Does Intent Modify Risk-Based Auditing?

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ABSTRACT: Risk-based auditing implies that auditors invest more (fewer) resources as reporting risks increase (decrease). We find from an interactive experiment that participants in an audit-like role reflect this reasoning to a lesser extent when risks arise from intentional actions of human reporters than when the same risks arise from an unintentional source. We interpret this pattern as reflecting an emotive “valuation by feeling” when risks arise from human intent, meaning that the presence of risk is more influential than the magnitude of risk, whereas unintentional risks reflect a “valuation by calculation” that conditions audit resources on risk magnitudes. Because our experiment constrains intentional and unintentional risks to have equivalent magnitudes, probabilities, and consequences, these results could seem irrational in a strict economic sense. Outside the laboratory, however, reporters can strategically increase the level of intent-based risk in response to the auditor's low-risk strategy, such that an audit strategy that is relatively insensitive to the level of intent-based risk would be less vulnerable to strategic exploitation.

Keywords: risk-based auditing; fraud; intent; risk; scale insensitivity; experimental economics.

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I. INTRODUCTION

Audit practitioners (e.g., see Weil 2004; Bell, Peecher, and Solomon 2005; Knechel 2007) and regulators (e.g., Public Company Accounting Oversight Board [PCAOB] 2010a, 2010b) have embraced the concept of “risk-based auditing,” under which auditors expend more resources to address significant risks and fewer resources when risks are lower. In this study, we investigate why this reasoning might not apply equally to risks arising from intentional and unintentional sources. In particular, we apply the theory of “valuation by feeling” (Hsee and Rottenstreich 2004) to develop the premise that people are more sensitive to the presence of risk than to the magnitude of risk when individuals sense that they could be cheated by others’ intentional actions. If so, risks stemming from willful intent could dampen the mapping from risk magnitudes to desired audit resources, ceteris paribus. We design an interactive, compensated experiment to test this premise.

From a regulatory standpoint, recent PCAOB risk assessment standards state that, while “more evidence is needed to respond to significant risks” (PCAOB 2010b, ¶5), “a fraud risk is a significant risk” by its very nature (PCAOB 2010a, ¶71). In practice, one reason fraud risks can be significant is because they can lead to more pervasive consequences at the financial statement level than risks arising from unintentional errors. Setting this point aside, our research premise speaks to the more fundamental possibility that risks stemming from the willful intent of others can trigger a “significant” response independent of the magnitudes and consequences of such risks. That is, when facing a known intentional risk, “valuation by feeling” suggests that the desired level of audit resources is relatively invariant to the level of risk.

Our study seeks a deeper understanding of what “risk-based auditing” means from a behavioral perspective. Specifically, if auditors react similarly to high and low levels of intent-based risks, then this propensity would suggest an incremental aversion to intent that goes beyond a strict cost-benefit interpretation of risk-based auditing. It is difficult to isolate any such aversion using archival or narrative-based experimental approaches, as intentional and unintentional sources of risk generally imply different economic consequences. The experimental economics approach we use affords greater control to hold risk magnitudes and consequences constant, thereby allowing us to isolate the behavioral effects of intentional versus unintentional risks.

We design a 2 × 4 factorial experiment with risk source as a between-participants factor (two levels) and risk magnitude as a within-participants factor (four levels). In the “intentional” risk source condition, auditor-participants choose how much they wish to spend to verify the assertions of human reporters who decide on levels of misrepresentation. We use neutral terminology to avoid prompting participants’ behavior with vivid words such as “fraud” (Haynes and Kachelmeier 1998), but risks in this condition clearly arise from other participants’ decisions. We then structure an “unintentional” risk source condition in which auditors make the same decisions against a computer program that determines the extent of misrepresentation. We program the computer in the unintentional risk sessions to mimic the reports of the intentional risk sessions, such that auditors literally face the same monetary risks. We also provide auditor-participants in both conditions with the same ex ante probability distributions of misrepresentations that we obtain from a pilot experiment, establishing the same expectation benchmarks. In short, we use the tools of experimental economics to hold risk magnitudes and probabilities constant, thereby isolating the qualitative construct of whether the same risks arise from the decisions of another participant or from a computer program.

To operationalize risk levels, the experiment presents auditor-participants with four discrete magnitudes of potential losses from misreporting, a proxy for different levels of risk exposure. Auditors can protect against this exposure by investing to verify the reported amount, with greater investments lowering the probability of loss at the stated level of risk. We elicit the maximum...
investments auditors are willing to pay at each risk level, thereby obtaining a mapping for each participant from different levels of risk to different audit resources. This design enables us to compare risk-to-investment mappings when risks reflect willful human intent to the mappings that occur when the same risks arise from an unintentional source.

Our primary finding is a significant interaction between the source of risk and the level of risk. Within the unintentional risk condition, audit expenditures decline markedly as risks decline, consistent with what Hsee and Rottenstreich (2004) characterize as a "valuation by calculation" that weighs costs against benefits. Within the intentional risk condition, expenditures are similar to the unintentional risk condition when the level of risk is high, but do not decline as much when risks decline, resulting in a flatter mapping from risk levels to audit resources. At the lowest risk level, average investments in the intentional risk condition even exceed the total amount at risk. This pattern is consistent with what Hsee and Rottenstreich (2004) characterize as "valuation by feeling," whereby responses to emotive stimuli, captured in our setting by the potential for being cheated by another party, are relatively insensitive to scale.

Within our controlled experimental setting, one could argue that the behavior we observe is economically "irrational," at least from a monetary perspective, insofar as participants expend different amounts to protect themselves from the same magnitudes and probabilities of monetary loss across the intentional and unintentional risk conditions. Accordingly, our findings suggest the possibility that heightened sensitivity to intent-based risks could be dysfunctional if fraud risks are truly low, leading auditors to do too much work. Real-world audit settings, however, cannot provide the strict control our experiment uses to hold the stated risk levels constant. In particular, unlike unintentional risks that arise in practice from mostly exogenous sources, risks that arise in practice from human intent are endogenous, meaning that clients can respond strategically to opportunities presented by auditors' actions (Bowlin 2011). Specifically, if an auditor were to invest low resources in the presence of low fraud risk, then that risk might not stay low later in the current or the next audit period if the client responds to the auditor's low-risk strategy by increasing the level of misstatement to exploit the auditor's vulnerability (e.g., Weil 2004). Our experiment precludes this possibility by design, but to the extent that our findings generalize outside the laboratory, the behavioral tendency we observe could serve to protect auditors in practice. Many simplifying behavioral heuristics can be seemingly "irrational" in isolation and yet can also be beneficially adaptive in more complex environments (Gigerenzer, Hertwig, and Pachur 2011). Similarly, a tendency to be relatively insensitive to the magnitude of risk when intent is involved could serve to protect auditors from strategic vulnerability when clients can observe auditors' strategies and change the level of misstatement risk in response.

In a richer, multiperiod economic setting, auditors and reporters could plausibly achieve equilibrium by "mixing," with reporters varying the level of misreporting and auditors varying the level of audit resources across periods to guard against predictable strategic responses (e.g., Bowlin, Hales, and Kachelmeier 2009). While our single-stage experiment does not address this possibility, we identify a simpler behavioral response to the presence of intentional risk, namely, that of always investing a similarly high level of audit resources when facing risk arising from human intent, irrespective of the level of that risk. If audit resources are relatively invariant to the level of intentional risk, then auditors might well be overauditing when the level of intentional risk is low, but auditors would be less vulnerable to the possibility of underauditing when the level of intentional risk is high, especially in an environment in which it is difficult to estimate the true level of intentional misreporting risk due to strategic variability in that risk.

