balance (Hanley et al 2018). Specific security-level characteristics are associated with greater deviation from fair value (Hanley et al 2018), suggesting that such cues should heighten an auditor's professional skepticism. However, evidence from experimental research examining whether information cues can trigger heightened professional skepticism indicate that cues alone may not be sufficient. Cues may enhance auditors' ability to combine their existing knowledge with new information to recognize patterns; however, this occurs only when a situational cue such as higher engagement risk increases the auditor's motivation to incorporate the information into their risk assessment (Griffith 2018). Auditors also pay more attention to certain cues and improve their informational processing when intrinsic motivation for their job is made more salient (Kadous and Zhou 2019). Overall, experimental research suggests the need for motivation or prompting to heighten professional skepticism and incorporate relevant evidence into auditors' risk assessment.

Due to factors such as information overload and complexity, cues may go unnoticed if auditors view them as just another piece of information that does not trigger a reaction. Therefore, an auditor may need sufficient experience and motivation to incorporate relevant cues into his/her problem representation (Hammersley 2006; Griffith 2018). Prior research considers the role of auditor expertise and documents that expertise contributes to an auditors' ability to detect anomalies across firms and identify risks of material misstatement (Owhoso et al. 2002; Low 2004; Hammersley 2006; Glover et al. 2017; Bhattacharjee et al. 2019). We expect that auditors with greater expertise will be more likely to identify settings when enhanced testing approaches are necessary (e.g., obtaining evidence from multiple pricing sources), which improves their ability to identify potential fair value errors. If differences are identified, the auditor must also negotiate with the client to make adjustments as necessary (Emmet et al. 2018). Given the difficulty of this task in a setting where the "right answer" is unknown, expert auditors that hold higher status in the market may be more likely to command deference in these negotiations (Taylor 2010; Knechel and Leiby 2016).[2] Based on these arguments, we expect that auditors with greater expertise will be associated with less fair value error compared to non-expert auditors in the presence of cues suggesting heightened risk of material misstatement.

To empirically test our predictions, we use data from the property and casualty (P&C) insurance industry. The P&C insurance industry provides a powerful setting to test our research questions because insurers' financial statements are comprised of significant accounting estimates with investment securities being the primary asset. Given the significance of investment securities, the auditors' risk assessment process would likely require enhanced consideration of asset fair values. Direct examination of a specific financial statement balance offers more compelling tests of the construct of interest (Petroni et al. 2000; Stein 2019), which is helpful to understand the performance of experts in the audit market (Lawrence et al. 2017). Insurance companies must provide asset-specific disclosures, which allow us to examine the fair value reporting choices across insurers for identical securities at the same point in time. Following prior research, we calculate the consensus ("true") fair value for each security based on the mode value across all entities holding the same security in a given year (Hanley et al. 2018).[3] The fair value error of each

[2] Auditors may achieve greater status and prestige from being the largest auditors in the overall market or being dominant players in a particular industry or location (e.g., Jensen and Roy 2008). Status is defined as having the ability to "influence outcomes based on perceived skills, qualities, and personal attributes" (Badolato et al. 2014, 208).

[3] We use the terms consensus value and "true" value interchangeably throughout the paper similar to Hanley et al. (2018). Hanley et al. (2018) perform several tests to confirm that the consensus value is the value that most likely corresponds to guidance in the accounting standards. Moreover, in our sample of securities held by five or more insurers, we note that a substantial portion are valued exactly at the mode (339,190 out of 1,320,406 securities, or 25.7 percent). This evidence provides further support for the mode being a commonly adopted value.

security is calculated as the difference from the consensus value.[4] We classify two types of auditors with greater expertise: (1) Big 4 firms based on their national industry practice and access to pricing resources, and (2) dominant leaders in local markets (based on client count) due to their deep personal knowledge gained from direct experience in the insurance industry.

Our security-level sample covers the period 2012 through 2018 and includes 1,320,405 securities that meet our sample criteria. In this sample, the mean fair value error is 0.5 percent of par. While this value is significantly greater than zero suggesting fair value inflation on average (Hanley et al. 2018), the magnitude is relatively low. However, when we separate the sample into securities with positive fair value errors and securities with negative fair value errors, we find much larger errors that offset in insurers' aggregate portfolios. In the positive (negative) subsample, the mean absolute fair value error is 16.2 percent (16.8 percent). The existence of these offsetting errors is important, as PCAOB inspection reports specifically criticize the evaluation of the aggregate portfolio, which results in auditors missing security-level differences (PCAOB 2012b; Emett et al. 2018).[5] We find that 34.6 percent of securities represent audit differences (i.e., a difference greater than 5 percent at the security-level as in Emmet et al. 2018). Collectively, these descriptive statistics indicate systematic errors in the fair values of investment securities, on average, during our sample period.

[4] While we cannot conclude that the consensus value is definitively the most appropriate value for each security, we argue that the value adopted by the most entities in the sample can be viewed as the most reasonable and supportable estimate from the auditor's perspective. It is also important to note that auditors do not know the consensus value at the time of their testing; thus, our prediction relates to whether expert auditors gather more and/or better types of evidence and require adjustments if needed such that their clients are more likely to end up with a reasonable estimate, which we then assess *ex post* based on whether the value is closer to the consensus value.

[5] For example, the PCAOB stated the following deficiency in the Report on 2011 Inspection of KPMG LLP (PCAOB 2012b, 20-21): "the Firm obtained estimates of fair values from external pricing services for comparison to the issuer's fair value measurements. The Firm established a threshold to identify pricing differences for further testing. The threshold, however, was for an aggregate difference at the portfolio level; this threshold caused the Firm not to identify significant differences in prices for individual securities."

We begin our multivariate analysis by evaluating whether specific cues that are available during the auditors' risk assessment process or substantive testing are associated with differences in fair value estimates. These cues represent high and low integrative complexity, which is defined as the complexity of connections required to incorporate information in making a judgement or decision (Tetlock 1983; Elliott et al. 2007). We first examine two security-level cues with low integrative complexity that are most relevant during substantive procedures (i.e., deviations from the norm level classification and self-estimated securities). We find that both cues are associated with a significant increase in positive fair value errors. The increase is economically meaningful, with internal pricing and deviations from norm level classifications being associated with 80 and 69 percent increase in positive fair value differences, relative to the sample mean for absolute fair value difference in the positive subsample. Further, classifying securities at a higher risk level than the norm is associated with an 11.5 percent increase in the likelihood of a positive audit difference.

Next, we examine two high integrative complexity cues related to insurer-level information which we expect to be important during the risk assessment phase of the audit engagement (i.e., large inflation in the prior year portfolio and evidence of bias in another significant estimate). We find that significant prior year inflation is associated with greater fair value error in both the positive and negative subsamples. When examining the likelihood of audit differences, we find that large prior year portfolio inflation is associated with 3.3 and 3.1 percent increases in the likelihood of a positive and negative audit differences, respectively. While bias in another significant estimate is not associated with higher levels of positive fair value differences, this cue is associated with a 4.8 percent increase in the likelihood of a positive audit difference. These collective results indicate that cues have the potential to provide insight related to audit risk within the fair value estimate account.

Finally, we examine whether auditors with greater expertise are associated with incremental reductions in fair value errors when there are cues indicating an increased risk of material misstatements. We find that both Big 4 and local industry expertise are effective at mitigating fair value errors in the presence of security-level cues available during the substantive testing phase. However, neither type of auditor expertise is associated with a decrease in fair value error in the presence of insurer-level cues indicating risk at the engagement level, indicating that even expert auditors may struggle to incorporate high integrative complexity cues into their judgement and decision-making process. Interestingly, we find that in the presence of bias in another significant estimate (i.e., claim loss reserves), local industry experts are associated with an *increase* in fair value error. This increase in fair value error may be due to the fact that local industry experts recognize the risk in the claim loss reserve and reallocate resources to directly addressing the risk in that area, which results in a reduced focus on the investment account. Collectively, we view the evidence as supportive of our prediction that expert auditors are better able to identify and respond to cues indicating higher risk to increase the effectiveness of fair value audit procedures compared to less experienced auditors, but this response is isolated to security-level cues with low integrative complexity. The cue response offers a potential explanation for the generally superior performance by expert auditors that is documented in prior literature; however, a broader consideration of more complex cues could be integrated to further improve experts' performance.

Our study makes several contributions to research and practice. First, the significance and prevalence of fair values suggests greater need to understand the mechanisms that constrain errors in these estimates. Consistent with regulatory concerns, our data indicate that a large portion of the investment securities in our sample are recorded at values that are significantly different than the estimated consensus value, including 34.6 percent of securities that differ by an amount large enough to warrant further auditor consideration. However, at the overall portfolio level, aggregate differences are only 0.5 percent on average. These results suggest that—despite regulator concerns—auditors are comfortable with, or can justify, significant differences on an individual security level if the overall portfolio difference is reasonable.

Second, in an attempt to enhance the guidance for auditors in this area, the PCAOB recently adopted a new standard—PCAOB AS 2501: *Auditing Accounting Estimates, Including Fair Value Measurements*—to replace the three prior standards related to auditing estimates, fair value measurements, and derivatives (PCAOB 2018). One of the key areas in which the new standard provides enhanced guidance involves "providing direction to prompt auditors to devote greater attention to addressing potential management bias in accounting estimates" (PCAOB 2018, 2). Prompting auditors should heighten professional skepticism and result in auditors identifying and responding to cues consistent with a heightened risk of misstatement, whether income-increasing or income-decreasing. Our examination extends existing experimental research to specific cues that arise during the planning and substantive phases of the audit and provides evidence suggesting that these cues enhance expert auditors' performance when testing fair values. Consistent with this prior research, our results indicate that experts respond to risk-related cues with low integrative complexity encountered during substantive testing of fair values. However, we fail to find evidence that auditors effectively incorporate cues involving high integrative complexity that are arise during the risk assessment phase. The high integrative complexity cues require more connections to be drawn year-over-year or across different financial statement accounts, and thus, our findings suggest a potential limit to auditor expertise in the context of cue recognition. Overall, we provide insight into specific factors that affect auditors' ability to evaluate these types of complex estimates (Bratten et al. 2013).

