THE EFFECT OF OPAQUE AUDIT METHODS AND AUDITOR OWNERSHIP ON RELIANCE ON INDEPENDENT EXPECTATIONS

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Dedicated to Bryan Church

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SUMMARY

Increasing access to data and advanced statistical methods can help auditors generate independent expectations of estimates, but expectations are not useful unless auditors rely on them. However, advanced methods are likely more opaque (i.e., more difficult to understand due to a lack of transparency), which in turn affects understanding of the output of the method, such as independent expectations. I predict that auditors rely less on independent expectations generated with more opaque audit methods. I further predict that developing psychological ownership of independent expectations increases reliance on expectations generated using more opaque methods, while ownership is not critical for reliance on expectations generated using less opaque methods. In an experiment with senior auditors, I find results supporting my predictions, specifically for auditors with relevant task experience. This study provides insights into auditors' use of independent expectations and advanced methods that are becoming more pervasive in practice.

CHAPTER 1. INTRODUCTION

1.1 Motivation and Research Question

Auditors tend to over-rely on management's assertions when auditing estimates, but this issue can be improved by auditors' use of independent expectations of estimates (PCAOB 2018; Griffith, Hammersley, and Kadous (hereafter "GHK") 2015). Auditors generate independent expectations less often than they test the assumptions in management's estimates in part because they often lack data or knowledge to do so (GHK 2015; Glover, Taylor, and Wu 2017; Cannon and Bedard 2017). Increasing access to data and advanced statistical methods may help auditors more readily develop independent expectations. However, independent expectations will be valuable only to the extent that auditors rely on them relative to management's estimates, and I argue that attributes of the methods auditors use to generate independent expectations can impact their reliance on expectations. In this research, I experimentally examine whether the opacity inherent in advanced methods affects auditor reliance on independent expectations and how auditors' psychological ownership of the expectations interacts with opacity to affect reliance.

1.2 Summary of Predictions

I predict that auditors rely less on independent expectations generated with more opaque audit methods. At its broadest definition, opacity is "the quality of being difficult to understand or know about" resulting from a lack of transparency (Cambridge, n.d.). Audit firms use increasingly advanced statistical methods, such as audit data analytics ("ADA"), to more efficiently perform audit tasks that could otherwise be done using basic analytical techniques such as manual examination of numbers and simple calculations (Deloitte 2016; AICPA 2017; Austin, Carpenter, Christ, and Nielsen 2020). Advanced methods are likely more opaque, for a few reasons. One, as complexity of processes increases, it becomes more difficult and sometimes not feasible to clearly explain or show the processes. The inputs and output of an audit procedure may be relatively clear while the process linking them is not, leading to reduced transparency and in turn understanding of the output. Two, previous familiarity with the methods can affect understanding and perceptions of opacity even when the processes are explained (Burton, Stein, and Jenson 2020).

Research finds that individuals often prefer to rely on their own judgments or human expert advice relative to recommendations from statistical sources such as artificial intelligence and decision aids (Whitecotton and Butler 1998; Chen, Hudgins, and Wright 2018; Commerford, Dennis, Joe, and Ulla 2020). I argue that greater *opacity* of the decision process underlying these statistical sources likely causes individuals to prefer their own judgment, since they are more aware of their own process.

Greater trust in their own or a human expert's judgment likely also affects individuals' reliance on statistical sources. I predict that increased auditor psychological ownership—a feeling that something is "yours"—of independent expectations increases their reliance on expectations, but only when using more opaque audit methods. Psychological ownership of independent expectations should increase when auditors use more professional audit judgment to develop expectations because of increased feelings of control and critical thinking (Pierce, O'Driscoll, and Coughlin 2004; Brown, Pierce, and Crossley 2014). Research shows that individuals more positively evaluate objects of ownership (Beggan 1992; Nesselroade, Began, and Allison 1999). Thus, auditors should rely more on their "own" expectation, shifting reliance away from management evidence. However, ownership is likely less critical for increasing reliance on independent expectations generated with less opaque audit methods since they are easier to understand.

1.3 Summary of Research

I test my hypotheses using an experiment with senior auditors from two Big 4 audit firms. I developed a case in which auditors generate an independent expectation of product warranty accrual and use it to assess the reasonableness of management's estimate. I manipulate the method opacity (More Opaque or Less Opaque) and psychological ownership (More Ownership or Less Ownership) in a 2x2 between-participants design.

I manipulate opacity in two ways—familiarity of the method used to generate the independent expectation and visibility of the process linking the inputs and output. In the More Opaque (Less Opaque) condition, instructions explain that a predictive model (calculation) computes expected warranty claims in a data analytics tool (Excel). Then, the tool output, which provides the independent expectation, shows only the inputs and the output (More Opaque condition), or shows the calculation linking the inputs to the output as well (Less Opaque condition). In the More Ownership (Less Ownership) condition, participants specify (are told their team has specified) a critical input to the independent expectation. I operationalize opacity using ADA given recent academic, regulator, and practitioner interest in the topic and its relevance to my constructs of interest (e.g., Deloitte 2016; Austin et al. 2020, PCAOB 2020).

My dependent variable is participants' reliance on the independent expectation. Specifically, I infer reliance from their assessed likelihood that management's estimate is misstated. I hold constant the dollar value of the independent expectation, which is materially higher than management's estimate, indicating an understatement. If participants rely more on the independent expectation, they should place more weight on it and assess greater likelihood that management's estimate is misstated.