From this perspective, our study complements a related, but conceptually distinct, experiment by Bowlin (2011), who also uses an experimental economics approach. In Bowlin (2011), participants in the auditor role expend resources to test accounts with both unintentional and intentional risks of misstatement. Bowlin (2011) manipulates the unintentional risks at either high
or low levels, while the intentional risks emerge endogenously from the decisions of human reporters. He finds that auditors are vulnerable to strategic exploitation by reporters when the level of unintentional risk is low, unless prompted to consider the potential for willful misstatement. In our study, by contrast, risks arise entirely from an unintentional source or entirely from the intent of reporters, holding risk magnitudes and probabilities constant. Because we manipulate human intent as a treatment factor, the sensitivity to intent is likely very salient to participants in our intent-based condition. Bowlin’s (2011) findings show that, absent a strategic reasoning prompt, intent is not so salient in settings that combine intentional and unintentional risks, which helps to explain why auditors can devote too little resources to fraud risks in practice. Once sensitized to intent, however, our findings suggest that such sensitization is not merely a “main effect” that shifts the risk-to-resource mapping upward. Rather, human intent appears to exert an interactive effect that flattens the risk-to-resource mapping by changing the cognitive mindset of risk from a magnitude-based calculation to a more basic aversion to the presence of intent-based risks, irrespective of magnitude.

Section II discusses the literature in greater detail as the basis for our key hypothesized interaction between risk source and risk level. Section III describes the incentivized experiment we design to test our hypothesis. Section IV presents our results and supplemental analyses to validate our key findings, and Section V concludes.

II. THEORY AND HYPOTHESIS

Isolating the Incremental Effect of Intent

Recent years have highlighted audit failures involving fraudulent misreporting, whereas cases in which an auditor fails to detect an unintentional error draw far less attention (e.g., Palmrose, Richardson, and Scholz 2004; Hennes, Leone, and Miller 2008). Despite the apparent importance of fraudulent intent, it is difficult to isolate the incremental effect of intent on auditors using archival data, due to the different magnitudes, likelihoods, and consequences of the intentional versus unintentional reporting risks that auditors face. This difficulty is present even in narrative-based experiments of the “judgment and decision-making” tradition, as contextually rich descriptions of intentional versus unintentional misstatements can imply different economic scenarios even if the amounts of misstatement are equivalent (e.g., Houston, Peters, and Pratt 1999). In the current study, a more abstract experimental economics approach enables us to isolate any incremental sensitivity to misreporting risks reflecting human intent, relative to unintentional risks with the same magnitudes, probabilities, and consequences.

The importance of our research question is further illustrated in comparison to recent experiments by Bowlin (2011) and by Hoffman and Zimbelman (2009). Using an experimental economics design, Bowlin (2011) finds that auditor-participants can be exploited by intentional misreporting that arises endogenously in a setting with a low risk of unintentional error, unless prompted to consider the strategic implications of their resource allocations. In a more contextually rich experiment in the psychology-based “judgment and decision-making” tradition, Hoffman and Zimbelman (2009) find that a strategic reasoning prompt and “brainstorming” techniques can sensitize auditors to fraud risks in modifying audit plans.

While these experiments show how sensitizing auditors to intent-based risks can modify auditors’ strategies, their designs do not directly compare auditor responses to intentional versus unintentional risks and, hence, they do not capture the extent of any incremental aversion to intent-based risks. Accordingly, we direct our study to the more fundamental question of whether there is any differential sensitivity to risks that are entirely intentional or entirely unintentional, ceteris paribus. If so, our study can help to identify the cognitive mechanism through which strategic
reasoning prompts such as those examined by Bowlin (2011) and Hoffman and Zimbelman (2009) can be effective. Specifically, we examine how human intent can change the way that people view risk, from a “calculative” interpretation based on the magnitude of risk to a more qualitative interpretation based primarily on the presence of risk. With such a mindset, auditors would be less likely to “back off” even when perceiving fraud risks to be low, which could help to protect auditors from strategic vulnerability in richer settings that present reporters with opportunities to change the level of fraud risk after observing auditor actions.

In behavioral neuroeconomics, Baumgartner, Heinrichs, Vonlanthen, Fischbacher, and Fehr (2008) assert that the feeling of being cheated by another human triggers a visceral, “hard-wired” aversion in the human psyche that is incremental to the associated economic loss.1 Bohnet and Zeckhauser (2004) and Bohnet, Greig, Herrmann, and Zeckhauser (2008) test this premise in simple lottery experiments, in which participants specify the minimum probability of success at which they prefer the lottery over a certain cash payoff. They find an incremental risk premium when the probability of success depends on the action taken by a different participant than when the probability of success is determined mechanically to be the same as in the intent-based condition. Houser, Schunk, and Winter (2010) find more mixed results in a “trust game” (Berg, Dickhaut, and McCabe 1995), with no discernable difference in average investments between human and equivalently structured mechanical trustees, but with greater variability in the version with human trustees. Perhaps the most vivid illustration of an incremental aversion to intentional harm is a study by Gray and Wegner (2008), in which participants report the same (real) electric shocks to be more painful when they are told that another participant has assigned them to a task involving mild electric shocks than when the same task is represented as having been assigned randomly. Overall, these studies suggest an incremental sensitivity to human intent, but the findings vary, the settings do not capture the defining audit characteristic of verifying reports, and the results are limited to the main effect of intent rather than the interaction between intent and the level of risk.

In the management accounting literature, Evans, Hoffman, and Rau (1994), Birnberg, Hoffman, and Yuen (2008), and Birnberg and Zhang (2011) find that experimental participants are willing to pay a premium for human accountability in designing control systems. That is, people seem to care not only about control risks per se, but also about whether such risks reflect vulnerability to human intent. Like the behavioral economics studies cited above, these authors do not examine the interaction between intent and the level of control risk.

In auditing, Houston et al. (1999) conduct an experiment in which auditors specify the audit resources and fees they would demand for a client that, due to the prior detection of a material error or irregularity, has a high current likelihood of either an unintentional error or an intentional reporting irregularity. Participants in the irregularity condition are more sensitive to business risk, driving increases in audit resources and a greater risk premium in audit pricing. The contextually rich materials in Houston et al. (1999) allow the authors to examine features that are not present in our experiment, such as audit fees and experienced auditors. However, a related limitation is that participants could potentially infer different probabilities of loss, different implied consequences, and/or other economic differences between the “error” and “irregularity” conditions, thereby making it difficult to isolate the qualitative construct of human intent. Further, because Houston et al. (1999) compare their error and irregularity conditions at only one level, they do not address the association between audit resources and different risk levels that is central to our interest in risk-based auditing. We now turn to this association in developing a predicted interaction between the intentional versus unintentional source of risk and the level of risk.

1 From a social evolutionary perspective, a natural aversion to being cheated has likely arisen over the centuries as a protective means to punish and, hence, deter behavior that is harmful to society, similar to the phenomenon of “altruistic punishment” (Fehr and Gächter 2002).
Intent and Risk-Based Auditing

Our study’s primary contribution is to go beyond the main effect of intent to examine the interaction between intentional versus unintentional risk and the level of such risk, thereby examining intent within the context of risk-based auditing. To develop a theoretical basis for an interaction between intent and risk levels, we turn to a different literature that contrasts the rational, calculative responses that characterize economic reasoning against the more visceral reactions people associate with stimuli of a more emotional nature. The primal finding from this literature is that emotional, visceral responses tend to be characterized by scale insensitivity, meaning that the presence of a stimulus is more important than the level of that stimulus (Kahneman, Ritov, and Schkade 1999; Hsee and Rottenstreich 2004; Pham 2007). Of particular importance to our study is Hsee and Rottenstreich’s (2004) distinction between “valuation by calculation” and “valuation by feeling.” Standard economic trade-offs fall under the “valuation by calculation” form of reasoning, whereby decision-makers balance the costs of a decision against the benefits obtained. Conversely, when an emotion-laden stimulus prompts “valuation by feeling, value is highly sensitive to the presence or absence of a stimulus (i.e., a change from zero to some scope) but is largely insensitive to further variations in scope” (Hsee and Rottenstreich 2004, 23). Similarly, Pham (2007, 163) concludes from a review of several studies that, “when integral affective [i.e., emotional or visceral] responses are used as proxies for value, these responses are not scaled properly for either magnitude or probability.”