Finally, much of the extant research on the external auditor's role in the evaluation of fair value estimates uses experimental, survey, or interview approaches (Griffith et al. 2015a; Griffith et al. 2015b; Cannon and Bedard 2017; Glover et al. 2017; Joe et al. 2017; Backof et al. 2018; Emett et al. 2018; Griffith 2018; Bucaro 2019; Griffith 2019). Often due to disclosure and data constraints, archival research in this area is limited (DeFond and Zhang 2014).[6] Data constraints for archival research are especially apparent when evaluating investment securities because the lack of asset-specific disclosures prevents researchers from understanding the choices made by firms to derive fair value estimates (Emett et al. 2018; Hanley et al. 2018). Our unique setting with asset-specific information for fair values, input levels, and estimation sources allow us to explore the factors affecting auditors' performance in this area.

2. Prior Research and Hypotheses Development

2.1 Fair Value Estimate Errors and the Role of the Auditor

Errors in fair value estimates are well-documented in prior literature (e.g., Beatty and Weber 2006; Vyas 2011; Li and Sloan 2017; Hanley et al. 2018). This evidence is important because errors or bias that arise due to the subjective nature of estimates can potentially impact the value relevance of financial statement information. Consistent with this notion, several studies report, based on aggregated "levels" disclosure data (i.e., estimates with Level 1, 2, or 3 inputs[7]), that investors discount fair value estimates derived from lower quality inputs (Petroni and Wahlen 1995; Song et al. 2010; Riedl and Serafeim 2011; Goh et al. 2015). On a disaggregated level,

[6] For example, DeFond and Zhang (2014, 312) state that "historically, auditors' primary differential advantage has been their expertise in verification of historical cost information. Thus, an important question is whether auditors' expertise, and hence audit quality is applicable to a fair value accounting model. … there is little archival research on the role of auditing in fair value estimation." Exceptions include studies examining asset impairments (e.g., Ayres et al. 2019; Stein 2019) and PCAOB inspections (Stuber and Hogan 2020), or settings with fair value data aggregated based on the overall Level 1, 2, and 3 (Ettredge et al. 2014; Ahn et al. 2019).

[7] In accordance with FASB ASC 820: *Fair Value Measurement*, Level 1 represents quoted prices in active markets for identical assets or liabilities, Level 2 is based on observable inputs but allow for adjustments (e.g., similar assets or inactive markets), and Level 3 reflects unobservable inputs.

Hanley et al. (2018) utilize security-level analyses to document significant differences in reported fair values relative to “true” fair values when insurance companies use lower quality inputs and elect to self-estimate rather than employ a third-party source. While prior studies assume that discretion in fair values only occurs at Level 3, the evidence in Hanley et al. (2018) also reveals errors and self-estimation in Level 2 estimates. Consequently, fair values based on inputs other than Level 1 are more difficult to derive, depend on management’s judgment, and can be subject to opportunism (Kothari et al. 2010; Bratten et al. 2013). Given that prior studies document material fair value estimate errors in audited financial statements, the motivating question for our study is whether certain types of auditors are more likely to identify, and require adjustment for, such deviations from commonly accepted fair values when they exist.

Standards related to the audit of fair value estimates provide guidance for auditors during the planning phase as well as the substantive testing phase. First, standards require auditors to evaluate management’s process for developing fair value estimates, and then assess the risks of material misstatement arising from fair value estimates. Based on their assessment of risk, auditors then approach their testing of fair value estimates by applying one, or a combination of, the following substantive procedures: test management’s process for developing the estimate, develop an independent estimate, and/or review subsequent events and transactions (PCAOB AS 2502).[8] Thus, observed estimate errors may arise from auditors failing to properly assess a higher risk of misstatement during the planning phase, failing to properly perform substantive tests of the fair value estimates, or a combination of both. To highlight the need for auditors’ knowledge and discretion in developing their plan, the PCAOB stated the following in a recent inspection briefing:

[8] The PCAOB recently adopted a new standard, *Auditing Accounting Estimates, Including Fair Value Measurements, and Amendments to PCAOB Auditing Standards*, that provides additional emphasis on considering potential bias in management estimates and provides a more detailed discussion of the use of pricing services and valuation specialists (PCAOB 2018). However, guidance related to the general approach to auditing estimates remains the same in the revised standard, which is effective for audits of fiscal years ending on or after December 15, 2020.

"because of the wide range of possible fair value measurements from relatively simple to complex and the varying levels of risk of material misstatement associated with the process for determining fair values, the auditor's planned audit procedures can vary significantly in nature, timing, and extent" (PCAOB 2017b, 10).

To audit fair values with observable inputs, auditors typically obtain independent third-party estimates from external pricing services (Glover et al. 2017; Emett et al. 2018).[9] In contrast, auditors generally employ in-house specialists to support testing of fair values based on unobservable inputs given their significant estimation uncertainty (Cannon and Bedard 2017; Glover et al. 2017). These third-party sources apply a variety of approaches to derive estimates for a given security, which may increase the variation in evidence provided from different sources.[10] Since the "correct" value for an estimate is not known, the auditor has several options at his/her disposal to gain more comfort about the fair value estimate. For example, auditors can obtain quotes from multiple pricing sources and/or pricing sources that differ from those used by management (Glover et al. 2017). Auditors can also choose between pricing services and valuation specialists (whether in-house or external) depending on the nature of the security.[11]

After obtaining evidence based on one of the approaches described above, the auditor determines a range of acceptable amounts for the fair value while also taking into account measurement uncertainty, and then compares the client's recorded amount to this range. PCAOB

[9] Auditors typically obtain client fair value estimates immediately after the end of the year to allow for this testing.

[10] For example, the PCAOB (2014, 44-45) highlights how "the nature of evidence obtained from third-party sources varies based on the type of instrument being valued and the source of information used by pricing services. Some pricing services provide consensus prices; that is, a value derived from prices provided by each subscriber to the services. Other pricing services use their own methodology based on various market data obtained or derived from other sources, including trades of comparable instruments, broker quotes, and historical trade activity to determine a value. Pricing services also may combine multiple approaches to arrive at a value for a particular instrument."

[11] A quote from an audit partner in Glover et al. (2017, 78) highlights this decision: "We would typically use a pricing service by default to the extent possible and then move to a valuation specialist in instances where a pricing service was unable to value the security or where we had concerns over the quality of what a pricing service could provide based on the nature of the security and our understanding of the methodologies they employ."

AS 2810, *Evaluating Audit Results*, indicates that any difference between the endpoint of an auditor's range of a best estimate of a value and the actual recorded value should be considered a misstatement (paragraph .13). While not explicitly stated in the standards, the PCAOB's inspection process highlights that this criteria should be applied on a security-by-security basis when auditing a client's investment portfolio (PCAOB 2012b; Emmet et al. 2018). The standards also require auditors to consider whether the collective differences indicate potential management bias based on qualitative factors such as patterns favoring higher or lower income and changes in estimates from the prior year to achieve desired earnings outcomes (PCAOB AS 2810.27). Given that Hanley et al. (2018) report the existence of significant errors in fair value estimates at the individual security level, auditors do not appear to be systematically enforcing this regulatory guidance in practice.

2.2 *Challenges and Strategies in the Audit of Fair Value Estimates*

PCAOB inspections of accounting firms often reveal deficiencies related to a lack of professional skepticism (PCAOB 2012a), which is considered fundamental to performing a high-quality audit. In the case of auditing fair values, these deficiencies may be the result of a lack of knowledge or confidence that impedes skeptical judgments, or characteristics of individual auditors that influence his/her ability to recognize cues that additional work is required (Hurtt et al. 2013).[12] Despite providing additional implementation guidance related to auditing estimates, the PCAOB emphasizes that "this area remains challenging and practices among firms currently vary" and "inspections staff continues to identify deficiencies at both larger and smaller audit firms" (PCAOB 2017a, 2). Moreover, Christensen et al. (2012) highlight the extreme estimation

[12] The PCAOB (2012a, 5) cited the following example to illustrate the lack of skepticism as a contributing factor to an audit deficiency: "For certain hard-to-value Level 2 financial instruments, the engagement team did not obtain an understanding of the specific methods and/or assumptions underlying the fair value estimates that were obtained from pricing services or other third parties and used in the engagement team's testing related to these financial instruments. Further, the firm used the price closest to the issuer's recorded price in testing the fair value measurements, without evaluating the significance of differences between the other prices obtained and the issuer's prices."

uncertainty in fair value estimates and raise questions about whether auditors can reasonably opine on these values under current auditing standards.

Concerns such as these expressed by regulators and others have motivated a significant number of field and experimental research studies related to the audit of fair value estimates. This research provides evidence that auditors struggle with testing in this area due to complexity, biases, and other challenges. Specifically, the high degree of subjectivity in the assumptions, third parties who are unable or unwilling to provide detail for data used in their models, inadequate management understanding, lack of concise auditing guidance, and gaps between auditors' and regulators' expectations are important factors contributing to the challenge of auditing estimates (Cannon and Bedard 2017; Glover et al. 2019). Compounding these challenges, research indicates that auditors rely too much on management's process rather than engaging in critical, independent analysis of the estimate (Griffith et al. 2015a). Auditors also appear to place too much focus on quantitative data or the composition of benchmarks in client-provided evidence (Joe et al. 2017; Bhattacharjee et al. 2019) as well as quantitative judgment rules in the standards instead of qualitative bias assessments (Emmet et al. 2018). When working with internal valuation specialists to perform the audit, Griffith (2019) finds that auditors do not fully accept the work of valuation specialists and instead rely on them more for comfort rather than insight on the fair value estimates.

A growing stream of experimental research focuses on strategies to improve auditors' performance when evaluating complex estimates. Extant research examines approaches such as inducing deliberative mindsets (Griffith et al. 2015b), using low-level, concrete thinking (Backof et al. 2018), applying system-thinking perspectives (Bucaro 2019), invoking intrinsic motivation (Kadous and Zhou 2019), and negatively framing audit steps (Maksymov et al. 2018). Griffith et al. (2019) also document that auditors' need for cognition—a disposition related to a person's tendency to enjoy and engage in analytical thinking—is associated with better judgments when evaluating complex estimates. While this collective body of research provides important information about auditors' ability to assess complex estimates, we have little archival analysis using data on specific estimates, and it is important to triangulate our understanding of the topic using various methods (Bloomfield et al. 2016). Further, much of the experimental research relies on participants from the Big 4 accounting firms such that archival analyses can extend our understanding to a broader set of external auditors.