Results indicate that specifying a critical input to the independent expectation increases psychological ownership of the expectation, as expected; however, initial analysis does not indicate an effect of opacity or psychological ownership on reliance on the expectation. I test my predictions with planned contrast tests because my theory development led me to predict a specific pattern of means (Guggenmos, Piercy, and Agoglia 2018). Further analysis reveals that task experience (e.g., familiarity with product warranty), which also affects auditors' understanding of the estimate and inputs, moderates my predicted effects. Specifically, I find a 3-way interaction indicating that the effect of opacity and ownership differ for participants who report more versus less task experience.

Low experience with the independent expectation setting (e.g., product warranty) affects understanding of the inputs to the expectation, and my theory and independent variables assume understanding of the inputs (Libby, Bloomfield, and Nelson 2002). For participants with some task experience, I re-perform my planned contrast tests. Test results indicate that my hypotheses are supported. I find a good visual fit of the pattern of means suggested by my contrast codes (-3 for the More Opaque, Less Ownership condition, +1 for all other conditions) with my observed data. The significant contrast test result suggests that given some task experience, auditors' reliance on independent expectations is lower when they use more opaque methods to generate expectations, but that developing ownership over expectations mitigates the effect of opacity.

Results further indicate that when using more opaque methods, the effect of ownership on reliance may differ for auditors with more versus less task experience. When there is both opacity and less involvement required, such as in the Less Ownership condition, reduced understanding of the setting could lead to lower motivation to scrutinize the evidence, resulting in “blind” reliance on the independent expectation (Parasuraman and Manzey, 2010). However, the accountability that auditors have for their conclusions could alleviate motivation issues, and participants were not required to document or explain the reasonableness judgment. Further research may be warranted to examine the effects of task experience.

1.4 Contributions

This study makes several contributions to the literature. I add to research on auditors’ judgments in the audit of estimates and independent expectations (e.g., Griffin 2014; Griffith, Hammersley, Kadous, and Young 2015; Griffith 2018; Austin, Hammersley, and Ricci 2020; Fitzgerald, Williams-Smith, Wolfe, and Garza 2020). I examine whether auditors’ reliance on contradictory evidence can be improved (e.g., Bratten, Gaynor, McDaniel, Montague, and Sierra 2013; GHK 2015), and I examine factors that affect auditors’ reliance on independent expectations that have not been well explored in prior research (e.g., Griffin 2014; Fitzgerald et al. 2020).

This study also answers a call to understand the behavioral implications of ADA, given my operationalization of opacity (Brown-Liburd, Issa, and Lombardi 2015). Recent research has examined reliance on data analytic sources relative to human advice (Chen et al. 2018; Commerford et al. 2020) and the effect of data visualizations on auditor judgments (Rose, Rose, Sanderson, and Thibodeau 2017 and 2019). I extend this work by examining reliance on different methods and the effects of opacity and auditor psychological ownership of ADA.

In addition, this study also has practical implications. My findings suggest that when auditors use more opaque methods, their involvement in and ownership of the output of the methods and their task experience are both critical factors to consider when implementing the methods in practice. Specialists may be heavily involved in developing such procedures, but engagement teams have superior knowledge about client inputs relative to specialists.

CHAPTER 2. BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Independent Expectations and ADA

Auditing standards allow for three different methods to substantively test estimates—testing management's process and assumptions, testing subsequent events or transactions, and developing an independent expectation of the estimate (PCAOB 2018). Audit inspections and academic research find that auditors most often choose to test management's process and assumptions (GHK 2015; Cannon and Bedard 2017; PCAOB 2017) but that auditors often over-rely on management evidence when testing their process and assumptions (Bratten et al. 2013; PCAOB 2017). Research suggests that generating independent expectations of estimates can help mitigate over-reliance on management evidence (PCAOB 2018; GHK 2015; Fitzgerald et al. 2020).[1]

Availability of data is cited by auditors as a key reason that they may not choose to generate independent expectations and instead only test the assumptions in management's estimates (Glover et al. 2017). Increasing access to data and proliferation of advanced statistical methods, such as ADA that allow auditors to accomplish tasks in a more efficient and potentially more effective manner could help auditors more readily generate independent expectations (e.g., Deloitte 2016; Austin et al. 2020).

[1] According to auditing standards, "Developing an independent expectation involves the auditor using some or all of his or her own methods, data, and assumptions to develop an expectation of the estimate for comparison to the company's estimate" (PCAOB, 2018).

However, generating independent expectations does not necessarily result in auditors' full reliance on them. Auditors compare independent expectations to management's estimates and may still test management's assumptions and process, requiring auditors to compare evidence. Research finds that even when auditors have evidence that contradicts management's assertions, auditors are often reluctant to challenge management's assertions, leading them to over-rely on management's evidence (Bratten et al. 2013; GHK 2015). Reluctance to challenge management's assertions can be driven by a variety of factors; for example, auditors often anchor to or have incentive to confirm management's estimates, and the subjectivity inherent in estimates further adds to the subjectivity of auditor reliance on independent expectations. (Bratten et al. 2013; GHK 2015; Cannon and Bedard 2017; Glover et al. 2017).

Therefore, it is important to better understand auditors' reliance on independent expectations. Prior research has examined whether the level of subjectivity or precision (i.e., narrow or wide range) of independent expectations (Griffin 2014) and the timing of generating independent expectations relative to receiving management's estimates (Fitzgerald et al. 2020) affect reliance. In this study, I examine whether the method auditors use to develop independent expectations affects their reliance on expectations. Specifically, I argue that the opacity inherent in certain methods, such as ADA, affects auditors' reliance on the output (e.g., an independent expectation) of the methods, and that psychological ownership of expectations can moderate the effect of opacity.