We posit that a potential loss from an intentionally misstated report likely prompts an emotional, visceral reaction to the thought of being cheated by someone else. If so, the logical appeal of risk-based auditing should be less pronounced for intent-based reporting risks, to the extent that “valuation by feeling” leads auditors to perceive the presence of an intentional misstatement risk as more important than the magnitude of that risk. In contrast, an unintentional misreporting risk is likely to prompt a more reasoned “valuation by calculation,” whereby auditors balance different costs of investigation against different levels of exposure.

The PCAOB hints at an interaction of this nature in its recent suite of risk assessment standards. Specifically, in listing the criteria an auditor should consider in gauging the significance of risks for audit planning, the PCAOB (2010a, ¶71) first lists the “likelihood and potential magnitude of misstatement.” The second criterion is to assess “whether the risk is a fraud risk,” noting that “a fraud risk is a significant risk” by its very nature. The most likely intent of this wording is to suggest that fraud risks can imply pervasive concerns at the financial statement level. Nevertheless, viewing all fraud risks as significant is also consistent with a “valuation by feeling” for such risks, as opposed to the “valuation by calculation” from other misstatement risks that hinge more on specific likelihoods and magnitudes.

In the accounting literature, Zimbelman (1997) is one of the few studies that compare high and low fraud risks. Specifically, Zimbelman’s (1997) contextually rich experiment manipulates (1) whether auditors are prompted to evaluate fraud risk separately or as part of a holistic assessment of misstatement risk, and (2) whether the cues in the experimental materials suggest a high or low level of fraud risk. The study’s primary finding is that decomposing the fraud-risk assessment leads to an increase in budgeted audit hours. An intriguing secondary finding, however, is that auditors do not appear to differentiate between the high and low fraud risk settings. In a follow-up study, Glover, Prawitt, Schultz, and Zimbelman (2003) find more evidence of auditor sensitivity to the level of fraud risk. Nevertheless, Zimbelman’s (1997) original finding suggests behavior consistent with a scale-insensitive “valuation by feeling” for fraud risks, which we believe warrants further consideration in our experimental economics design that directly compares different levels of intent-based risks against the same levels of risk from an unintentional source.
To summarize, behavioral economics studies suggest that harm arising from human intent triggers an emotive aversion that is incremental to the aversion associated with the harm itself. In addition, the literature on scale insensitivity indicates that people perceive magnitude to be less important for emotive “valuations by feeling” than for the “valuations by calculation” that characterize nonemotive reasoning. Together, these two bodies of literature motivate our core hypothesis of how the intentional versus unintentional source of risk is likely to interact with the level of risk in determining the desired level of audit resources:

**H:** The mapping from different levels of risk to different levels of audit resources will be less pronounced for risks arising from human intent than for the same risks arising from an unintentional source, *ceteris paribus.*

### III. METHOD AND DESIGN

**Task**

We recruit 83 undergraduate business student volunteers to participate in a one-shot experiment that we program using the “Z-tree” computer architecture for interactive experiments ([Fischbacher 2007](#)). Of the 83 participants, 55 assume a role analogous to an auditor, randomly assigned between the intentional risk condition (n = 28) and the unintentional risk condition (n = 27). The remaining 28 participants serve as human reporters in the intentional risk condition. The 55 auditor-participants use the “strategy” method to specify the maximum amounts they are willing to pay to protect against different specified levels of misreporting risk. Throughout, the experimental instructions avoid contextually rich terms such as “auditor” or “fraud” to minimize any unintended influences of role playing ([Haynes and Kachelmeier 1998](#)). All participants must correctly answer a series of computerized pre-experimental questions to confirm their understanding of the instructions before continuing to the experimental task.³

A one-shot game precludes any moderating effects of reputations or feedback (e.g., [King 1996; Mayhew 2001](#)). The reason for this design choice is that reputations and feedback could prompt auditors to try to influence subsequent misreporting by “punishing” early misreporting. Because the same behavior would not be possible in the unintentional risk condition, a multiperiod setting could threaten our ability to maintain equivalent intentional versus unintentional misreporting risks. Thus, while future research could incorporate multiperiod considerations, this study seeks to isolate any incremental aversion to intent-based risks in a setting that minimizes the potential for alternative interpretations.

Auditor-participants begin with an endowment of $30.00, with the understanding that they will subsequently learn one of five reported values from a human reporter (intentional risk condition) or from a computer (unintentional risk condition). The five potential reported values are $10.00, $17.50, $25.00, $32.50, or $40.00, which are also the five potential actual values underlying the reports. However, the reported value can be less than the actual value. Auditor-participants face loss exposure equal to 75 percent of any excess of the actual over the reported values. To protect themselves against this exposure, auditor-participants can invest any whole-dollar amount of their $30.00 endowment as a maximum verification fee, where greater investments offer greater protection, as explained below.

To simplify the task and avoid complex interactions among reporters, auditors, and investors, we operationalize risk as *under-reporting* to an auditor charged with protecting the entrusted funds,

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2 We obtained human-subjects approval from the university in which the experiment took place.

3 Incorrect answers direct the participant to a tutorial screen, followed by repeating the same question.
rather than over-reporting to inflate a security’s perceived value to investors. Accordingly, our setting is best characterized as stewardship reporting (e.g., see O’Connell 2007). This design choice makes the notion of “feeling cheated” more salient in the intent-based condition, because the auditor directly incurs the cost of misappropriation from under-reporting, as in the Baiman, Evans, and Noel (1987) auditing model. In real-world audit settings, the consequences of misreporting to auditors are more indirect, generally involving actions instigated by third-party investors. Nevertheless, real-world auditors do tend to incur higher regulatory and/or civil penalties for bigger misrepresentations, and if those misrepresentations are intentional, then auditors could experience the intent-based aversion that drives our theoretical premise. Thus, while real-world auditing features could dampen the phenomena we test, our experiment maintains the fundamental auditing characteristic of investing resources to verify reports, tested in a setting that gives us a “best shot” to detect whether the source and level of reporting risk interact.

The verification fee auditors are willing to spend serves as our proxy for audit resources. Under the strategy method, participants specify a maximum verification fee for each potential reported value before the outcomes are realized. To elicit theoretically unbiased reservation prices, we adopt the Becker, DeGroot, and Marschak (1964) “willingness-to-pay” mechanism, whereby the participant pays either a randomly drawn fee if the random fee is less than or equal to the participant’s maximum fee, or pays nothing and does not verify the report otherwise.4 We structure the mechanism such that, with probability X/30, an auditor-participant verifies the report and protects himself or herself from all misreporting loss, where X is the participant’s maximum fee ($0 ≤ X ≤ $30). Accordingly, auditor-participants receive one of two possible cash payoffs:

Auditor payoff = $30 – random verification fee, if the random verification fee is less than or equal to the participant’s maximum acceptable fee so that verification occurs.