2.3 Development of Hypotheses

Measurement uncertainty results from the subjectivity of observable inputs (Level 2) as well as unobservable inputs (Level 3) such that two parties measuring the same security could arrive at different fair values (Bratten et al. 2013). As a result, auditing fair values requires an evaluation of the reasonableness of these subjective inputs and assumptions rather than confirmation of past events (Griffith et al. 2015b). Building on the inherent difficulty of assessing fair values, auditors face *ex post* regulatory scrutiny when testing these estimates since the PCAOB or peer reviewing firms evaluate the appropriateness of audit procedures and conclusions (with the benefit of hindsight).[13] Given these circumstances, we expect that auditors have an incentive to identify fair value estimates that are supported by significant evidence in an effort to minimize outliers that are more difficult to justify. We expect that this effort will be concentrated in those clients where there are cues indicating increased risk.

While auditors have an incentive to reduce outliers in fair value estimates, not all auditors have the ability to do so. Evidence primarily from experimental research suggests that auditors with greater expertise possess two characteristics that likely improve their performance when

[13] For example, Westermann et al. (2019, 709) provide auditors' perceptions of the PCAOB inspection process and note that "auditors are doing what they think inspectors would want (if selected) out of fear of repercussions." While the audits of private insurance companies in our sample would not face the threat of PCAOB inspection, they are subjected to peer and internal firm reviews. Moreover, deficiencies in any of the inspection and review processes (especially a frequently reviewed area such as fair value estimates) often result in changes to audit firms' methodologies that could affect the general approach on all clients.

testing fair values: (1) greater knowledge and experience, and (2) higher status. First, several studies document that expertise contributes to the auditors' ability to detect anomalies across firms (Low 2004; Hammersley 2006; Glover et al. 2017) and auditors with industry expertise are better able to identify risks of material misstatement (Wright and Wright 1997; Owhoso et al. 2002). Bhattacharjee et al. (2019) report that audit managers' task-specific experience related to investment fair values improves their performance in analyzing the appropriateness of benchmarking data. Moreover, using aggregated disclosure data, Ettredge et al. (2014) document that banks with higher proportions of fair-valued assets pay more fees when their auditor is an industry specialist.[14] This result suggests that auditors with greater experience assess higher risk and perform more work for more complex types of assets. Developing a reasonable range of fair value estimates for a particular security requires knowledge about the security's risk as well as third party's pricing methods and assumptions. Therefore, we expect that auditors with greater expertise from serving other similar clients will be more likely to identify settings when enhanced approaches are necessary, such as in the presence of cues indicating greater risk. These factors increase the expert auditor's ability to reduce potential fair value errors.

Second, prior research finds certain types of auditors hold higher status in the market than others (Jensen and Roy 2008), where status refers to the "ability to influence outcomes based on perceived skills, qualities, and personal attributes" (Badolato et al. 2014, 208). Auditors may achieve greater status and prestige from being the largest auditors in the overall market or being dominant players in a particular industry or location. Auditing fair values represents a setting in which a specific "right answer" is not clear such that negotiations are necessary when the auditor derives an estimate that differs from the client. Auditors with high status may be more likely to

[14] While Ettredge et al. (2014) find that this fee effect for specialist auditors is concentrated in Level 2 assets, Ahn et al. (2019) find that only expertise with auditing Level 3 (not Level 2) assets translates into fewer fair value-related restatements and comment letters.

command deference from clients in these negotiations, which aligns with prior research indicating that specialist auditors are more confident in their assessment of risks (Taylor 2010) and that status motives combined with specialized knowledge results in more precise recommendations (Knechel and Leiby 2016).[15] Consequently, we predict that status motivates expert auditors to adhere to norms such that they are less likely to allow clients' estimates to deviate significantly from fair value estimates provided by pricing services or other sources.

We expect that the presence of cues indicating a greater risk of material misstatement can incrementally improve the expert auditor's ability to identify outliers when testing the client's fair value estimates. For example, Hammersley (2006) finds that auditors with industry expertise develop more complete problem representations and assess a higher risk of misstatement when they are presented with partial or full cues that are diagnostic of a possible misstatement, relative to when they receive no cues and also relative to experienced auditors without industry expertise. Griffith (2018) also finds that receiving a relational cue from valuation specialists enhances auditors' ability to combine their existing knowledge with incoming cues or stimuli to recognize patterns; however, she finds that this only occurs when a situational factor such as higher engagement risk increases the auditor's motivation to incorporate the cue into their risk assessment. In contrast, for non-expert auditors, a cue is just another piece of information that may or may not trigger a reaction. Thus, evidence from experimental research suggests that cues can trigger heightened professional skepticism, but the auditor must have sufficient expertise and motivation to incorporate the information into his/her problem representation. Therefore, our hypothesis, presented in alternative form, is as follows:

> ***H1:*** *In the presence of cues suggesting heightened risk of material misstatement, auditors with greater expertise are associated with incrementally less fair value estimate error.*

[15] In a relevant example related to audit committees, Badolato et al. (2014) document that companies with audit committees that have high relative status and financial expertise are associated with less earnings management.

3. Research Design and Data

3.1 Empirical Model

To test H1, we estimate the following model at the security-level to assess effect of the interaction between expert auditors and cues indicating higher risk on fair value estimate errors:

$$\begin{aligned} &\textit{FV Difference}_{sit} \text{ or } \textit{Audit Difference}_{sit} = \beta_1 \textit{Risk Cue}_{sit} + \beta_2 \textit{Auditor Expertise}_{it} \\ &\quad + \beta_3 \textit{Risk Cue x Auditor Expertise}_{it} + \beta_4 \textit{Size}_{it} + \beta_5 \textit{ROA}_{it} + \lambda_g + \pi_t + \varepsilon_{sit} \end{aligned} \tag{1}$$

where *FV Difference* and *Audit Difference* represent two different dependent variables to capture fair value errors. First, *FV Difference* represents the signed difference between the reported fair value estimate for security *s* held by insurer *i* in year *t* and the consensus (mode) fair value estimate for security *s* across all insurers in year *t* (Hanley et al. 2018). A positive (negative) value for *FV Difference* indicates inflation (deflation) of the security relative to the consensus fair value. Second, *Audit Difference* reflects the fact that small deviations between the consensus fair value and a client's reported fair value at the individual security level may be within a range that is considered acceptable by the auditor, and thus, may not require an audit adjustment (PCAOB AS 2810.13). While auditors are required to consider whether any differences in estimates are qualitatively indicative of management bias, we are also interested in those differences falling outside of the quantitative range considered acceptable to the auditor.[16] Based on conversations with practicing auditors, the typical range considered acceptable at the security-level is based on the hierarchy classification of the securities; for example, the range of tolerance will often be between 1 and 2 percent for Level 1, 5 percent for Level 2, and 10 percent for Level 3. Given that our sample consists of mode Level 2 securities, we consider any difference of greater than 5 percent between the consensus fair value and the reported fair value to be an audit difference

[16] We differentiate between audit differences, which should be compiled and evaluated as a whole prior to completion of the audit, and material errors, which individually exceed an engagement-level materiality threshold (e.g., percent of total assets or equity).

(Emmet et al. 2018). Therefore, *Audit Difference* is an indicator variable equal to one if *Abs(FV Difference)* for security *s* held by insurer *i* is greater than 0.05 (5 percent) of the mode value in year *t*, and zero otherwise.[17] Appendix A provides detailed variable definitions.

The specific cues (*Risk Cue*) used in our models represent various factors where we expect experienced auditors to recognize a heightened risk of material misstatement, and thus, adjust audit procedures accordingly.[18] We focus on two security-level cues that are most relevant during the performance of substantive procedures, and two insurer-level cues related to prior year information which we expect to be most relevant during the risk assessment phase of the audit engagement. Our first cue represents instances when the reported investment level differs from Level 2. As discussed further in Section 3.2, we limit our sample to securities with a mode Level 2, which comprise most securities in insurers' investment portfolios. Given that restriction, any deviation in reported levels different from Level 2 (*Reported Level=1* or *Reported Level=3*) suggests that the insurer is deviating from the norm classification, potentially for strategic reasons (Hanley et al. 2018). We also examine whether the security is priced internally (*Self-Estimated*) rather than obtained from a third-party source as we expect this factor to highlight greater risk of misstatement (Hanley et al. 2018). Both the level deviation and pricing source cues are considered to be most relevant during the substantive testing phase of the audit.

To evaluate cues most relevant to the risk assessment stage of the audit, we examine two insurer-level measures. We select both of these cues based on guidance in the auditing standards; specifically, paragraph 64 of AS 2401 states that the auditor "should perform a retrospective review of significant accounting estimates reflected in the financial statements of the prior year to

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[17] Our inclusion of both group and year fixed effects makes the estimation of a linear probability model (LPM) using OLS preferable to logit or probit approaches, particularly given that the assumption of a constant auditor effect is reasonable. However, logit and probit estimations yield qualitatively similar results.