2.2 Use of Opaque Audit Methods (H1)

An important point is that using more advanced audit methods does not necessarily improve effectiveness of audit procedures, such as accuracy of independent expectations, relative to using less advanced audit methods to perform the same task. For example, different methods can use historical relationships among the same data to generate independent expectations of management's estimate. Accuracy may not necessarily improve when using more advanced statistical methods because inputs and specific calculations are often highly subjective or subject to change. Given similar effectiveness of different audit methods, auditors' reliance on the specific output of the different methods when forming their audit conclusions should not necessarily differ.

However, the process underlying advanced statistical methods is often a "black box," meaning that the process linking the inputs and output is not shown or explained. Opacity is inherent in many advanced methods simply because it becomes more difficult to explain processes as complexity increases (Burton et al. 2020). While complexity and opacity are often correlated, they are distinct. That is, complexity may increase opacity, but opacity can exist without the underlying process necessarily being complex. More specifically, I expect that "black box" processes remain relatively opaque to the user, even if they are not necessarily complex.

To illustrate an example: the mathematics underlying even a *simple* linear regression are typically not explained or shown. On the other hand, auditors can generally "see" a calculation that uses familiar analytical techniques such as manual examination of numbers and calculations, even if it is relatively *complex* (e.g., a compound calculation done in spreadsheet software).

Additionally, opacity is in the mind of the beholder. Familiarity or previous experience with a method can also affect understanding and, in turn, perceived opacity of the process (Burton et al. 2020). A process may remain opaque to an individual even when the process is explained; for example, auditors may not well understand even relatively simple statistical methods such as a linear regression with a few predictor variables if the underlying statistics are not well explained or if auditors do not have much experience with them or understanding of the calculations underlying regressions. I therefore expect that previous familiarity with audit methods further exacerbates perceived opacity of the methods.

Opacity likely affects auditors' ability to process and understand the output of more or less opaque audit methods, and I argue that opacity, in turn, affects *reliance* on the output of the methods. Research finds that individuals often prefer to rely on their own judgments or human expert judgments relative to non-human sources such as "algorithm" advice and decision tools (Whitecotton and Butler 1998; Lee and See 2004; Hoff and Bashir 2015; Parkes 2017; Dietvorst, Simmons, and Massey 2018; Chen et al. 2018; Commerford et al. 2020).[2] I argue that opacity impacts the aversion to relying on non-human sources. For example, non-human sources are often relatively opaque because the decision process underlying the non-human source is not well explained. On the other hand, individuals are aware of their own decision process, leading them to prefer their own judgment over that of the non-human source.

[2] I classify decision aids and automated decision tools as data analytic tools because they utilize data inputs and various analytics to generate recommendations to support individuals' decision-making or fully automate decisions.

The directional effects of opacity on reliance on the output of different methods likely depends on motivation and incentives. When individuals do not have strong incentive or motivation to scrutinize opaque decision tools, users may use the recommendation as a heuristic in place of information processing (Parasuraman and Manzey 2010). For example, Chen et al. (2018) find that aversion to non-human advice is mitigated when individuals do not have incentive to deeply assess the source of the advice. In certain cases, individuals may even rely more on recommendations from non-human sources than human advice, particularly when the human advisor is not an expert (Logg, Minson, and Moore 2019). I expect that because auditors often unconsciously anchor to or have incentive to confirm management's estimate, auditors do have incentive to consider the source of information. Therefore, I predict:

> **Hypothesis 1:** Auditors rely less on independent expectations generated with more opaque audit methods than independent expectations generated with less opaque audit methods.

2.3 Auditor Psychological Ownership of Independent Expectations (H2)

Given an opaque source, individuals may also prefer their own judgment or that of a human expert because they are more familiar with or trust the source more. Research finds that individuals have an overall lower trust of non-human sources and believe the decision process from human experts are easier to understand (Yeomans, Shah, Mullainathan, and Kleinberg 2017; Castelo, Bos, Lehmann 2019). Auditors may therefore rely more on independent expectations if they feel they are their own. I argue that auditors' *psychological ownership* of independent expectations increases reliance on expectations, but only when using more opaque audit methods. Psychological ownership is a feeling that something is "mine" and can be felt towards tangible and intangible targets (Shu and Peck 2011; Brown et al. 2014). For example, individuals can feel psychological ownership of their work (Pierce et al. 2004; Bauer et al. 2018) or items they create (Parè, Sicotte, and Jacque 2006; Franke, Schreier, and Kaier 2010).

Psychological ownership develops through three routes—investing ones' own ideas, skills, and cognitive resources into the target; experiencing control over the target and how tasks are carried out; and having a depth and breadth of knowledge, understanding, and association with the target (Pierce, Kostova, and Dirks 2001; Brown et al. 2014). Research also finds that certain aspects of work environments, such as autonomy, participative decision-making, and job complexity, affect development of psychological ownership (Pierce et al. 2004; Brown et al. 2014). Auditors can have different levels of responsibility for generating independent expectations, such as completing steps to calculate an independent expectation based on inputs that are provided to them or using their professional judgment to develop the inputs and calculate the expectation. When auditors are more involved in decision-making, particularly using their professional judgment, they should develop more psychological ownership of independent expectations because they will experience greater control and critical thinking.