Auditor payoff = $30 – [0.75 × (actual value – reported value)] otherwise.

Intentional Risk Condition

In the intentional risk condition, we match 28 auditor-participants with 28 additional participants who serve as reporters. We keep the pairings anonymous by placing the auditor-participants and reporter-participants in adjacent rooms, assigning these roles randomly upon arrival at the experimental laboratory. Similar to the process for auditor-participants, we use the strategy method for the reporter-participants in the intentional risk condition, eliciting the value each participant wishes to report for each equally probable actual value ($10.00, $17.50, $25.00, $32.50, $40.00). We randomly determine the actual values at the end of the sessions. Like the auditor-participants, reporter-participants earn one of two possible cash payoffs, depending on whether the auditor-participant verifies the report:

Reporter payoff = actual value – [0.50 × (actual value – reported value)] if the random verification fee is less than or equal to the corresponding auditor-participant’s maximum acceptable fee so that verification occurs.

Reporter payoff = actual value + (actual value – reported value) otherwise.

Given this structure, truthful reporting maximizes the reporter-participant’s payoff if the auditor-participant verifies the report, thereby avoiding an under-reporting penalty, but under-reporting

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4 In expected value terms, the auditor can expect to pay half of his or her maximum reservation fee in the case of verification, due to the random-price rule. Becker et al. (1964) demonstrate analytically that this mechanism is “truth-revealing,” including truthful revelation of risk preferences. The intuition is that if risk preferences made the maximum reservation fee unacceptable, then an individual with such preferences would specify a lower maximum fee instead to avoid the possibility. Any frictions in this reasoning should apply equally across the treatment conditions.
maximizes the reporter’s payoff otherwise.\(^5\) Thus, auditor-participants can hold reporter-participants “accountable” (Evans et al. 1994) in the intentional risk condition by increasing their maximum acceptable verification fees to increase the probability of verification.

Unintentional Risk Condition

The unintentional risk condition follows the same instructional wording and steps as in the intentional risk condition, but without reporter-participants. Instead, the instructions in the unintentional condition refer to determinations from a computer. Auditor-participants in the unintentional condition face the same levels of potential loss exposure and realize cash payoffs in the same manner as in the intentional condition. To establish equivalent reporting risks, we program the computer in each unintentional risk session to follow the same distribution of reported values as those from an intentional risk session.\(^6\) Thus, participants in both conditions literally face the same risks.

Establishing Equivalent Expectations

Besides holding potential loss magnitudes and reports constant, to compare intentional and unintentional risks with all else equal, our experiment must also equate ex ante expectations between these two conditions. To achieve this objective, we conduct a pilot experiment with 12 auditor-participants and 12 reporter-participants, using the materials for the intentional risk condition. Data from the pilot experiment provide truthful prior probabilities of reported values for each possible actual value that we then communicate to auditor-participants in the intentional and unintentional conditions of the primary experiment. We communicate these probabilities in the intentional risk condition by stating:

For each possible Actual Value, the table below lists the distribution of the values reported in an earlier session of this experiment. While we cannot tell you the distribution of how the people in the other room will report in today’s session, we recruited the people in the other room from the same population (i.e., the same set of classes) as the earlier session. Thus, you can expect the distribution of Reported Values in today’s session to be similar to that of the earlier session.

The unintentional risk condition precludes referring to reports from “people,” but we otherwise use the same wording as much as possible, as follows:

For each possible Actual Value, the table below lists the distribution of the values reported in an earlier session of this experiment. While we cannot tell you the distribution of the values that will actually be randomly drawn in today’s session, these values will be drawn from the same population as in the earlier session. Thus, you can expect the distribution of Reported Values in today’s session to be similar to that of the earlier session.

Following these descriptions, the instructions to auditor-participants within each condition provide the same table of probabilities from the pilot experiment for each combination of reported

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\(^5\) Because the instructions do not allow reporters to report a value that exceeds the actual value, reporters cannot benefit from a “negative penalty” by over-reporting if verification occurs. Thus, the best the reporter can do in the event of verification is to report honestly. It makes little sense to think of managers reversing the direction of misappropriation by adding to the entrusted assets and then benefiting from an audit investigation that uncovers such additions.

\(^6\) In both conditions, a random draw determines the equally probable actual value realizations. Under the strategy method, each such actual value corresponds to a prespecified reported value chosen by one of the reporter-participants in the intentional risk condition that we match to a session in the unintentional risk condition.
and actual values. We do not communicate the pilot data to reporter-participants in the intentional risk condition in order to avoid influencing reporters’ behavior relative to the pilot. Auditor-participants are aware of this point because we inform them of the reporter-participants’ instructions. As we discuss in a supplemental analysis, the pilot and actual experimental sessions generate similar distributions of reported values, with no statistically significant differences. Thus, all auditor-participants start from the same baseline of pilot-generated prior probabilities that correspond to the actual probabilities they face.

IV. RESULTS

Primary Analysis

Figure 1, Panel A summarizes our primary findings by plotting auditor-participants’ maximum verification fees at each reporting level from $10.00, the highest under-reporting risk, to $32.50, the lowest risk. We do not elicit verification fees or plot outcomes for $40.00 reports because a $40.00 report can only arise if the actual value is also $40.00. Figure 1, Panel B documents the means plotted in Panel A, in addition to showing the standard deviation of responses within each experimental cell. As Figure 1 indicates, auditor-participants’ maximum verification fees decrease as the auditor’s risk decreases, but with a steeper slope in the unintentional risk condition than in the intentional risk condition. The increased spread between the intentional and unintentional risk conditions as the risk level declines is consistent with our core hypothesis, as we corroborate statistically next.

We test the pattern in Figure 1 using a mixed regression model that controls for the repeated observations from each auditor-participant, similar to firm-specific clustering in archival research (e.g., see Petersen 2009; Gow, Ormazabal, and Taylor 2010). Although similar to repeated-measures ANOVA, the mixed regression model we use is not an ANOVA because risk level enters the model as a single regressor that takes on four equidistant values, as opposed to a four-level categorical ANOVA factor. Thus, the regression captures the ordering of the four risk levels we test. Essentially, we regress each auditor-participant’s vector of verification fees across the four risk levels, testing the average linear slope of this relation as the main effect of risk level and the average difference across risk levels as the main effect of risk source (intentional versus unintentional). To test our hypothesized interaction between risk source and risk level, we estimate the difference in risk-level slopes between the two risk-source conditions.

Table 1, Panel A shows that average verification fees are higher in the intentional risk condition than in the unintentional risk condition, supporting a main effect of risk source (t = 2.00, one-tailed p = 0.026). Verification fees decline as risk declines, supporting a main effect of risk level (t = −4.42, one-tailed p < 0.001). More importantly, the decline in verification fees is significantly less pronounced (i.e., flatter) in the intentional risk condition than in the unintentional risk condition, supporting our core hypothesis of an interaction between risk levels and the source of that risk (t = 2.00; one-tailed p = 0.024).

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7 See Singer and Willett (2003, Chapter 3) for further detail.
8 Although not formally hypothesized, we apply one-tailed tests to the main effects of risk level and risk source, under the rationale that it would be implausible to posit that resources would increase as risks decrease or that unintentional risks would command a premium over intentional risks. Nevertheless, the primary statistical inferences in Table 1, Panel A do not depend on whether we halve the p-values in one-tailed tests.
9 We favor a regression approach with a single, four-level independent variable for risk levels because “risk level” is not a categorical factor so much as it is a linear progression from highest to lowest risks. Nevertheless, if we instead apply a contrast-coded ANOVA model (Buckless and Ravenscroft 1990), with contrast weights to capture an interaction pattern of a flat line across risk levels within the intentional risk condition and a downward-sloping line in the unintentional risk condition, then the hypothesized contrast is highly significant (t = 3.28, p < 0.01).
Panels B and C of Table 1 follow up on the overall regression by testing the individual risk-level slopes within each intentionality condition (Panel B), as well as the simple effects of intent at each risk level (Panel C). Panel B shows a statistically significant downward slope of verification fees as risks decline within both the intentional and unintentional risk conditions, although the −1.79 slope (t = −4.55, p < 0.001) within the unintentional condition is 2.6 times the magnitude of the −0.69 slope (t = −1.78, p = 0.039) within the intentional condition.