[18] In Section 4, we begin our tests by examining the association between the main effect of Risk Cue and our dependent variables. This analysis allows us to evaluate whether these cues are informative of fair value errors prior to examining the interaction effect in H1.

determine whether management judgments and assumptions relating to the estimates indicate a possible bias on the part of management." Therefore, our first insurer-level cue reflects whether there is aggregate prior year inflation in an insurer's investment portfolio. We define significant prior year inflation (*PY Inflation*) using an indicator variable equal to one if the aggregate FV difference is in the top quartile of insurers in year *t*-1, and zero otherwise. Our next insurer-level measure captures cues from potential estimation bias in other financial statement accounts. Specifically, we focus on the claim loss reserve because it is the most significant liability on insurers' financial statements. Prior inaccuracies in claim loss estimates, particularly those suggesting management bias, should alert auditors to potential estimate errors elsewhere in the financial statements. Our measure is based on the two-year reserve development to policyholders' surplus ratio (Ratio 12), which is a key regulatory ratio related to error in the claim loss reserve.[19] Therefore, we define *Reserve Error* as an indicator variable equal to one if the insurer has been in violation of NAIC guidelines for Ratio 12 for both the current and prior year. We consider a two-year history as being indicative of a pattern of understating reserves, which should alert auditors to potential increased risk.[20]

Separately, we measure *Auditor Expertise* based on two variables commonly used in prior research. Our first measure is an indicator variable equal to one if the auditor is a Big 4 auditor, and zero otherwise (*Big 4*). Specific to audits of investment securities, we expect Big 4 auditors to have a larger pool of resources to draw from relative to non-Big 4 auditors when examining fair value measures, including internal valuation specialists, national office technical experts, and audit

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[19] According to guidance from the National Association of Insurance Commissioners (NAIC), "if the insurer's ratio results consistently show adverse development and/or the two-year reserve development to policyholders' surplus ratio result is consistently worse than the one-year reserve development to policyholders' surplus, the insurer may be intentionally understating its reserves" (NAIC 2016, 24). This ratio is part of a series of twelve key Insurance Regulatory Information System (IRIS) ratios that are a focus of regulators in their evaluation of insurer portfolios.
[20] Our results are robust to requiring a longer history of Ratio 12 violations. We focus on a two-year history due to the regulator's emphasis on two-year loss development.

technology. For example, Big 4 firms have their own national pricing desk that "includes valuation specialists employed who help the engagement teams develop FVM (fair value measurement) estimates, as well as evaluate management-developed FVM estimates" (Glover et al. 2017, 64). Moreover, the survey evidence in Glover et al. (2017, 73) indicates that Big 4 partners are more likely to obtain estimates of individual securities from multiple pricing services relative to non-Big 4 partners, suggesting that auditors at Big 4 firms seek more evidence when necessary to evaluate the reasonableness of management's estimates. Along with experience and resources, Big 4 auditors also possess high status in the audit market relative to non-Big 4 auditors (Jensen and Roy 2008). Status provides authority to the decisions that are made, which is important if the auditor derives an estimate that differs from the client and must negotiate an adjustment.

Our second measure captures expertise based on auditors with significant involvement serving clients in the insurance industry. A substantial portion of an insurance client's total assets represent investments, such that we expect industry specialists to have a large degree of experience with auditing fair values. Glover et al. (2017, 73) report survey evidence consistent with this notion as they find that partners specializing in financial industries are more likely than non-specialist partners to use pricing services different from those used by management. Since audits are managed out of local engagement offices, the auditor's position in a given local market for a specific industry also likely reflects their status in this market. In other words, we expect that auditors also achieve greater status and prestige from being dominant players in a particular industry within that local market. We consider experience with a large number of insurance clients to best capture the auditors expertise evaluating different types of security portfolios, thus we focus on a count-based measure of city-level expertise.[21] Therefore, we create our second auditor

[21] Our inferences are unchanged when *City Expert* is defined based on amount the amount of assets audited. Note that audit fees are not available in our data.

expertise variable, *City Expert*, as an indicator variable equal to one if the insurer engages the auditor with the largest local market share based on client count in year *t* and that market share is at least 10 percent greater than the next closest competitor, and zero otherwise. Since we are able to obtain data for the auditor's public *and* private clientele given regulatory reporting requirements for insurance companies, our measure provides a more accurate reflection of expertise in this industry relative to prior audit archival studies that are limited to public clientele. Our data includes the auditor's office location, which allows us to create the expertise measure at the local (i.e., MSA) level. Local expertise reflects auditors' deep personal knowledge gained from direct experience that may not be readily transferred across offices (Reichelt and Wang 2010).

Given the PCAOB's emphasis on auditors evaluating differences on a security-by-security basis (PCAOB 2012b; Emmet et al. 2018), we perform our analyses at the security-level. Moreover, we use the full sample as well as separate subsamples for securities with fair value inflation and deflation. For these separate analyses, we drop the securities that are exactly equal to the mode from both subsamples.[22] Our models include controls for insurer *Size* and *ROA* since these variables represent common client characteristics that typically to differ across auditor expertise measures (Lawrence et al. 2011; Minutti-Meza 2013). We also include insurer-group (λ_g) and year (π_t) fixed effects. In particular, group fixed effects are important because decisions related to fair value estimates and reported levels are often made at the group level rather than the individual insurer level (Hanley et al. 2018).[23] Further, the group fixed effects control for time invariant differences across insurer groups (e.g., factors representing relatively "sticky"

[22] Due to concerns that the Big 4 or city experts audit a substantial number insurers with large investment portfolios and may be setting the mode/consensus value, we also perform our full sample tests after excluding observations with a *FV Difference* equal to zero. Our findings (untabulated) are unchanged using this alternative approach.

[23] We define an insurer group consistent with NAIC as those affiliated insurers that file a consolidated statutory group financial statement, in addition to an individual company financial statement. Insurance companies are often part of a group that may consist of companies with stock and mutual ownership structures. In our sample, 81.3 percent of insurers are part of a group, and each group contains an average of 4.5 individual insurers. If an insurer is not part of a group, we use issuer-level fixed effects to represent the level at which fair value decisions are determined.

characteristics such as publicly traded status, governance, general portfolio complexity, management ability, and governance oversight). Year fixed effects control for time-trends in fair value errors and audit differences.

3.2 Data and Sample

We obtain Schedule D data for P&C insurance companies from the National Association of Insurance Commissioners (NAIC) for the period 2012 to 2018.[24] Part 1 of Schedule D provides the fair value estimate, input level (Level 1, 2, or 3), and valuation source (pricing service, broker/custodian, exchange, NAIC, and self-estimation) for each individual security in an insurer's portfolio at the end of the fiscal year. While financial reports filed with the NAIC are based on Statements of Statutory Accounting Principles (SSAP) instead of GAAP, SSAP 100 provides a similar definition of fair value such that fair values of investment assets should be estimated similarly under SSAP as they are under GAAP (Hanley et al. 2018).[25] Moreover, both GAAP and SSAP require insurers to disclose the inputs used in estimating fair values based on the level hierarchy. As a result, the detailed security-level information reported in Schedule D for statutory reporting purposes provides useful information for examining management's incentives surrounding the development of fair values for both GAAP and SSAP purposes. Financial reports prepared for both GAAP and SSAP purposes are required to be audited. While management likely prepare both reports simultaneously, deadlines for SSAP audited reports occur after those required

[24] We begin our sample in 2012 since it is the first year that insurers are required to report fair value estimate levels. Our sample ends in 2018 because it was the most recent year available when data collection commenced.

[25] One difference between SSAP and GAAP is that GAAP requires fair value accounting for assets classified Available for Sale (with unrealized gains and losses flowing through Other Comprehensive Income) while assets classified as Held to Maturity are carried at amortized cost. In contrast, the determination of whether P&C insurance companies must carry investments at fair value or amortized cost depends on the credit quality of the security. Specifically, the NAIC's Securities Valuations Office (SVO) categorizes each security with a value of 1 to 6 and P&C insurers are required to carry securities at fair value for SVO categories between 3 and 6.

by GAAP. As a result, auditors of public insurers generally focus on the investments reported on a GAAP basis first and then analyze the differences between GAAP and SSAP.[26]

Our focus in this study is on fixed income securities since they comprise most of P&C insurers' investment portfolios and they are traded less frequently such that opportunistic fair value reporting is more likely to occur (Hanley et al. 2018). We retain all fixed income securities with non-missing fair value estimates, levels, and source data and also require positive values for the par value and fair value of the security. To mitigate the influence of extreme values that could derive from data entry errors, we truncate the data at the 0.5 and 99.5 percentiles of the investment fair values. For our tests, we also require additional insurer characteristics from the annual financial statements filed with the NAIC. To be included in our sample, the insurer must have positive, non-zero total assets. Moreover, information about the auditor identity and location must be available, along with data for the remaining test and control variables.

We also require that each security be held by at least five different unaffiliated insurers (i.e., insurers not within the same group) in each year to ensure that we can determine a reasonable mode fair value and investment level.[27] Figure 1 presents a summary of the frequency with which security-year observations in the sample are held by various numbers of insurers for the full population of investment securities. Following Hanley et al. (2018), we create measures that capture the consensus ("true") fair value and input level of a specific security using the mode fair value estimate and mode reported level across all insurers holding that security at the same point

[26]Annual statements are due to be filed with the state of domicile by the end of February; therefore, most public insurers file their 10-Ks before or around the same time that their statutory filings are complete. However, the audits of the annual statutory filings are not due until later, at which time the insurer will file an amended statement if the audit results in any changes. While the Model Audit Rule allows for discretion by state, most states adopt a June 1 deadline for the audit report (https://www.naic.org/documents/prod_serv_fin_receivership_gca_zu.pdf). As discussed in our research design section, we include group fixed effects in our model to account for any differences in reporting for public versus private insurers.

[27] We count either a group of affiliated insurers or an unaffiliated individual insurer as one holder and require a minimum of five holders with the same security in a given year to calculate these modes.

in time. This process allows us to identify instances of potential managerial bias when a security's fair value and reported level significantly differs from the "true" value or level. These requirements of at least five holders for each security result in an initial sample of 1,424,449 observations, as detailed in Panel A of Table 1. Panel B of Table 1 provides a summary of the reported versus mode level for the securities in our full sample.

Finally, we concentrate our analyses on the fixed income securities whose fair values are estimated using inputs with a mode level of 2, which reduces our sample to 1,320,406 securities. We focus on securities with a mode level of 2 since these securities represent the majority of our sample (92.6 percent) and this design allows us to observe deviations in reported levels both above and below the mode. In addition, auditing Level 2 fair values often involves certain procedures, such as obtaining independent third-party estimates and comparing them to reported client values that differ from other asset types (Glover et al. 2017; Emett et al. 2018).

3.3 Descriptive Statistics

Panel A of Table 2 presents descriptive statistics at the insurer-year level. Our sample consists of 14,795 insurer-years, of which 61.4 percent are audited by a Big 4 auditor (*Big 4*) and 42.2 percent are audited by a city-level industry expert (*City Expert*). In untabulated statistics, we note that 37.7 percent of the sample engages a *Big 4* auditor that is not also a *City Expert*, 18.3 percent engages a *City Expert* that is not also a *Big 4* auditor, and 22.1 percent engages an auditor that is both a *Big 4* auditor and a *City Expert*. This information indicates that the *Big 4* and *City Expert* variables have some overlap as expected, but non-Big 4 auditors are the dominant auditor in local insurance markets in a reasonably large portion of our sample. Insurers in our sample are also generally profitable with a mean *ROA* of 0.025. The average total assets for insurers in our sample is $0.637 billion, and 59.2 percent of the insurer's assets consist of fixed-income bonds (*% Bonds*). These statistics reflect the importance of this type of asset on a P&C insurance company's balance sheet. On average, insurers hold approximately 97 securities in their investment portfolio (*Count Securities*).[28] The average aggregate gross FV difference of these investments is 0.2 percent (*Agg FV Difference*) and the average absolute aggregate FV difference (*Agg Abs(FV Difference)*) is 12.2 percent, revealing significant offsetting FV differences within an insurer's portfolio. Moreover, we observe that a sizeable proportion—26.7 percent—of the Level 2 securities in the average portfolio exhibit FV differences of greater than five percent *(Audit Difference*=1).