Research further shows that psychological ownership affects judgments and decisions related to targets of ownership. For example, psychological ownership of ones' work is associated with greater commitment to and favorable evaluations of ones' job and organization as well as ones' own ideas and skills (Mayhew, Ashkanasy, Bramble, and. Gardner 2007; Bauer et al. 2018; MacKenzie 2019). Favorable evaluations of targets of ownership occur because individuals associate the targets with themselves, and people have an innate desire to look good to others (Beggan 1992; Gawronski, Bodenhausen, and Becker 2007).

Favorable evaluation of tangible items is greater when the items are chosen or created relative to when individuals simply possess or use items (Gawronski et al. 2007; Franke et al. 2010; Troye and Supphellen 2012). Relatedly, research finds that preference to rely on human versus non-human sources, including decision aids and "algorithm advice," is partially mitigated when individuals are more involved in the development of the non-human decision tool, likely because they experience more control and critical thinking (Whitecotton and Butler 1998; Kaplan, Reneau, and Whitecotton 2001; Parè et al. 2006; Dietvorst et al. 2018).

I expect that auditors will rely more on their "own" independent expectations relative to expectations for which they feel less ownership. I argue, however, that the effect of auditors' ownership on increasing their reliance on independent expectations is more critical when using more opaque methods. Increased ownership of and familiarity with the process underlying independent expectations could help reduce feelings of opacity. Alternatively, because understanding of independent expectations should be higher when using less opaque audit methods, developing psychological ownership of independent expectations likely has less impact on reliance. Formally stated:

> **Hypothesis 2:** The effect of auditor psychological ownership of independent expectations on their reliance on expectations is greater when they use more opaque audit methods than when they use less opaque audit methods.

Refer to Figure 2-1 – Predicted pattern of auditors' reliance on independent expectations, across levels of opacity and ownership of the independent expectation.below for a graph representing the predicted pattern of means indicated by Hypothesis 1 and Hypothesis 2.

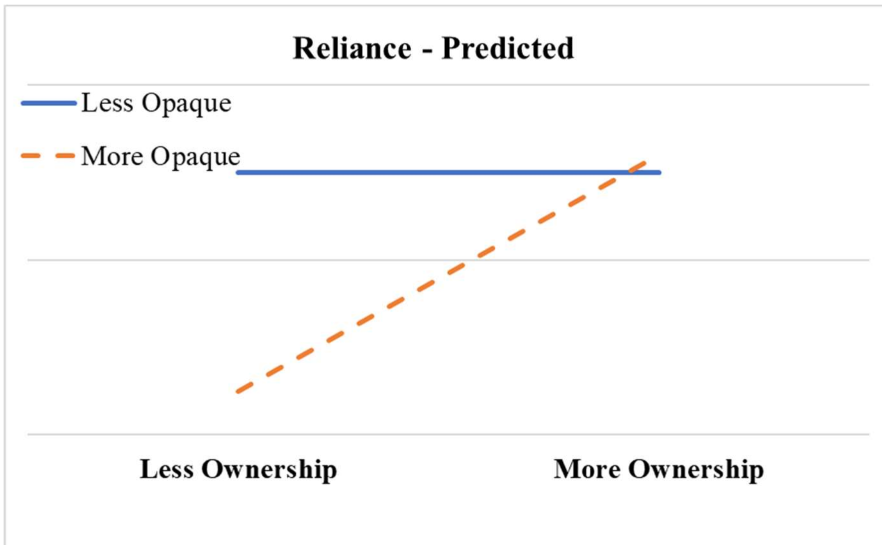

Figure 2-1 – Predicted pattern of auditors' reliance on independent expectations, across levels of opacity and ownership of the independent expectation.

CHAPTER 3. RESEARCH DESIGN

3.1 Setting and Experimental Design

I test my hypotheses with an experiment using practicing senior auditors.[3] I developed a case wherein participants assume the role of an in-charge auditor tasked with completing year-end substantive testing of a hypothetical client's product warranty accrual. Participants complete certain steps to generate an independent expectation of the accrual and assess the reasonableness of the client's recorded account balance. I use warranty accrual in the case because warranty accruals are often material and can be used to manage earnings (Cohen, Durrough, Huang, and Zach 2017). Time limits were not given so as to not introduce time pressure as a potential confounding factor.

I recruited senior auditors from two Big 4 audit firms to complete the experiment. 167 auditors completed the study in person with a paper and pencil instrument. I drop six participants who viewed incorrect information, which affects the validity of their responses (discussed in more detail below), leaving me with a final sample of 161 participants.[4] One participant is a manager, 32 (19.9 percent) are experienced seniors, and the remaining 128 (79.5 percent) are first-year seniors. Participants receive background information that is relevant to their tests of the product warranty accrual, the current and prior year accrual balances, and a description of the client's process to estimate the accrual. They then receive

[3] I received IRB approval from the university where the study was conducted.

[4] Note that not all participants responded to all dependent variables or post-experimental questionnaire ("PEQ") items. I use all available responses in my analyses; thus, sample sizes may differ across analyses.

information to generate the independent expectation. Finally, participants receive the materiality threshold, respond to the dependent variable, and complete a brief questionnaire.

3.2 Independent Variables

I manipulate two independent variables related to the method to generate the independent expectation, for a 2 (*method opacity*) x 2 (*psychological ownership*) between-participants design.