Panel C of Table 1 examines how these slopes differ. Namely, average verification fees do not significantly differ between the intentional and unintentional risk conditions at the two highest risk levels.

FIGURE 1
Average Maximum Verification Fee at Each Risk Level

Panel A: Plot of Average Maximum Verification Fees

Panel B: Descriptive Statistics

<table>
<thead>
<tr>
<th>Average Maximum Verification Fee</th>
<th>$10.00 (Highest Risk Level)</th>
<th>$17.50</th>
<th>$25.00</th>
<th>$32.50 (Lowest Risk Level)</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intentional Risk Condition</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>$12.21</td>
<td>$11.07</td>
<td>$10.93</td>
<td>$9.96</td>
<td>$11.04</td>
</tr>
<tr>
<td>(Standard Deviation)</td>
<td>($8.62)</td>
<td>($5.77)</td>
<td>($6.96)</td>
<td>($7.24)</td>
<td>($5.75)</td>
</tr>
<tr>
<td>Unintentional Risk Condition</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>$10.37</td>
<td>$9.67</td>
<td>$7.63</td>
<td>$5.07</td>
<td>$8.19</td>
</tr>
<tr>
<td>(Standard Deviation)</td>
<td>($7.93)</td>
<td>($6.25)</td>
<td>($4.50)</td>
<td>($4.65)</td>
<td>($4.81)</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>$11.31</td>
<td>$10.38</td>
<td>$9.31</td>
<td>$7.56</td>
<td></td>
</tr>
<tr>
<td>(Standard Deviation)</td>
<td>($8.26)</td>
<td>($6.00)</td>
<td>($6.06)</td>
<td>($6.53)</td>
<td></td>
</tr>
</tbody>
</table>
levels of $10.00 and $17.50 reports (one-tailed $p = 0.207$ and $p = 0.195$, respectively). The convergence of verification fees at higher risk levels is not merely a ceiling artifact, as the $12.21$ average maximum verification fee at the highest $10.00$ risk level within the intentional risk condition lies well below the $30.00$ maximum fee allowed or the $22.50$ maximum exposure (i.e., $0.75 \times \frac{40.00 \text{ actual value}}{10.00 \text{ reported value}}$) an auditor-participant faces at that risk level.

Thus, participants in both the intentional and unintentional risk conditions converge on a relatively high (but not the maximum) resource investment as risks increase.

Conversely, Table 1, Panel C indicates significant differences in maximum verification fees between the intentional and unintentional risk conditions at the two lowest risk levels of $25.00$ and $32.50$ reported values (one-tailed $p = 0.021$ and $p = 0.002$, respectively). As Figure 1 depicts, verification fees diverge as risks decline, with auditor-participants who face unintentional risks significantly “backing off” with lower verification fees, while those who face the same risks from a human counterparty generally do not. At the lowest risk level of a $32.50$ report, auditor participants in the intentional risk condition invest an average of $9.96$, which even exceeds the $5.63$ maximum exposure at that level (i.e., $0.75 \times [40.00 \text{ actual value} – 32.50 \text{ reported value}]$). It seems clear that these participants are reacting to more than just their potential economic loss.

### TABLE 1

**Mixed Regression Analysis of Treatment Effects**

**Panel A: Primary Analysis**

<table>
<thead>
<tr>
<th>Dependent Variable = Maximum Verification Fee</th>
<th>t-statistic</th>
<th>p-value$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Risk source</strong> (average effect of intentional versus unintentional risks, manipulated between subjects)</td>
<td>2.00</td>
<td>0.026</td>
</tr>
<tr>
<td><strong>Risk level</strong> (average linear slope of verification fees across four possible reported values, manipulated within subjects)</td>
<td>−4.42</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td><strong>Risk source \times Risk level</strong> (test of the difference in risk-level slopes between the intentional and unintentional risk-source conditions)</td>
<td>2.00</td>
<td>0.024</td>
</tr>
</tbody>
</table>

**Panel B: Simple Effects of Risk-Level Slopes**

<table>
<thead>
<tr>
<th>Slope of Linear Regression of Maximum Verification Fees on Risk Levels:</th>
<th>Slope Estimate</th>
<th>t-statistic</th>
<th>p-value$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intentional risk condition</strong></td>
<td>−0.69</td>
<td>−1.78</td>
<td>0.039</td>
</tr>
<tr>
<td><strong>Unintentional risk condition</strong></td>
<td>−1.79</td>
<td>−4.55</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Difference in slopes = interaction effect</td>
<td>1.10</td>
<td>2.00</td>
<td>0.024</td>
</tr>
</tbody>
</table>

**Panel C: Simple Effects of Risk Source at Each Risk Level**

<table>
<thead>
<tr>
<th>Effect of Intentional versus Unintentional Risk Source on Maximum Verification Fees:</th>
<th>t-statistic</th>
<th>p-value$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest risk level ($10.00$ reported value)</td>
<td>0.83</td>
<td>0.207</td>
</tr>
<tr>
<td>$17.50$ reported value</td>
<td>0.87</td>
<td>0.195</td>
</tr>
<tr>
<td>$25.00$ reported value</td>
<td>2.08</td>
<td>0.021</td>
</tr>
<tr>
<td>Lowest risk level ($32.50$ reported value)</td>
<td>2.97</td>
<td>0.002</td>
</tr>
</tbody>
</table>

$^a$ Reported p-values are one-tailed, conditional on *ex ante* predictions.
This pattern of results suggests that high levels of risk command relatively high audit resources, irrespective of whether risk arises from intentional or unintentional misreporting. By contrast, when risk is low, participants in the unintentional risk condition apparently reason that fewer costly resources are necessary, whereas participants in the intentional risk condition continue to be averse to the potential for harm from the willful intent of others. Because intent-based risk is likely to elicit more of what Hsee and Rottenstreich (2004) term a “valuation by feeling” than a “valuation by calculation,” scale becomes less important and verification fees remain relatively high. Below, we report supplemental analyses to corroborate our primary analyses and interpretations.

**Supplemental Analyses**

**Confirming Equivalent Expectations**

By design, our experiment maintains the same risk magnitudes and communicates the same table of *ex ante* reporting probabilities across the intentional and unintentional risk conditions. Nevertheless, it is important to corroborate that our participants perceive equivalent risks in both conditions. To test this equivalence, a post-experimental questionnaire administered after eliciting all decisions, but before revealing final outcomes, asks auditor-participants in the intentional (unintentional) risk conditions to answer the question, “I thought it was likely that my paired person (the computer) would report values lower than the Actual Value,” using a seven-point Likert scale from 1 = strongly disagree to 7 = strongly agree. Average responses do not statistically differ between the intentional and unintentional risk conditions (5.36 versus 4.89, respectively; $t = 1.23$, two-tailed $p = 0.22$). We also construct a composite measure of expected under-reporting based on summing responses to post-experimental questions that elicit the most likely reported values that auditor-participants anticipated for each possible actual value. This composite measure does not statistically differ between the intentional and unintentional risk conditions ($t = 0.60$, two-tailed $p > 0.50$). Based on these tests, we conclude that the experiment establishes similar risk expectations across conditions.