Panel B of Table 2 presents descriptive statistics for the security-level sample. The mean fair value of securities in our sample (*FV*) is 103.35, where *FV* is the fair value per $100 of par value, and the mean *FV Difference* is 0.5 percent. The data also reveal that 8.0 percent of securities are reported as Level 1 (*Reported Level = 1*) and 0.4 percent are reported as Level 3 (*Reported Level = 3*) despite having a mode level of 2. The data show 1.2 percent of securities in the sample are self-estimated (*Self-Estimated*). However, there is variation in which securities are self-estimated, as 14.2 percent of securities (untabulated) are self-estimated by some but not all insurers. *PY Inflation* captures insurers in the top quartile of aggregate FV difference in the prior year (25.7 percent of securities), and 2.7 percent of security-years are associated with an insurer with two consecutive years of reserve error ratio (Ratio 12) violations (*Reserve Error*).

Panel C of Table 2 provides an analysis of the *FV Difference* and *Abs(FV Difference)* variables for the full sample as well as separately for securities with a positive value for *FV Difference* (fair value inflation) or a negative value for *FV Difference* (fair value deflation). Consistent with Hanley et al. (2018), the mean *FV Difference* is significantly greater than zero for the full sample. In addition, the mean *FV Difference* in the positive subsample is 16.2 percent (p-

[28] This variable reflects the count of securities that meet our sample restriction, requiring that a security be held by at least five insurers in the same year.

value < 0.01) and the mean *FV Difference* in the negative subsample is 16.8 percent (p-value < 0.01), indicating substantial fair value errors in both directions.

4. Empirical Results

4.1 Effect of Risk Cues

Prior to performing tests of H1, it is important to establish whether the identified cues are informative of fair value errors and audit differences. Therefore, we modify model (1) to include only the main effect of *Risk Cue* and present these results in Table 3. Given the inclusion of group fixed effects in our model, the coefficients on the cue measures capture within-group variation in the informativeness of these cues to errors in fair value estimates. Within each panel in Table 3, columns (1) through (3) present the results of a regression of *FV Difference* on the *Risk Cue* while columns (4) through (6) present the results of a regression of *Audit Difference* on *Risk Cue*.

Panel A presents the analysis of the substantive testing cue related to deviation from the norm security level classification. Specifically, we find positive and significant coefficients on *Reported Level=3* in columns (3) and (4), consistent with a 79.6 percent increase in positive fair value differences and a 54.8 percent increase in negative fair value differences relative to their sample mean values (i.e., 0.162 and 0.168 as reported in Panel C of Table 2, respectively). In column (5), we also find a positive and significant coefficient on *Reported Level=3*, indicating an 11.5 percent increase in the likelihood of a positive (i.e., inflationary) audit differences when norm Level 2 securities are instead reported as Level 3. In contrast, we find negative and significant coefficients on *Reported Level=1* in columns (4) through (6), indicating that classifying securities at a lower level (i.e., Level 1 when the norm classification is Level 2) is associated with a decrease in the likelihood of an audit difference. Therefore, only deviating to a lower level (*Reported Level=3*) appears to be a cue indicative of greater audit risk.

Panel B presents the analysis of internally priced securities as our second substantive testing cue. In general, we do not find a significant association between *Self-Estimated* and the likelihood of audit differences. However, in column (2), we find a positive and significant coefficient on *Self-Estimated* for positive fair value differences, indicating that internally priced securities are associated with a 69.1 percent increase relative to the sample mean for positive fair value differences (0.162). Overall, the results in Panels A and B are consistent with Hanley et al. (2018), who report that security-level cues involving level deviations and internal pricing are associated with increased risk of fair value errors.

Panel C presents the association between our first risk assessment cue related to significant inflation in the prior year investment portfolio (*PY Inflation*) and our dependent variables. We find a positive and significant coefficients on *PY Inflation* across columns (1) through (6), indicating a significant increase in both fair value differences and audit differences. In terms of magnitude, for example, *PY Inflation* is associated with a 3.1 percent increase in the likelihood of any audit difference and a 3.3 (3.2) percent increase in the likelihood of a positive (negative) audit difference. Given the pervasive association between this cue and greater fair value errors, these results suggest that *PY Inflation* is an important cue that is available during the risk assessment phase when auditors are planning the current year audit.

Finally, Panel D presents the association between our second risk assessment cue involving errors in another significant accounting estimate (*Reserve Error*) and our dependent variables. We find a positive and marginally significant coefficient on *Reserve Error* in column (1), indicating *Reserve Error* is associated with an increase in aggregate fair value differences. In columns (4) and (5), we find positive and significant coefficients on *Reserve Error*, indicating that *Reserve Error* is associated with a 3.6 percent increase in the likelihood of any audit difference and a 4.8 percent increase in the likelihood of a positive audit difference. Consistent with the auditing standards (PCAOB AS 2401), these findings indicate potential management bias in one account can be associated with bias or errors in other financial statement accounts. Overall, the results in Panels C and D support the use of both *PY Inflation* and *Reserve Error* as strong indicators of increased risk in the audit of fair value estimates.

4.2 Interaction of Risk Cues and Auditor Expertise

In Tables 4 through 7, we seek to understand whether auditors with greater expertise are more likely to identify and respond to cues that suggest an increased risk of material misstatement as shown in Table 3. Consistent with previous discussion, the coefficients of interest should be interpreted as within-group variation in cues and auditor expertise based on the inclusion of group fixed effects in the models.

4.2.1 Substantive testing cues

We begin our analysis by examining the interaction between auditor expertise and the substantive testing cue related to deviations from the norm security level in Table 4. Panel A (Panel B) presents our tests using Big 4 auditors (local industry experts) as measures of auditor expertise. In Panel A, we find that the coefficients for the interaction of *Big 4 x Reported Level=3* are negative and significant for the full sample and the subsample of security-years with positive fair value differences in columns (1) and (2). Similarly, we find a significant decrease in the likelihood of an audit difference for the *Big 4 x Reported Level=3* interaction in columns (4) and (5) for the full sample and positive subsample. In Panel B, we continue to find negative and significant coefficients for the interaction of *City Expert x Reported Level=3* in the full sample and subsample of security-years with positive fair value differences in columns (1) and (2). Further, in column (5), the results show a marginally lower likelihood of an *Audit Difference* for the *City Expert x Reported Level=3* interaction in the positive subsample. Collectively, this evidence indicates that auditors with greater expertise are associated with significant reductions in fair value errors in the presence of a substantive testing cue related to deviations from the norm security classification.

Table 5 presents the results of the analyses of our second substantive testing cue that captures instances when the insurer self-estimates an investment security's fair value. In the analysis of Big 4 expertise presented in Panel A, we find that the coefficient on the interaction of *Big 4 x Self-Estimated* is negative and significant for the full sample in column (1) as well as the separate fair value inflation and deflation subsamples in columns (2) and (3). Further, we find that the coefficients on *Big 4 x Self-Estimated* in columns (4) and (5) are negative and significant, indicating a lower likelihood of audit differences for a self-estimated security audited by a Big 4 relative to a non-Big 4 auditor. This evidence suggests that Big 4 auditors identify the pricing source of a security as a risk-relevant cue, resulting in a reduction in fair value errors and audit differences. We find less consistent results for our second measure of auditor expertise (*City Expert*), as presented in Panel B. While the *City Experts* are associated with a lower fair value differences and the likelihood of an audit difference for a self-estimated security compared to non-experts, the effects are concentrated in the negative fair value difference subsamples (columns (3) and (6)). While these collective tests provide evidence that auditors with greater expertise are associated with significant reductions in fair value errors in the presence of a cue related to self-estimation of securities, the type of error constrained (i.e., fair value inflation or deflation) varies based on the nature of the auditor's expertise.

4.2.2 Risk assessment cues

Table 6 presents the results examining the cue related to significant prior year aggregate inflation in an insurer's portfolio. In Panel A, we find that the coefficient on the interaction of *Big4 x PY Inflation* has the opposite, positive sign in columns (1) and (2). We do not find significant coefficients on the interaction of *Big 4 x PY Inflation* related to the likelihood of audit differences in columns (4) and (5), with the only negative and significant coefficient in the negative subsample in column (6). Similarly in Panel B, we only find a negative and significant coefficient on *City Expert x PY Inflation* in column (1), but a positive coefficient in column (6) for the likelihood of audit differences in the negative subsample. Taken together, these mixed and insignificant findings do not provide clear evidence of whether Big 4 auditors are able to identify and respond to the cue related to inflation in the insurer's prior year portfolio.

Finally, we examine the cue involving previous management bias in an unrelated accounting estimate in Table 7. In Panel A, the regression results reveal insignificant coefficients across all columns for the *Big 4 x Reserve Error* interaction, indicating that Big 4 expertise does not have a differential effect identifying and responding to cues indicating errors or bias in other significant estimates. In Panel B, we find positive and significant coefficients for *City Expert x Reserve Error* across all regressions except column (1). These results indicate that for clients with prior errors in the claim loss reserve, local level city experts are associated with higher fair value differences and an increased likelihood of audit differences, compared to non-expert auditors. One reason that local experts may be associated with increased error is that these auditors may be identifying and responding to risk in claim loss reserves; however, rather than incorporating the cue into the overall audit engagement response, these local experts may be diverting resources specifically to address risks in testing claim loss reserves. As a result, less attention may be assigned to investment fair values, leading to an increase in outliers relative to consensus fair values.