3.2.1 Opacity Manipulation

I manipulate opacity in both the description of the computational method used as well as the output from the method used to generate the independent expectation. Namely, the case states that the independent expectation is generated in a data analytics tool using predictive modeling (More Opaque condition) or in Excel using a specified calculation (Less Opaque condition).[5] The tool output, which they receive after the ownership manipulation (discussed below), indicates the same inputs and *total* output (i.e., expected warranty claims, which represents the independent expectation) across opacity conditions. The output does not (does) show the process, namely the specific calculation linking the inputs and outputs, in the More Opaque condition (Less Opaque condition). Refer to figures

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[5] I refer to the tool in the More Opaque condition as "a data analytics tool" rather than a specific software package based on feedback from a Big 4 audit firm who reviewed my materials. They noted that audit firms often develop their own proprietary software. On the other hand, I use "Excel" for the Less Opaque condition since all firms use it, and auditors use it daily for almost every audit task. Using a generic description does potentially allow for greater variability in participants' perception of the tool but allows for better comparison across firms. Untabulated analysis of PEQ questions indicates that participants perceived the tool in the More Opaque condition to be a "firm tool" more than in the Less Opaque condition ($p < .01$ one-tailed), providing evidence that participants thought about the data analytics software that their own firm uses.

below for excerpts from the experimental materials of the description (Figure 3-1, Panels A and B) and output (Figure 3-2, Panels A and B).

Figure 3-1 – Opacity Manipulation: Description of Method

Panel A: Less Opaque condition

<u>Background</u>

Assume **you are responsible for** the following test steps:

1. Generate an independent expectation of product warranty accrual based on information and evidence in this case. You will:

   - Receive a critical input to the independent expectation from your team.
   - Receive results of the independent expectation, which is generated in Excel using the specified inputs.

<u>Generating an Independent Expectation</u>

The engagement team has obtained multiple years of sales and warranty claim data, which allows for an independent expectation to be generated using a firm-recommended method**.**

The independent expectation is generated using a **calculation that computes expected future warranty claim costs based on relationships** between historical warranty costs and sales data and accounts for product factors for which warranty rates or costs may vary.

Panel B: More Opaque condition

Background

Assume **you are responsible for** the following test steps:

1. Generate an independent expectation of product warranty accrual based on information and evidence in this case. You will:
   - Receive a critical input to the independent expectation from your team.
   - Receive results of the independent expectation, which is generated in a Data Analytics tool using the specified inputs.

Generating an Independent Expectation

The engagement team has obtained multiple years of sales and warranty claim data, which allows for an independent expectation to be generated using a firm-recommended method**.**

The independent expectation is generated using a **predictive model that computes expected future warranty claim costs based on relationships** between historical warranty costs and sales data and accounts for product factors for which warranty rates or costs may vary.

Figure 3-2 – Opacity Manipulation: Output of Tool

Panel A: Less Opaque condition

Calculation Inputs		
Sales	1/1/15-12/31/17	
Warranty	8/1/15-7/31/18	**7 month sales to warranty lag*
Factors	**Product Line, Raw Material**	

Category	*Warranty / Sales*	*FY 2018 sales*	*Estimated Claims*
Gear			
Steel	2.3%	$ 1,658.2	$ 38.6
Plastics	-	-	-
Conveyor Equipment			
Steel	2.8%	464.9	13.1
Plastics	3.0%	587.0	17.5
Aerospace			
Steel	2.1%	1,157.3	24.3
Plastics	3.4%	251.2	8.5
	Total	**$ 4,118.6**	**$ 102.0**

Panel B: More Opaque condition

Model Inputs		
Sales	1/1/15-12/31/17	
Warranty	8/1/15-7/31/18	**7 month sales to warranty lag*
Factors	**Product Line, Raw Material**	

Input: FY 2018 sales	*Output: Estimated Claims*
$ 4,118.6	**$ 102.0**

3.2.2 Ownership Manipulation

Participants use their judgment to choose (More Ownership condition) or are told that their team has chosen (Less Ownership condition) a critical input to the independent expectation—namely, which product factor(s) to include in the calculation to account for factors for which warranty rates or costs may vary.[6] I make certain design choices to bolster the effect of their choices on psychological ownership, particularly experiencing control and critical thinking. One, the case does not provide explicit information as to the "correct" factors. Rather, the case provides background information to help participants understand and think about how warranty failure rates or costs could differ across product categories in general. In practice, such inputs are subjective and based on professional judgment.

Two, participants in the More Ownership condition are asked to briefly explain their choice so that they will be less likely to select factors without reason. In the study, participants do not face any real risks or costs associated with choosing any or all of the factors while in a real audit setting, auditors are generally required to document their decisions, which would entail justifying their choices. Refer to Figure 3-3, Panels A and B, below for excerpt from the experimental materials of the ownership manipulation. [7]

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[6] The factors that are included in the Less Ownership condition are based on those chosen by participants in pilot tests, so that the factors included in the independent expectation will be similar across conditions.

[7] It is critical that participants feel that the independent expectation is linked to the specified inputs and model or calculation. In the paper and pencil administration of the experimental instrument, I used an "envelope" system. In the More Ownership condition, I provided a sealed envelope for each factor or combination of factors. Participants were asked to open the envelope that corresponds to their specified factors and leave others sealed. The six participants I drop from the sample opened incorrect envelopes. I provided only one sealed envelope in the Less Ownership condition, which includes the factors stated in the case as selected by their team. Participants were told that the envelopes contain "the output from a data analytics tool (Excel) of the model (calculation), which was pre-generated using the specified inputs."