**Risk Preferences**

To ensure that different risk preferences do not confound the differences we attribute to the intentional versus unintentional risk conditions, we administer a post-experimental risk-preference exercise adapted from Boylan and Sprinkle (2001). We then extract a measure of risk tolerance from the results across 15 dichotomous lotteries. When we include this measure in the analysis, it is statistically significant in the expected direction of lower maximum verification fees for participants with higher risk tolerance ($t = 1.70$, one-tailed $p = 0.047$), but it does not alter the statistical conclusions for the treatment factors. More importantly, average risk tolerance scores do not significantly differ between the intentional and unintentional risk source conditions ($7.14$ versus $7.41$; $t = 0.43$, two-tailed $p > 0.50$), indicating that the differences we detect reflect our treatment manipulation rather than chance differences in risk tolerance.

**Construct Validation**

Similar to prior experiments by Bohnet and Zeckhauser (2004), Bohnet et al. (2008), and Houser et al. (2010), our study operationalizes “intent” as involving willful decisions by human participants to evaluate 15 lotteries that pay either $4 or $0, with probabilities of receiving $4 decreasing from 85 percent to 15 percent. The point at which a participant shifts from playing the lottery to accepting a certain payoff of $2 serves as the measure of risk tolerance, with earlier shifts reflecting lower tolerance for risk. To make the exercise meaningful, we choose one of the 15 lotteries at random for actual payouts consistent with each participant’s preference for that lottery.

---

The exercise requires participants to evaluate 15 lotteries that pay either $4 or $0, with probabilities of receiving $4 decreasing from 85 percent to 15 percent. The point at which a participant shifts from playing the lottery to accepting a certain payoff of $2 serves as the measure of risk tolerance, with earlier shifts reflecting lower tolerance for risk. To make the exercise meaningful, we choose one of the 15 lotteries at random for actual payouts consistent with each participant’s preference for that lottery.
participants, whereas the “unintentional” condition is mechanized. Given this operationalization, it is plausible that the treatment effects we observe could reflect the use of human reporters rather than their “intent” per se. That is, one could conceive of unintentional reporting errors made by human participants, but any attempt to operationalize such a setting would significantly complicate our ability to maintain the same probabilities and consequences of misstatement.

To address this issue, we first note that any incremental effect of human reporters, as opposed to the effect of their intentional decisions, would most likely take the form of a main effect rather than an interaction with risk level. Thus, to the extent that we observe a theory-consistent pattern of a flatter risk-to-resource mapping in the intentional risk condition than in the unintentional condition, the “valuation by feeling” reasoning we use to motivate this interaction provides the most likely explanation.

Notwithstanding this reasoning, a mediation analysis (cf. Baron and Kenny 1986) provides a more direct way to validate “intent” as the primary construct underlying our findings. Specifically, if intentional misstatement induces aversion to the feeling of being cheated by another party, as we reason in developing our hypothesized interaction, then a measure of feeling cheated should mediate the findings we detect. The most powerful setting for detecting this mediation is at the lowest risk level of a $32.50 report, where we observe the largest difference in verification fees between the intentional and unintentional risk conditions. A post-experimental question at this risk level elicits responses to the statement, “If I did not validate the report, I would feel cheated if $32.50 was the Reported Value when $40 was the Actual Value,” with $1 = strongly disagree, 4 = neither agree nor disagree, and 7 = strongly agree.

A median split occurs at the scale midpoint of 4, differentiating auditor-participants who tend to agree with the “feel cheated” question at the lowest risk level from those who tend to disagree. Table 1, Panel C first confirms that verification fees are significantly higher within the intentional risk condition at the lowest ($32.50) risk level, thereby indicating a treatment effect that could be mediated. Second, we establish that the intent manipulation leads to a higher percentage of above-median (i.e., 5, 6, or 7 on the Likert scale) responses to the post-experimental question about feeling cheated at the lowest risk level (43 percent in the intentional risk condition versus 7 percent in the unintentional risk condition; $t = 3.24$, one-tailed $p = 0.001$). Third, the “feeling cheated” mediator remains statistically significant when we test the intent manipulation and the mediator together ($t = 2.20$, one-tailed $p = 0.015$). Although the intent manipulation itself also remains statistically significant in this analysis ($t = 1.91$, one-tailed $p = 0.030$), its t-statistic falls from 2.97 in the separate analysis to 1.91 when the mediator is included. A Sobel test (Sobel 1982) confirms that this drop is statistically significant (Sobel test statistic $= 1.82$, one-tailed $p = 0.034$), supporting the conclusion that feelings of being cheated at least partially mediate the treatment effect of the intentional risk condition at the lowest risk level.11

We also ask the “feeling cheated” question at the highest risk level of a $10.00 report, for which the median response is 5 on the Likert scale, although there is no treatment effect of intent at this level and, hence, nothing to be mediated. Indeed, comparing the “feeling cheated” responses at the lowest and highest risk levels yields a pattern that is consistent with our primary findings. Within the intentional risk condition, the percentage above the median “feeling cheated” score remains nearly equivalent at the lowest and highest risk levels (43 percent versus 39 percent, respectively), consistent with a “valuation by feeling” that is more sensitive to the presence of misreporting risk than to its magnitude. Conversely, within the unintentional risk condition, the percentage above the median “feeling cheated” score increases from 7 percent at the lowest risk

11 Given that the median split indicator is dichotomous, we also conduct an alternative mediation analysis using a logistic regression approach (MacKinnon and Dwyer 1993), reaching the same statistical conclusions.
level to 26 percent at the highest risk level, consistent with a “valuation by calculation” that ties the degree of an aversive reaction to the magnitude of the potential loss.

**Reporter Behavior and Economic Baselines**

To confirm the designed equivalence in reporting across the intentional and unintentional risk conditions, an analysis of reports sheds insight on how auditor-participants’ verification fees compare to the potential losses they face. Table 2, Panel A documents the distribution of the actual values corresponding to each reported value, both for the pilot session and for the actual experimental sessions. The pilot distribution is relevant because the experimental instructions provide the pilot information from Table 2, Panel A as an expectation benchmark to auditor-participants in both the intentional and unintentional risk conditions, as explained in Section III. Untabulated Chi-square tests do not reject the null hypothesis of equivalent reporting distributions between the pilot and actual experimental sessions at each reported value (lowest p = 0.20), supporting our instructions to auditor-participants that these data are representative of the reported and actual values they could expect.

We present the pilot data in Table 2, Panel A to auditor-participants as a table of actual values conditional on each possible reported value, because this format facilitates the auditor’s need to estimate the likelihood of potential actual values, given an observed report. However, the reporter’s task is to determine a report conditional on the actual value, not vice versa. For example, while Table 2, Panel A shows that 75 percent of the $32.50 reports are associated with a $40.00 actual value, a $32.50 report is in fact relatively “honest,” even if the actual value is $40.00, given the ability to report a much lower value of $25.00, $17.50, or $10.00 instead.12 Indeed, even characterizing a $32.50 report as the “lowest risk level” only makes sense from the auditor’s perspective, as this means that, given a $32.50 report, the actual value can only possibly be $7.50 higher, or $40.00. A $32.50 report leads to lower risk for the auditor because it limits the potential loss from under-reporting that could have resulted from a smaller reported value. At the other extreme, all $10.00 actual values are reported honestly by construction, as $10.00 is the minimum report. Nevertheless, observing a $10.00 report conveys high risk to the auditor because it could reflect a $10.00 actual value that had to be reported as $10.00 or a much higher actual value that was under-reported as $10.00. The table of actual value probabilities conditional on each reported value provides auditor-participants in both risk-source conditions with the distribution of these possibilities.