4.2.3 Summary

Overall, the evidence provides support for the existence of cues available to the auditor at the risk assessment and substantive testing phases of the audit that indicate heightened risk of fair value estimate errors. We find that both Big 4 and local industry expertise are associated with reductions in fair value errors—including audit differences that would warrant further consideration—for substantive testing cues that exist at the security-level. In contrast, we fail to find consistent evidence of the predicted effect of Big 4 or local industry expertise in the presence of less obvious cues related to year-over-year or across-account comparisons available to the auditor during the auditor's risk assessment process. Thus, our findings suggest a potential limit to auditor expertise in settings with complex estimates and cue recognition. This conclusion is consistent with some evidence suggesting the benefits of expertise may not exist in circumstances with extremely difficult tasks (Koonce and Mercer 2005).

5. Conclusion

In this study, we examine the role of cues indicating heightened risk in a difficult audit area related to fair value estimates. While several recent field and experimental studies have emerged to better understand the setting and recommend strategies to improve auditors' performance in this complex area, archival research remains limited due to a lack of data with which to evaluate the appropriateness of fair value estimates. We overcome this limitation by using security-specific disclosures for P&C insurance companies; this data provides fair values for identical securities held by many holders at the same point in time, allowing us to derive a measure of the fair value error of an individual security. Using this data, we find both significant fair value inflation and deflation, with nearly 35 percent of sample securities having a fair value error large enough to warrant further auditor consideration (i.e., audit difference). Given the large differences at the security-level, our study examines whether certain types of auditors—specifically, auditors with greater expertise that have the knowledge, experience, and status to identify deviations and require adjustments if necessary—are associated with reductions in fair value errors.

We identify four risk-cues—two cues with low integrative complexity related to the substantive testing phase and two cues with high integrative complexity related to the risk assessment phase—that are associated with increased fair value differences, and specifically with increased differences likely to constitute and audit difference. We find that auditors with greater expertise identify and incorporate the information from low integrative complexity risk cues at the substantive testing phase to further reduce differences in fair value estimates. However, we fail to find consistent evidence that expert auditors incorporate high integrative complexity risk cues at the insurer-level to reduce fair value differences. In contrast with our prediction, local industry experts are associated with *increased* fair value differences in the presence of a cue indicating risk related to another significant accounting estimate (i.e., claim loss reserves). This result is consistent with experts failing to fully integrate the information from complex and seemingly unrelated risk cues across audit areas. Collectively, this evidence supplements prior experimental research indicating that expertise aids in recognizing patterns or cues that may alert the auditor to potential problems in the audit (Hammersley 2006; Nelson 2009; Glover et al. 2017), and suggests that auditors, even expert auditors, may benefit from incorporation of high integrative complexity cues indicating higher risk across other areas of the engagement.

Overall, our findings are consistent with auditors' expertise being important in reducing fair value errors as well as recognizing and responding to certain cues that suggest increased risk in the audits of these fair values. We acknowledge that we examine only a small subset of potential cues and signals that are available to auditors in planning and performing audit procedures and we focus on fair value estimates within a single industry. However, the use of the single industry setting allows us to provide archival evidence into the interaction of external auditor characteristics with risk-relevant cues and respond to calls for research into the auditing of fair value estimates (Bratten et al. 2013; DeFond and Zhang 2014). Given the PCAOB's emphasis on audits of fair value estimates, these findings are also important to understand the factors associated with improved auditor performance in this complex area.

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FIGURE 1
Number of Holders of Securities

This table presents the frequency of security-year observations by number of holders in the full population of 3,056,741 security-years for the period between 2012 and 2018.

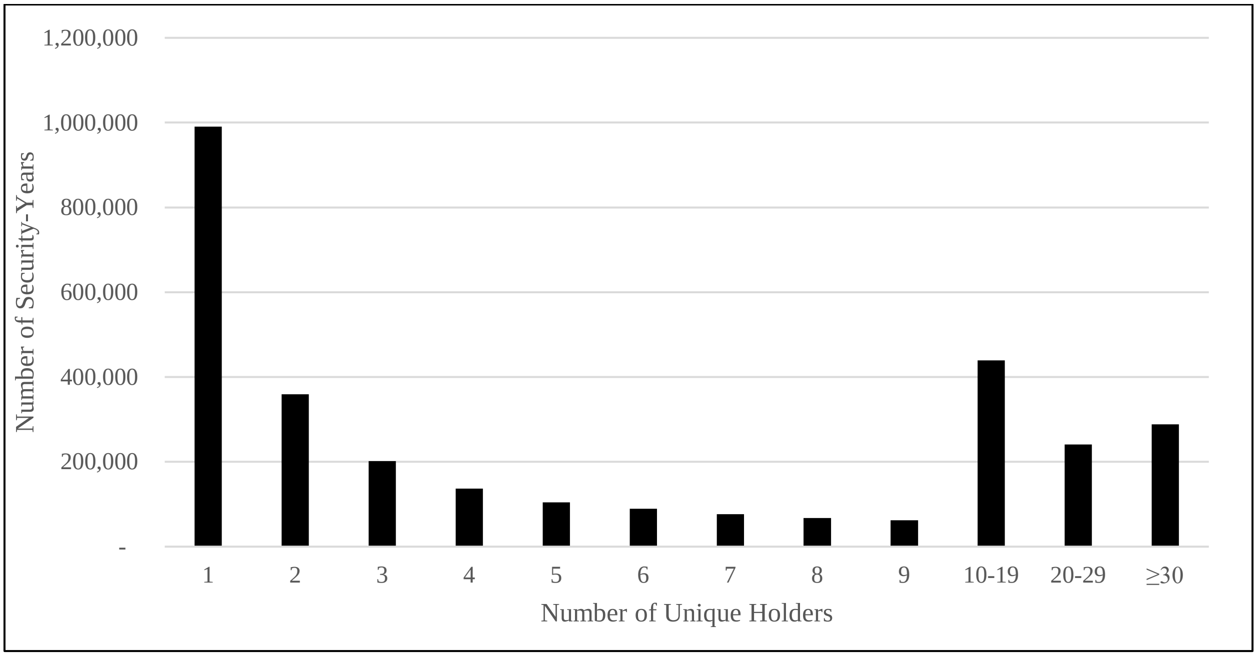

TABLE 1
Sample Selection

This table presents details of our sample. Panel A reports the sample selection procedures used to get to our final insurer-security-year sample, while Panel B presents the frequency of insurer-security-year observations by Reported Level and Mode Level. Reported Level is either the level reported by an individual insurer (for unaffiliated insurers) or the group mode level (for affiliated insurers). Mode Level represents the mode of Reported Level across all holders of a security in a given year.

Panel A: Details of Sample Selection

NAIC Schedule D Part 1 2012-2018 insurer-security-years (U.S. Insurers)	
Eliminate observations with non-positive par or fair values	3,476,652
Eliminate observations with missing necessary data	(402,999)
Truncate observations with fair values <0.5 or >99.5 percent	(16,912)
	3,056,741
Eliminate observations with less than 5 holders	(1,632,292)
	1,424,449
Eliminate observations without a mode level of 2	(104,043)
Final sample	1,320,406

Panel B: Summary of Reported Level versus Mode Level

	Mode Level			
Reported Level	1	2	3	All
1	61,679	106,155	6	167,840
2	41,943	1,209,286	109	1,251,338
3	27	4,965	279	5,271
All	103,649	1,320,406	394	1,424,449

TABLE 2
Descriptive Statistics

This table presents the descriptive statistics for our sample. Panel A provides descriptive statistics for the insurance companies in our sample, Panel B contains descriptive statistics for the investment securities in our sample with a mode level equal to 2, and Panel C provides a univariate analysis of fair value differences for our security-level sample. Appendix A provides variable definitions. Continuous variables are winsorized at the 1st and 99th percentiles.

Panel A: Insurer-Level Descriptive Statistics

	Mean	25th Perc.	Median	75th Perc.	Std. Dev.
Agg FV Difference	0.002	-0.019	0.000	0.019	0.135
Agg Abs(FV Difference)	0.122	0.015	0.055	0.143	0.197
% Audit Difference	0.267	0.077	0.188	0.446	0.244
Big 4	0.614	0.000	1.000	1.000	0.614
City Expert	0.422	0.000	0.000	1.000	0.494
Assets (billions)	0.637	0.025	0.087	0.333	2.028
% Bonds	0.592	0.433	0.625	0.776	0.238
Count Securities	96.86	14.00	44.00	111.00	179.96
ROA	0.025	0.006	0.024	0.047	0.056
Public	0.385	0.000	0.000	1.000	0.487
Insurer-Years	14,795				

Panel B: Security-Level Descriptive Statistics

	Mean	25th Perc.	Median	75th Perc.	Std. Dev.
FV	103.35	99.58	101.53	106.34	6.71
FV Difference	0.005	-0.001	0.000	0.004	0.255
Abs(FV Difference)	0.122	0.000	0.001	0.118	0.271
Audit Difference	0.346	0.000	0.000	1.000	0.476
Positive Audit Difference	0.184	0.000	0.000	0.000	0.388
Big 4	0.738	0.000	1.000	1.000	0.440
City Expert	0.393	0.000	0.000	1.000	0.488
Reported Level =1	0.080	0.000	0.000	0.000	0.272
Reported Level =2	0.916	1.000	1.000	1.000	0.278
Reported Level =3	0.004	0.000	0.000	0.000	0.061
Self-Estimated	0.012	0.000	0.000	0.000	0.110
PY Inflation	0.257	0.000	0.000	1.000	0.437
Reserve Error	0.027	0.000	0.000	0.000	0.163
Assets (in billions)	3.294	0.148	0.636	3.381	5.230
ROA	0.034	0.015	0.034	0.056	0.047
Public	0.464	0.000	0.000	1.000	0.499
Insurer-Years	1,320,406				

Panel C: Univariate Analysis of FV Differences

	Full Sample	Positive *FV Difference*	Negative *FV Difference*
Test: *FV Difference* = 0	0.005 ***		
	(23.45)		
Test: *Abs(FV Difference)* = 0	0.122 ***	0.162 ***	0.168 ***
	(517.71)	(389.72)	(369.37)

TABLE 3
Investment Fair Value Errors and Cues Indicating Greater Risk

This table presents the OLS regression results for the association between *Cues* and two different dependent variables: 1) the difference in reported fair values from the consensus (mode) fair value (*FV Difference*) in Columns (1)-(3) and 2) the likelihood of recording an audit difference in the investment fair values (Audit Difference) in Columns (4)-(6). Panel A provides regressions for the cue related to deviations in the reported level of the investment security from the consensus (mode) level using the variables *Reported Level=1* and *Reported Level=3*.Panel B provides regressions for the cue related to securities that are internally priced rather than priced by a third party using the variable *Self-Estimated*. Panel C provides regressions for the cue related to significant prior year aggregate inflation in an insurer's portfolio using the variable *PY Inflation*. For each dependent variable, the results are report for the full sample (Columns 1 and 4); only securities with a positive value for *FV Difference* (Columns 2 and 5), and only securities with a negative value for *FV Difference* (Columns 3 and 6). Note that instances where *FV Difference* equals 0 (i.e., the estimated fair value is equal to the mode) are included in columns (1) and (4) but are removed for purposes of separately examining only positive or negative subsamples. The dependent variable is *Abs(FV Difference)* for the analysis split by positive and negative differences to ease of interpretation. ***, **, * denote two-tailed significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Robust standard errors clustered by insurer are reported in parentheses. Appendix A provides variable definitions.