Figure 3-3 – Ownership Manipulation

Panel A: Less Ownership condition

<u>Generating an Independent Expectation</u>

The engagement team has obtained multiple years of sales and warranty claim data, which allows for an independent expectation to be generated using a firm-recommended method.

The independent expectation is generated using a **predictive model that computes expected future warranty claim costs based on relationships** between historical warranty costs and sales data and accounts for product factors for which warranty rates or costs may vary.

First, **you will receive a critical input** to the model from your team (described in further detail on next page).

<u>Input to the Model</u>

Please take note of the following critical input to the independent expectation.

Product factors:

Based on the data available, *the following factor(s)* could be included in the model to account for product factor(s) for which warranty rates or costs may vary (different category names are in parentheses):

- Product line (Gear, Conveyor, Aerospace)
- Raw material category (plastics, steel)
- Product category (standard product vs build-to-spec)

(continued on next page)

(continued)

Note that there is not one right answer. The team's judgment is valuable. The estimate should **focus on the factor(s) that are believed to be associated with different warranty claim rates and/or costs** for each category and those that **may differ between other factors**.

Recall that you may also go back to prior pages to review relevant information (e.g., CCI's sales and warranty information, factors that affect warranty rates and costs, etc.).

Note that your team specified that Raw Material and Product Category will be included in the calculation.

Panel B: More Ownership condition

Generating an Independent Expectation

The engagement team has obtained multiple years of sales and warranty claim data, which allows for an independent expectation to be generated using a firm-recommended method.

The independent expectation is generated using a **predictive model that computes expected future warranty claim costs based on relationships** between historical warranty costs and sales data and accounts for product factors for which warranty rates or costs may vary.

First, **you will specify a critical input** to the model (described in further detail on next page).

Input to the Model

Please take note of the following critical input to the independent expectation.

Product factors:

Based on the data available, *the following factor(s)* could be included in the model to account for product factor(s) for which warranty rates or costs may vary (different category names are in parentheses):

- Product line (Gear, Conveyor, Aerospace)
- Raw material category (plastics, steel)
- Product category (standard product vs build-to-spec)

(continued on next page)

(continued)

Note that there is not one right answer. The team's judgment is valuable. The estimate should **focus on the factor(s) that are believed to be associated with different warranty claim rates and/or costs** for each category and those that **may differ between other factors**.

Recall that you may also go back to prior pages to review relevant information (e.g., CCI's sales and warranty information, factors that affect warranty rates and costs, etc.).

Check at least 1 and up to all 3 factors below to specify which product factor(s) you will include in the model. Then, please *briefly* explain your decision in the space provided.

- ☐ Product line (Gear, Conveyor, Aerospace)
- ☐ Raw material category (plastics, steel)
- ☐ Product category (standard product vs build-to-spec)

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3.2.3 Information Controls

Across conditions, I control on the information and quality of the independent expectation in several ways. Specifically, I hold constant the *inputs* to the independent expectation (the description of the data used and the critical inputs), the *source* of the model or calculation (e.g., that it is a firm-prescribed method), the *description* of how it is used (e.g., that the model or calculation "computes expected future warranty claim costs based on relationships between historical warranty costs and sales data"), and the *dollar value* of the independent expectation.[8]

3.3 Dependent Variables

After receiving the independent expectation, participants respond to the dependent variable question. Specifically, participants evaluate whether the client's accrual balance is materially misstated on an 11-point Likert-type scale.[9] I infer auditors' reliance on the independent expectation from their responses: since participants both generate an independent expectation and receive management's estimate, and I hold constant the dollar values of both, greater (less) reliance on the independent expectation should result in more (less) weight placed on the expectation and in a higher (lower) assessed likelihood of material misstatement.

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[8] I ask a few questions in the PEQ to measure perceived differences in information or quality of the independent expectation across opacity conditions. Specifically, I ask participants whether (1) they are confident that the independent expectation is an accurate estimate of product warranty, (2) the method was prescribed by the firm, and (3) the independent expectation considered significantly more factors than management's estimate. Responses indicate no differences in perceptions of the method across opacity conditions (untabulated).

[9] Reliance is participants' response to the following question: "how likely is the client's product warranty accrual to be materially misstated?"

In the PEQ, I measure participants' psychological ownership of the independent expectation, which also serves as a manipulation check for psychological ownership, on an 11-point Likert-type scale.[10] These questions were adapted from scales developed and validated in prior research (Van Dyne and Pierce 2004; Brown et al. 2014).

I also ask participants how familiar they are with product warranty, which provides a measure of task experience. While my senior auditor participants are appropriately matched to an audit estimate task (Libby et al. 2002), those who lack familiarity with the specific type of estimate used in my experimental case, namely product warranty, may not be. One, low experience with a product warranty estimates would also affect understanding of the related independent expectation, over and above the understanding of a method used to generate that expectation. Two, the nature of my independent variable operationalizations requires reasonable understanding of key elements of the case. Recall that participants in the More Ownership condition are required to make a decision regarding a critical input to the product warranty independent expectation. Therefore, I include reported task experience as a measured variable in my analyses.[11]

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[10] I measure psychological ownership using two questions, ("I feel the independent expectation is my own." and "I feel a high degree of personal ownership of the independent expectation."). The Cronbach's alpha score for the two psychological ownership measures is 0.911, which is within accepted reliability thresholds (Peterson 1994). Therefore, for analyses involving psychological ownership, I use the average of these two questions. Inferences do not change if I use either of the two questions in my analyses.