The ordering of different risk levels hinges on the potential magnitudes, expected values, and variances of the losses auditors could incur at each level, as reported in Table 2, Panel B, which also documents the elicited maximum verification fees at each risk level for reference. Panel B uses the pilot data to calculate expected values and standard deviations because auditor-participants observed the pilot data when forming their expectations. It is possible to reconstruct these measures from the distributional information in Panel A, but we did not provide these calculations to participants so as not to unduly prompt their decisions with such benchmarks.

The maximum loss magnitudes at each risk level differ by design, set at 75 percent of the difference between the reported value and the maximum possible actual value of $40.00. Thus, irrespective of the reported versus actual value distribution in Table 2, Panel A, auditor-participants

12 From the reporter’s perspective, an untabulated analysis of reported values conditional on actual values (essentially, the obverse of Table 2, Panel A) shows that when given the greatest discretion, reporters misrepresented $40.00 actual values 86 percent of the time, with 24 percent of these misrepresentations occurring at the $32.50 reported value that would present the lowest risk to the auditor. Conversely, the lowest potential actual value that would still allow some reporting discretion would be a $17.50 actual value, which reporters misrepresented 54 percent of the time as a $10.00 reported value. Thus, reporters misrepresented more frequently as their reporting discretion increased.
know that the maximum loss for an unverified $10.00 report is $22.50 (¼ 0.75 3 [$40.00 /C0 $10.00]), and the maximum loss for an unverified $32.50 report is $5.63 (¼ 0.75 3 [$40.00 /C0 $32.50]). Comparing these calculations to the observed maximum verification fees, it is apparent that verification fees lie well below the maximum loss exposures for all combinations except the lowest ($32.50) risk level within the intentional risk condition, for which the average maximum

<table>
<thead>
<tr>
<th>Reported and Actual Values</th>
<th>Distribution from Pilot Sessiona</th>
<th>Distribution from Actual Experimental Sessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>$10.00 reported value (highest risk)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual value = $10.00</td>
<td>44%</td>
<td>50%</td>
</tr>
<tr>
<td>Actual value = $17.50</td>
<td>22%</td>
<td>25%</td>
</tr>
<tr>
<td>Actual value = $25.00</td>
<td>19%</td>
<td>13%</td>
</tr>
<tr>
<td>Actual value = $32.50</td>
<td>8%</td>
<td>6%</td>
</tr>
<tr>
<td>Actual value = $40.00</td>
<td>7%</td>
<td>6%</td>
</tr>
<tr>
<td>$17.50 reported value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual value = $17.50</td>
<td>50%</td>
<td>33%</td>
</tr>
<tr>
<td>Actual value = $25.00</td>
<td>25%</td>
<td>37%</td>
</tr>
<tr>
<td>Actual value = $32.50</td>
<td>8%</td>
<td>11%</td>
</tr>
<tr>
<td>Actual value = $40.00</td>
<td>17%</td>
<td>19%</td>
</tr>
<tr>
<td>$25.00 reported value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual value = $25.00</td>
<td>33%</td>
<td>16%</td>
</tr>
<tr>
<td>Actual value = $32.50</td>
<td>58%</td>
<td>61%</td>
</tr>
<tr>
<td>Actual value = $40.00</td>
<td>9%</td>
<td>23%</td>
</tr>
<tr>
<td>$32.50 reported value (lowest risk)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual value = $32.50</td>
<td>25%</td>
<td>9%</td>
</tr>
<tr>
<td>Actual value = $40.00</td>
<td>75%</td>
<td>91%</td>
</tr>
</tbody>
</table>

Panel B: Maximum Losses, Expected Values, and Standard Deviations at Each Risk Level

<table>
<thead>
<tr>
<th>Expected Benchmarks</th>
<th>Maximum Verification Fees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reported Value</td>
<td>Intentional Risk Condition</td>
</tr>
<tr>
<td>$10.00 (highest risk)</td>
<td>$12.21</td>
</tr>
<tr>
<td>$17.50</td>
<td>$11.07</td>
</tr>
<tr>
<td>$25.00</td>
<td>$10.93</td>
</tr>
<tr>
<td>$32.50 (lowest risk)</td>
<td>$9.96</td>
</tr>
</tbody>
</table>

a Instructions to auditor-participants (but not to reporter-participants) include the pilot distribution data from Panel A.
b To illustrate the expected loss computation, consider the $10.00 report distribution for the pilot session. In this cell, the expected loss value is 0.44(0) + 0.22[0.75 × ($17.50 – $10.00)] + 0.19[0.75 × ($25.00 – $10.00)] + 0.08[0.75 × ($32.50 – $10.00)] + 0.07[0.75 × ($40.00 – $10.00)] = $6.30. Other calculations follow in a similar manner.
verification fee of $9.96 is $4.33 more than the $5.63 maximum loss auditor-participants could realize at that risk level. This observation is consistent with our premise that participants in the intentional risk condition tend to “value by feeling” rather than by weighing economic costs and benefits.

Turning to expected values, we obtain expected loss values for an unverified report by weighting the potential loss at each reported versus actual value combination by the probability of that combination from the pilot distribution in Table 2, Panel A. Consistent with the ordering of risk levels from highest to lowest, Panel B shows that expected loss values for an unverified report from the pilot distribution follow an ordinal ranking from highest risk (expected loss value of $6.30 for a $10.00 report) to lowest risk (expected loss value of $4.22 for a $32.50 report). Comparing these expected loss values to the maximum verification fees reveals that fees exceed the expected values, implying risk aversion, because the Becker et al. (1964) method we use to elicit verification fees should equate maximum verification fees to expected loss values for a risk-neutral participant. Notwithstanding this point, maximum verification fees in the unintentional risk condition converge toward expected value as the risk level declines, from a high of $10.37 that is 65 percent above the expected loss value of $6.30 at the highest risk level ($10.00 report) to a low of $5.07 that is 20 percent above the expected loss value of $4.22 at the lowest risk level ($32.50 report). Conversely, within the intentional risk condition, maximum verification fees do not converge toward expected loss values as risks decline, instead maintaining a large premium above expected value across the four risk levels.

Because risk exposure also involves outcome variances, Table 2, Panel B also documents the standard deviations of potential misreporting losses from the pilot distribution at each risk level. Consistent with the rankings for maximum loss exposures and expected loss values, the standard deviations of potential losses decline monotonically across risk levels, from a high of $7.07 for a $10.00 report to a low of $2.45 for a $32.50 report. Consistent with our other analyses, maximum verification fees track the pattern of decreasing variances across risk levels more closely in the unintentional risk condition than in the intentional risk condition.

V. CONCLUSIONS AND FUTURE DIRECTIONS

Under risk-based auditing, the level of risk an auditor faces determines the level of resources the auditor expends. We examine risk-based auditing in a laboratory setting in which four potential risk magnitudes arise solely from human reporters in the intentional risk condition or from a benchmark that our design holds constant across treatment conditions.

For example, consider the distribution from the pilot session for a $10.00 report. In this cell, the expected loss value is $6.30. Calculations for other cells follow in a similar manner.