Panel A: Reported Level Deviation Cue

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Reported Level=1	**-0.006**	**-0.009**	**-0.000**	**-0.025***	**-0.052*****	**-0.032****
	(0.005)	**(0.011)**	**(0.009)**	**(0.015)**	**(0.020)**	**(0.015)**
Reported Level=3	**0.022**	**0.129*****	**0.092*****	**0.067**	**0.115****	**0.005**
	(0.014)	**(0.034)**	**(0.034)**	**(0.045)**	**(0.050)**	**(0.045)**
Size	0.002***	0.010***	0.008***	0.003**	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ROA	-0.016	0.051	0.024	0.010	0.041	0.069
	(0.018)	(0.034)	(0.030)	(0.050)	(0.057)	(0.056)
Intercept	-0.014**	0.031**	0.064***	0.310***	0.299***	0.330***
	(0.006)	(0.013)	(0.014)	(0.015)	(0.020)	(0.020)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.113	0.099	0.175	0.225	0.162

Panel B: Internal Pricing Cue

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Self-Estimated	**0.021**	**0.112****	**0.024**	**-0.010**	**0.008**	**-0.023**
	(0.017)	**(0.046)**	**(0.019)**	**(0.027)**	**(0.039)**	**(0.027)**
Size	0.002***	0.010***	0.008***	0.003***	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ROA	-0.015	0.054	0.024	0.010	0.042	0.070
	(0.018)	(0.035)	(0.030)	(0.050)	(0.057)	(0.055)
Intercept	-0.016***	0.027**	0.063***	0.305***	0.287***	0.324***
	(0.006)	(0.013)	(0.014)	(0.016)	(0.020)	(0.020)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.113	0.099	0.175	0.224	0.162

Panel C: Significant Prior Year Inflation Cue

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
PY Inflation	**0.006*****	**0.016*****	**0.012*****	**0.031*****	**0.033*****	**0.032*****
	(0.002)	**(0.004)**	**(0.003)**	**(0.006)**	**(0.007)**	**(0.006)**
Size	0.002***	0.010***	0.008***	0.003**	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.016	0.052	0.025	0.011	0.043	0.072
	(0.018)	(0.035)	(0.030)	(0.050)	(0.056)	(0.055)
Intercept	-0.017***	0.024*	0.061***	0.299***	0.281***	0.319***
	(0.006)	(0.013)	(0.014)	(0.016)	(0.020)	(0.020)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.112	0.099	0.176	0.225	0.163

Panel D: Error in Claim Loss Reserves

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Reserve Error	**0.009***	**0.012**	**-0.006**	**0.036*****	**0.048*****	**0.013**
	(0.005)	**(0.008)**	**(0.010)**	**(0.012)**	**(0.017)**	**(0.015)**
Size	0.002***	0.010***	0.008***	0.003***	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ROA	-0.013	0.054	0.022	0.022	0.056	0.075
	(0.018)	(0.035)	(0.030)	(0.050)	(0.056)	(0.056)
Intercept	-0.016***	0.027**	0.063***	0.302***	0.284***	0.323***
	(0.006)	(0.013)	(0.014)	(0.016)	(0.020)	(0.020)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.112	0.099	0.175	0.225	0.162

TABLE 4
Reported Level Deviations from the Norm Classification and Auditor Expertise

This table presents the OLS regression results for the association between FV differences and cues indicating heightened risk in settings where auditors have greater expertise. In this model, the cue relates to deviations in the reported level of the investment security from the consensus (mode) level. Panel A reports the results using Big 4 auditors (*Big 4*) while Panel B reports the results using local industry expert auditors (*City Expert*) as measures of *Auditor Expertise*. For each auditor type, the results are report for the full sample (columns 1 and 4), only securities with a positive value for *FV Difference* (columns 2 and 5), and only securities with a negative value for *FV Difference* (columns 3 and 6). Note that instances where *FV Difference* equals 0 (i.e., the estimated fair value is equal to the mode) are included in columns (1) and (4) but are removed for purposes of separately examining only positive or negative subsamples. ***, **, * denote two-tailed significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Robust standard errors clustered by insurer are reported in parentheses. Appendix A provides variable definitions.

Panel A: Big 4 Expertise and Reported Level Deviation Cue

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Big 4	-0.006	-0.023**	0.014	-0.039***	-0.063***	-0.010
	(0.005)	(0.010)	(0.014)	(0.015)	(0.017)	(0.017)
Reported Level=1	0.000	0.008	0.025*	-0.012	-0.025	-0.009
	(0.007)	(0.020)	(0.013)	(0.020)	(0.028)	(0.020)
Reported Level=3	0.128***	0.232***	0.070	0.287***	0.318***	0.144
	(0.036)	(0.067)	(0.070)	(0.098)	(0.106)	(0.109)
Big 4 × Reported Level=1	**-0.011**	**-0.034***	**-0.042*****	**-0.026**	**-0.055***	**-0.040**
	(0.008)	**(0.020)**	**(0.016)**	**(0.025)**	**(0.033)**	**(0.026)**
Big 4 × Reported Level=3	**-0.130*****	**-0.132***	**0.026**	**-0.270*****	**-0.262****	**-0.162**
	(0.038)	**(0.074)**	**(0.080)**	**(0.103)**	**(0.113)**	**(0.117)**
Size	0.002***	0.010***	0.008***	0.003***	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.017	0.048	0.021	0.006	0.035	0.065
	(0.018)	(0.034)	(0.030)	(0.050)	(0.057)	(0.056)
Intercept	-0.011	0.045***	0.055***	0.334***	0.338***	0.336***
	(0.007)	(0.015)	(0.014)	(0.019)	(0.024)	(0.023)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.033	0.113	0.100	0.176	0.226	0.162

Panel B: City Expertise and Reported Level Deviation Cue

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
City Expert	0.005**	0.001	-0.020***	-0.016**	-0.003	-0.026***
	(0.003)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Reported Level=1	-0.002	-0.006	-0.006	-0.024	-0.040*	-0.034**
	(0.006)	(0.014)	(0.010)	(0.016)	(0.022)	(0.017)
Reported Level=3	0.046**	0.168***	0.127***	0.108*	0.159**	0.046
	(0.021)	(0.043)	(0.040)	(0.064)	(0.066)	(0.061)
City Expert* × *Reported Level=1	**-0.009**	**-0.008**	**0.017**	**-0.001**	**-0.030**	**0.011**
	(0.007)	**(0.015)**	**(0.015)**	**(0.023)**	**(0.028)**	**(0.026)**
City Expert* × *Reported Level=3	**-0.057****	**-0.109****	**-0.075**	**-0.099**	**-0.122***	**-0.088**
	(0.024)	**(0.049)**	**(0.053)**	**(0.068)**	**(0.073)**	**(0.072)**
Size	0.002***	0.010***	0.008***	0.003**	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ROA	-0.014	0.051	0.019	0.005	0.038	0.061
	(0.019)	(0.035)	(0.030)	(0.050)	(0.057)	(0.055)
Intercept	-0.017***	0.030**	0.072***	0.316***	0.300***	0.341***
	(0.006)	(0.013)	(0.015)	(0.016)	(0.021)	(0.019)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.113	0.100	0.175	0.225	0.163

TABLE 5
Internal Pricing of Securities and Auditor Expertise

This table presents the OLS regression results for the association between FV differences and cues indicating heightened risk in settings where auditors have greater expertise. In this model, the cue relates to securities that are internally priced rather than priced by a third party. Panel A reports the results using Big 4 auditors (*Big 4*) while Panel B reports the results using local industry expert auditors (*City Expert*) as measures of *Auditor Expertise*. For each auditor type, the results are report for the full sample (columns 1 and 4), only securities with a positive value for *FV Difference* (columns 2 and 5), and only securities with a negative value for *FV Difference* (columns 3 and 6). Note that instances where *FV Difference* equals 0 (i.e., the estimated fair value is equal to the mode) are included in columns (1) and (4) but are removed for purposes of separately examining only positive or negative subsamples. ***, **, * denote two-tailed significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Robust standard errors clustered by insurer are reported in parentheses. Appendix A provides variable definitions.