[11] The mean (median) of reported familiarity with product warranty is 3.43 (3.00). For analyses involving reported task experience, I use a median split based on reported experience.

CHAPTER 4. RESULTS

4.1 Manipulation Checks

As discussed, opacity is manipulated in two ways. One, the independent expectation is generated either with predictive modeling (More Opaque condition) or a basic calculation in Excel (Less Opaque condition). Participants report less (more) experience using tools “similar to the one described in the case” in the More Opaque condition (Less Opaque condition) (t_{154} = 3.624, p = 0.001 one-tailed). Two, the detail underlying the calculation process in the More Opaque condition (Less Opaque condition) is not (is) provided in the tool output. Participants report less (more) ability to “clearly see the process to calculate the independent expectation” in the More Opaque condition (Less Opaque condition) (t_{157} = 3.099, p = 0.001 one-tailed). Further, responses to post-experimental questions indicate that participants understand the independent expectation less (more) in the More Opaque condition (t_{157} = 2.409, p = 0.009 one-tailed).

To assess whether participants attended to my psychological ownership manipulation, I evaluate responses to the PEQ questions related to the development of psychological ownership. I find that choosing the critical input is associated with greater feelings of contribution to the development of the expectation (t_{158} = 2.828, p = 0.003 one-tailed); control over the development of the independent expectation (t_{157} = 4.333, $p < .001$ one-tailed); and overall feelings of ownership of the independent expectation (t_{158} = 1.885, p = 0.031 one-tailed). Overall, my manipulations appear to have worked as intended.

4.2 Tests of Hypotheses

4.2.1 Summary of hypotheses

I predict that auditors rely less on independent expectations generated using more opaque methods than expectations generated using less opaque methods (H1). Further, I predict that the effect of auditor psychological ownership of independent expectations on reliance is greater when using more opaque versus less opaque methods, thus mitigating the negative effects of method opacity on reliance (H2). My theory suggests that ownership increases reliance on independent expectations more when using more opaque audit methods because the opacity underlying opaque methods could affect understanding of the output but that auditors would be more willing to rely on their "own" expectations. Refer to Figure 2-1 for a visual representation of my hypotheses.

4.2.2 Results of ANOVA (Opacity x Ownership)

I first examine the effect of my two independent variables on my dependent variable, using a full-factorial 2x2 ANOVA. Figure 4-1 plots the means by experimental condition, and Table 4-1, Panel A reports the means and standard deviations by experimental condition. The ANOVA (

Table 4-1, Panel B) indicates that the predicted interaction term is not significant ($F_{1, 150} = 0.059$, $p = 0.809$), nor are the remaining effects.

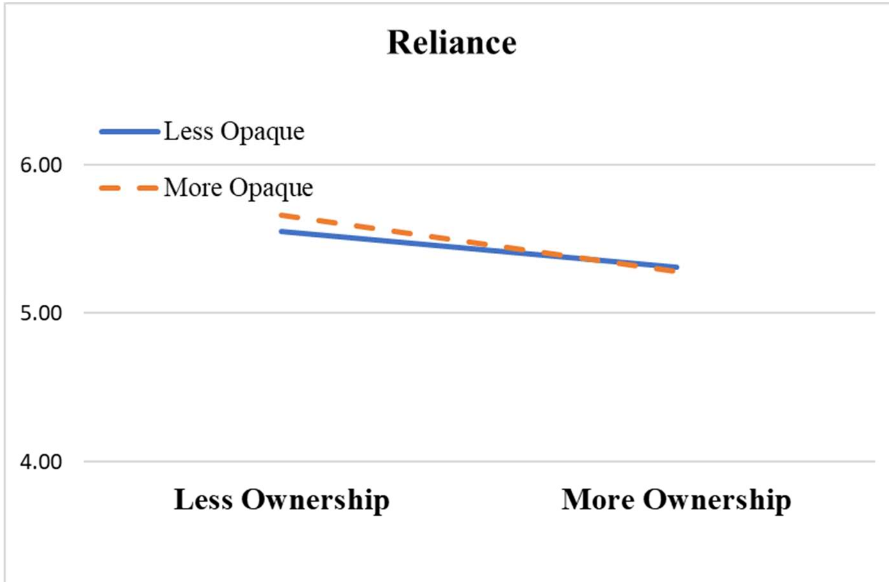

Figure 4-1 – Plot of observed means of dependent variable measuring participants' reliance on the independent expectation, across experimental conditions.

Table 4-1, Panel A – Descriptive statistics for dependent variable measuring reliance on the independent expectation, across experimental conditions (mean, (standard deviation))

	Psychological Ownership		
Opacity	*Less Ownership*	*More Ownership*	*Overall*
Less Opaque	5.55 (2.36) n = 42	5.31 (2.29) n = 36	5.44 (2.32) n = 78
More Opaque	5.66 (2.47) n = 35	5.28 (2.33) n = 39	5.46 (2.39) n = 74
Overall	5.60 (2.40) n = 77	5.29 (2.29) n = 75	

Table 4-1, Panel B – Reliance 2x2 ANOVA

Source of Variation	df	MS	F-statistic	p-value
Opacity (**H1**)	1	.012	.002	.963
Psychological Ownership	1	3.807	.690	.408
Opacity x Ownership **(H2)**	1	.324	.059	.809
Error	150	5.519		

4.2.3 Results of contrast tests

I next perform follow-up contrast tests. Recall that H2 predicts an ordinal interaction, and more specifically, my hypothesis development led me to predict the specific pattern of means noted in Figure 2-1. The standard ANOVA test does not allow me to test the specific pattern of means in H2; therefore, I use planned contrast testing as a more powerful test of my interaction and to allow me to test the predicted pattern of means (Buckless and Ravenscroft 1990; Guggenmos, Piercey, and Agoglia 2018).