The ordinal ranking of expected loss values does not quite hold for reports in the actual (as opposed to the pilot) experimental sessions, as the highest risk level ($10.00 report) generates an expected loss value of $5.23 that is lower than that calculated for the $17.50 (expected loss = $6.53) or $25.00 (expected loss = $6.02) risk levels. We do not believe that this apparent anomaly compromises our conclusions, for four reasons. First, auditor-participants base their expectations only on the pilot distribution that was provided to them, and do not observe the realizations from their own session until after they specify all elicited decisions. Second, the maximum loss values and variances of the loss distributions follow a monotonic ordering from highest to lowest risk in both the pilot and actual sessions. Third, even if we delete the highest risk level ($10.00) from our analyses, this does not change the nature of our inferences or conclusions. Fourth, we program the computer in the unintentional risk condition to mimic the intentional condition, ensuring equivalent reporting outcomes by design.

For a maximum verification fee of X, an auditor-participant pays an expected actual fee of X/2 with probability X/30, and incurs an expected loss of L from the difference between the reported and actual values with probability (30 – X)/30. For a risk-neutral participant who evaluates prospects at their expected values, the loss function \[ (X/2)(X/30) + L(30 – X)/30 \] is minimized when X = L. We do not attempt an equilibrium solution to the broader auditor-reporter game, but the calculated values that a risk-neutral auditor would specify, given the observed reports, serve as a benchmark that our design holds constant across treatment conditions.
computer that we program to mimic the same reporting distribution in the unintentional risk condition. We provide auditor-participants in both conditions with the same report probabilities from a pilot experiment in order to establish equivalent expectations. Our primary finding is that the mapping from the level of misreporting risk to the level of audit resources is steeper in the unintentional risk condition than in the intentional risk condition, meaning that auditor-participants are less inclined to “back off” as risks decline when those risks are from human reporters. This pattern is consistent with what Hsee and Rottenstreich (2004) term a “valuation by calculation” for a nonemotive prompt such as the computer in our unintentional risk condition, as opposed to a “valuation by feeling” for the emotive nature of intent-based risk that is more sensitive to the presence of such risk than to its magnitude.

Our findings shed both theoretical and practical insights. For theory, prior behavioral economics studies that compare intentional and unintentional risks focus on the main effect of intent (e.g., Bohnet and Zeckhauser 2004; Bohnet et al. 2008; Houser et al. 2010). We extend this literature by applying Hsee and Rottenstreich’s (2004) contrast between “valuation by calculation” for economic trade-offs and “valuation by feeling” for emotive stimuli to hypothesize an interaction that detects a larger effect of intent for low levels of risk than for high levels of risk. For audit practice, the interaction we detect relates to the PCAOB’s efforts to differentiate fraud risks from the more general logic that risks should be evaluated based on magnitudes and likelihoods. In stating that “a fraud risk is a significant risk” by its very nature (PCAOB 2010a, ¶71), the PCAOB’s likely intent is to imply that fraud risks can be more pervasive than other risks. Our experiment precludes this possibility by design, with controls to ensure equivalent magnitudes, probabilities, and consequences across the intentional and unintentional risk conditions. Nevertheless, our study suggests a more fundamental sense of the PCAOB’s wording, insofar as we find that people are more comfortable conditioning audit resources on risk magnitudes for unintentional reporting risks than for the same risks arising from human intent.

Given that our experiment isolates human intent as a qualitative construct, apart from the economic differences normally associated with intent, our participants appear to be acting “irrationally” from an expected-payoff perspective because they invest different amounts to address the same monetary risks. That is, our results suggest that auditors could be doing too much work when intentional risks are truly low. However, a key difference between our experimental setting and real-world audit settings suggests a more benign interpretation. Practice environments cannot ensure the stability of risk levels that we establish in our experiment. In particular, unlike unintentional risks that arise from exogenous sources, intent-based risks in practice can fluctuate endogenously as clients respond to observed audit strategies. Thus, if an auditor were to invest low resources to guard against a low risk of fraud, then a strategic client could attempt to exploit the auditor’s low-risk strategy by increasing the level of reporting risk later in the audit or in the next audit period. Accordingly, to the extent that our findings generalize to practice, a propensity to be less sensitive to the level of risk when that risk arises from human intent could serve to protect auditors from strategic vulnerability in richer settings in which the level of fraud risk can change in response to auditor behavior. This conclusion is consistent with the more general observation that many simplifying heuristics, while seemingly “irrational” in isolation, can nevertheless serve as beneficial adaptations in more complex settings (Gigerenzer et al. 2011).

From this perspective, it is useful to consider our findings in the context of related experiments on risk-based auditing by Hoffman and Zimbelman (2009) and Bowlin (2011). Those studies do not directly compare intentional and unintentional risks, but rather examine settings in which auditors who fixate on unintentional risk can be vulnerable to strategic exploitation unless prompted to think about the potential for intentional misreporting. Our manipulation of intentional misreporting as a treatment factor likely makes intent more salient in our study than in their experiments, in which participants underinvested in fraud-based risks in the absence of a strategic reasoning prompt. Our
study builds on their research by helping to identify the cognitive mechanism that is likely triggered by the strategic reasoning prompts they test. Specifically, our findings suggest that triggering sensitivity to intentional misstatement can change the auditor’s cognitive mindset for risk from a calculative interpretation based on the level of risk to a more qualitative interpretation based on the presence of intent-based risk.

In addition to manipulating intentional misstatement as a treatment factor, we acknowledge three other ways in which our experiment abstracts away from real-world audit settings. First, we do not incorporate multiperiod reputations, feedback, or mixed strategies, in order to control for differences between the intentional and unintentional settings that could arise from auditor attempts to influence future reporting behavior or from human reporters responding to observed auditor strategies. Second, our experiment does not include third-party investors. Accordingly, the auditor in our setting is more directly “cheated” by misreporting, rather than being cheated indirectly through third-party actions. Third, our experiment restricts auditors to making a basic decision of how much to expend, as opposed to the more complex decisions characterizing audit practice that also involve the pricing of audit services (e.g., Houston et al. 1999) and the design of different tests to address different sources of risk (e.g., Hoffman and Zimbelman 2009). We accept these abstractions in the spirit of focusing this study on the fundamental question of how intent moderates the mapping from different levels of audit risk to different audit resources, ceteris paribus. These limitations suggest potentially fruitful ways to extend our findings along the dimensions from which we abstract.

We see a continuing need for research on the theory and practice of risk-based auditing. Prior research in this area has documented, for example, the difficulty auditors face when assessing strategic risks (e.g., Bloomfield 1997), the vulnerability of risk assessments to “halo effects” (e.g., O’Donnell and Schultz 2005), and the dangers inherent in settings that combine intentional and unintentional risks (e.g., Hoffman and Zimbelman 2009; Bowlin 2011). Our study provides further evidence of the subtle nature of risk-based auditing. By way of analogy, the risks auditors face are not always like the risks of bad weather. Weather risks can be effectively addressed through the use of scientific forecasting models, and weather does not benefit strategically from harming its victims. Conversely, reporting risks in an audit setting can arise from willful managerial decisions that respond strategically to auditor actions. What our study adds to the accumulated literature in this area is that experimental participants in an audit-like setting tend to view unintentional and intentional risks differently, even under ceteris paribus conditions. Specifically, our participants are sensitive to the magnitude of unintentional risk, whereas they appear to be more sensitive to the presence of intentional risk, irrespective of magnitude. We are hopeful that future research can draw on this differential sensitivity in further developing the advantages and limitations of risk-based auditing.

REFERENCES


16 More generally, experiments can generate insights by constructing environments that isolate theoretical drivers of behavior even if those environments do not exist in the real world, such as our manipulation of human intent as being present or absent. Swieringa and Weick (1982) offer similar comments regarding “intentional experimental artificiality,” as do Libby, Bloomfield, and Nelson (2002, 798) on the benefits of experiments that investigate “unrealistically extreme” settings.


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