Panel A: Big 4 Expertise and Internal Pricing of Securities

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Big 4	-0.007	-0.026***	0.009	-0.041***	-0.067***	-0.013
	(0.004)	(0.010)	(0.013)	(0.014)	(0.016)	(0.016)
Self-Estimated	0.146**	0.381**	0.100**	0.126**	0.250***	0.011
	(0.067)	(0.159)	(0.039)	(0.052)	(0.081)	(0.053)
Big 4 × Self-Estimated	**-0.150****	**-0.333****	**-0.087***	**-0.162*****	**-0.298*****	**-0.039**
	(0.067)	**(0.161)**	**(0.044)**	**(0.061)**	**(0.088)**	**(0.066)**
Size	0.002***	0.010***	0.008***	0.003***	0.014***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.016	0.053	0.026	0.007	0.039	0.069
	(0.018)	(0.034)	(0.029)	(0.050)	(0.056)	(0.055)
Intercept	-0.012*	0.044***	0.057***	0.330***	0.328***	0.331***
	(0.007)	(0.015)	(0.014)	(0.019)	(0.024)	(0.023)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.033	0.115	0.099	0.175	0.225	0.162

Panel B: City Expertise and Internal Pricing of Securities

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
City Expert	0.004	0.000	-0.017***	-0.015**	-0.006	-0.023***
	(0.003)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Self-Estimated	0.010	0.170**	0.076***	0.035	0.037	0.066*
	(0.032)	(0.082)	(0.023)	(0.047)	(0.065)	(0.035)
City Expert × Self-Estimated	**0.020**	**-0.125**	**-0.102*** **	**-0.090***	**-0.061**	**-0.178*** **
	(0.034)	**(0.087)**	**(0.031)**	**(0.051)**	**(0.075)**	**(0.044)**
Size	0.002***	0.010***	0.008***	0.003***	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ROA	-0.014	0.055	0.018	0.004	0.040	0.062
	(0.019)	(0.035)	(0.030)	(0.050)	(0.057)	(0.055)
Intercept	-0.017***	0.026*	0.070***	0.310***	0.289***	0.332***
	(0.006)	(0.014)	(0.015)	(0.016)	(0.021)	(0.019)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.114	0.100	0.175	0.224	0.163

TABLE 6
Significant Prior Year Investment Portfolio Inflation and Auditor Expertise

This table presents the OLS regression results for the association between FV differences and cues indicating heightened risk in settings where auditors have greater expertise. In this model, the cue relates to significant prior year aggregate inflation in an insurer's portfolio. Panel A reports the results using Big 4 auditors (*Big 4*) while Panel B reports the results using local industry expert auditors (*City Expert*) as measures of *Auditor Expertise*. For each auditor type, the results are report for the full sample (columns 1 and 4), only securities with a positive value for *FV Difference* (columns 2 and 5), and only securities with a negative value for *FV Difference* (columns 3 and 6). Note that instances where *FV Difference* equals 0 (i.e., the estimated fair value is equal to the mode) are included in columns (1) and (4) but are removed for purposes of separately examining only positive or negative subsamples. ***, **, * denote two-tailed significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Robust standard errors clustered by insurer are reported in parentheses. Appendix A provides variable definitions.

Panel A: Big 4 Expertise and Significant Prior Year Inflation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Big 4	-0.010**	-0.033***	0.011	-0.038***	-0.071***	-0.007
	(0.005)	(0.010)	(0.013)	(0.015)	(0.017)	(0.016)
PY Inflation	0.000	0.004	0.016***	0.043***	0.029***	0.051***
	(0.003)	(0.007)	(0.005)	(0.009)	(0.009)	(0.012)
Big 4 × PY Inflation	**0.008****	**0.015***	**-0.006**	**-0.016**	**0.005**	**-0.027****
	(0.004)	**(0.008)**	**(0.007)**	**(0.010)**	**(0.011)**	**(0.014)**
Size	0.002***	0.010***	0.008***	0.003***	0.014***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.016	0.050	0.026	0.008	0.040	0.072
	(0.018)	(0.034)	(0.029)	(0.050)	(0.056)	(0.055)
Intercept	-0.011*	0.045***	0.054***	0.322***	0.324***	0.322***
	(0.007)	(0.014)	(0.014)	(0.019)	(0.023)	(0.023)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.113	0.099	0.176	0.225	0.163

Panel B: City Expertise and Significant Prior Year Inflation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
City Expert	0.007**	0.001	-0.018***	-0.018***	-0.005	-0.031***
	(0.003)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)
PY Inflation	0.010***	0.016***	0.012***	0.026***	0.034***	0.021***
	(0.002)	(0.005)	(0.004)	(0.007)	(0.008)	(0.007)
City Expert × PY Inflation	**-0.011****	**0.000**	**0.000**	**0.014**	**-0.002**	**0.031****
	(0.004)	**(0.008)**	**(0.006)**	**(0.011)**	**(0.012)**	**(0.012)**
Size	0.002***	0.010***	0.008***	0.003**	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.013	0.052	0.019	0.004	0.042	0.061
	(0.018)	(0.035)	(0.030)	(0.050)	(0.056)	(0.055)
Intercept	-0.020***	0.024*	0.069***	0.307***	0.283***	0.332***
	(0.006)	(0.013)	(0.015)	(0.016)	(0.020)	(0.020)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.112	0.099	0.176	0.225	0.163

TABLE 7
Prior Year Bias in Other Significant Estimates and Auditor Expertise

This table presents the OLS regression results for the association between FV differences and cues indicating heightened risk in settings where auditors have greater expertise. In this model, the cue relates to previous management bias in an unrelated accounting estimate (i.e., claim loss reserves) as indicated by the insurance regulator. Panel A reports the results using Big 4 auditors (*Big 4*) while Panel B reports the results using local industry expert auditors (*City Expert*) as measures of *Auditor Expertise*. For each auditor type, the results are report for the full sample (columns 1 and 4), only securities with a positive value for *FV Difference* (columns 2 and 5), and only securities with a negative value for *FV Difference* (columns 3 and 6). Note that instances where *FV Difference* equals 0 (i.e., the estimated fair value is equal to the mode) are included in columns (1) and (4) but are removed for purposes of separately examining only positive or negative subsamples. ***, **, * denote two-tailed significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Robust standard errors clustered by insurer are reported in parentheses. Appendix A provides variable definitions.

Panel A: Big 4 Expertise and Reserve Error

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
Big 4	-0.008*	-0.028***	0.009	-0.042***	-0.070***	-0.014
	(0.004)	(0.010)	(0.013)	(0.014)	(0.016)	(0.016)
Reserve Error	0.005	0.005	-0.008	0.021	0.028	-0.006
	(0.006)	(0.013)	(0.015)	(0.018)	(0.029)	(0.020)
Big 4 × Reserve Error	**0.006**	**0.008**	**0.005**	**0.021**	**0.027**	**0.029**
	(0.009)	**(0.016)**	**(0.020)**	**(0.025)**	**(0.036)**	**(0.029)**
Size	0.002***	0.010***	0.008***	0.003***	0.014***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ROA	-0.013	0.053	0.023	0.019	0.053	0.075
	(0.018)	(0.035)	(0.030)	(0.050)	(0.056)	(0.056)
Intercept	-0.012*	0.044***	0.058***	0.328***	0.327***	0.331***
	(0.007)	(0.015)	(0.014)	(0.019)	(0.024)	(0.023)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.112	0.099	0.175	0.225	0.162

Panel B: City Expertise and Reserve Error

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*FV Difference*	*Abs(FV Difference*	*Abs(FV Difference*	*Audit Difference*	*Audit Difference*	*Audit Difference*
	Full Sample	Positive	Negative	Full Sample	Positive	Negative
City Expert	0.004	-0.001	-0.020***	-0.019***	-0.010	-0.029***
	(0.003)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Reserve Error	0.008	0.001	-0.019*	0.014	0.026	-0.015
	(0.006)	(0.008)	(0.011)	(0.012)	(0.018)	(0.017)
City Expert × Reserve Error	**0.001**	**0.032****	**0.042****	**0.074*****	**0.068****	**0.086*****
	(0.009)	**(0.016)**	**(0.020)**	**(0.025)**	**(0.032)**	**(0.030)**
Size	0.002***	0.010***	0.008***	0.003***	0.013***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ROA	-0.012	0.052	0.015	0.013	0.050	0.064
	(0.019)	(0.035)	(0.030)	(0.050)	(0.056)	(0.056)
Intercept	-0.018***	0.027**	0.071***	0.310***	0.288***	0.334***
	(0.006)	(0.014)	(0.015)	(0.016)	(0.021)	(0.019)
Group and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,320,406	521,310	459,906	1,320,406	521,310	459,906
R^2	0.032	0.112	0.099	0.175	0.225	0.162

APPENDIX A
Variable Definitions

FV	fair value of security *s* (held by insurer *i* in year *t*) per $100 of par value.
FV Difference	difference between the fair value as proportion of par value for security *s* (held by insurer *i* in year *t*) and the consensus (mode) fair value as a proportion of par value of security *s* across all insurers in year *t*.
Abs(FV Difference)	absolute value of *FV Difference*.
Agg FV Difference	sum of fair value difference for all securities in the portfolio divided by the total par value of the portfolio of insurer *i* in year *t*.
Agg Abs(FV Difference)	sum of the absolute value of the fair value difference for all securities in the portfolio divided by the total par value of the portfolio of insurer *i* in year *t*.
Audit Difference	indicator variable equal to 1 if the *Abs(FV Difference)* of security *s* is greater than 0.05 (five percent) in year *t*, 0 otherwise.
Big 4	indicator variable equal to 1 if insurer *i* is audited by a Big 4 accounting firm in year *t*, and 0 otherwise.
City Expert	indicator variable equal to 1 if insurer *i* is audited by an auditor that is the market leader based on client count and also has at least 10 percent greater market share than its closest competitor within a given MSA in year *t*, and 0 otherwise.
Reported Level=1	indicator variable equal to 1 if the reported level of security *s* (held by insurer *i* in year *t*) is Level 1, and 0 otherwise.
Reported Level=2	indicator variable equal to 1 if the reported level of security *s* (held by insurer *i* in year *t*) is Level 2, and 0 otherwise.
Reported Level=3	indicator variable equal to 1 if the reported level of security *s* (held by insurer *i* in year *t*) is Level 3, and 0 otherwise.
Self-Estimated	indicator variable equal to 1 if the fair value of security *s* (held by insurer *i* in year *t*) is determined by the insurer and not by a third party, and 0 otherwise.

PY Inflation	indicator variable equal to 1 if the insurer was in the top quartile of aggregate FV difference in year *t-1*, 0 otherwise.
Reserve Error	indicator variable equal to 1 if the insurer was in violation of the acceptable range for the two-year development to policyholder surplus ratio (IRIS Ratio 12) for the current and prior year, 0 otherwise.
Assets	total assets of insurer *i* as of year-end *t* (in billions).
Size	natural logarithm of total assets (*Assets*) for insurer *i* as of year-end *t*.
Bonds	total bonds of insurer *i* as of year-end *t* (in millions).
% Bonds	total bonds as a percentage of total assets of insurer *i* as of year-end *t*.
Count Securities	count of sample securities held by insurer *i* as of year-end *t*.
ROA	net income before policyholder dividends and taxes divided by total assets for insurer *i* in year *t*.
Public	indicator variable equal to 1 insurer *i* is publicly traded (i.e., listed on CRSP), and 0 otherwise.