I follow the three-step approach established by Guggenmos, et al. (2018) to test my hypotheses. I assign a contrast code of -3 to the More Opaque, Less Ownership condition and codes of +1 to all other conditions. I first examine the visual fit of the contrast codes and the observed data. I note that the pattern suggested by my hypotheses and contrast codes (Figure 2-1) does not match the observed data (Figure 4-1). I next examine the statistical results of the contrast test and the between-cells variance test. As reported in Table 4-1, Panel C, test results indicate a non-significant contrast ($p = 0.532$) and a non-significant residual between-cells variance (p = 0.841). I evaluate the contrast variance residual metric, or q^2, which identifies the proportion of between-cells variance that the contrast does not explain. Results (untabulated) indicate that $q^2 = 0.452$, which indicates that the contrast does not explain 45.2% of the between-cells variance.

Table 4-1, Panel C – Contrast and residual between-cells variance test

Source	SS	df	MS	F-statistic	p-value
Contrast	2.167	1	2.167	0.393	**0.532**
Residual between-cells variance	1.908	2	0.954	0.173	0.841
Error	827.899	150	5.519		

4.3 Effect of Task Experience

4.3.1 Results of ANOVA (Opacity x Ownership x Task Experience)

As discussed in the preceding section, auditors' relative task experience could also affect understanding of, and in turn reliance on, independent expectations. My predictions therefore assume experiment participants have sufficient knowledge of the product warranty setting used in the case (Libby et al. 2002). However, many participants reported little or no familiarity with product warranty, which could be driven by industry specialization. The mean (median) of reported familiarity with product warranty is 3.43 (3.00) on an 11-point Likert-type scale, with 43.3 percent reporting below the median (2 or less).

To examine the potential effects of task experience, I split participants into two groups based on the median of their reported experience with product warranty and include it with my two independent variables in a full-factorial 2x2x2 ANOVA. The ANOVA (Table 4-2, Panel A) indicates a marginally significant 3-way interaction term for the method opacity, auditor psychological ownership, and task experience ($F_{1, 144} = 2.999$, $p = 0.085$) and a marginally significant interaction term of method opacity and task experience ($F_{1, 144} = 2.704$, $p = 0.102$). None of the remaining main effects or interaction terms are significant. The results suggest that the effect of ownership on reliance on the independent expectation differs across levels of opacity, as expected, but that task experience also matters in my setting.

Table 4-2, Panel A – Reliance 2x2x2 ANOVA

Source of Variation	df	MS	F-statistic	p-value
Opacity (**H1**)	1	.839	.155	.694
Psychological Ownership	1	.566	.105	.747
Task Experience	1	8.294	1.532	.218
Opacity x Ownership **(H2)**	1	.714	.132	.717
Opacity x Task Experience	1	13.115	2.422	.122
Ownership x Task Experience	1	14.641	2.704	.102
Opacity x Ownership x Task Experience	1	16.238	2.999	**.085**
Error	144	5.415		

To further understand these results, I examine the effects of opacity and ownership on participants' reliance on the independent expectation separately for each of the two task experience groups. Figure 4-2 and Figure 4-3 plot the means for the More Task Experience and Less Task Experience groups, respectively. Across both levels of experience, when auditors generate an expectation using a less opaque method, increased auditor ownership of the expectation does not appear to affect reliance, consistent with my theory. When auditors generate an expectation using a more opaque method, auditor ownership appears to affect reliance, but task experience also matters.

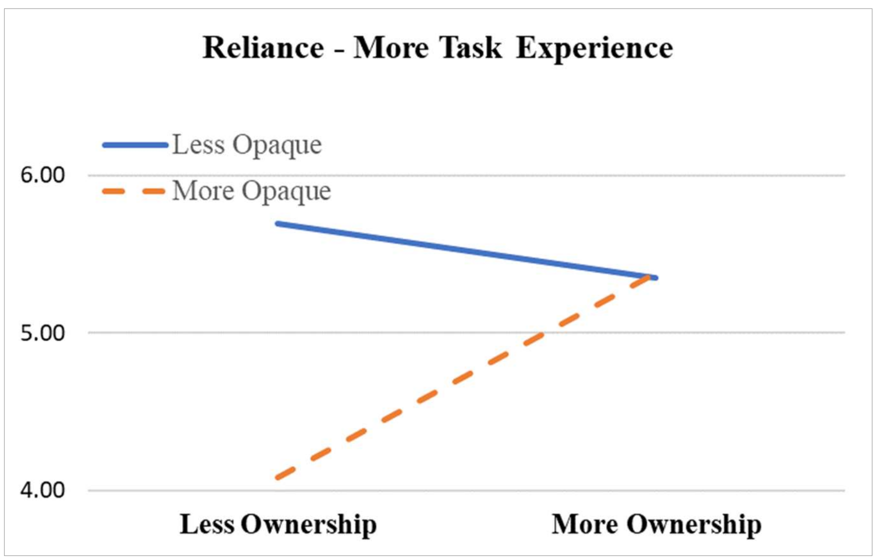

Figure 4-2 – Plot of observed means of dependent variable measuring participants' reliance on the independent expectation, across experimental conditions, for participants who report more task experience

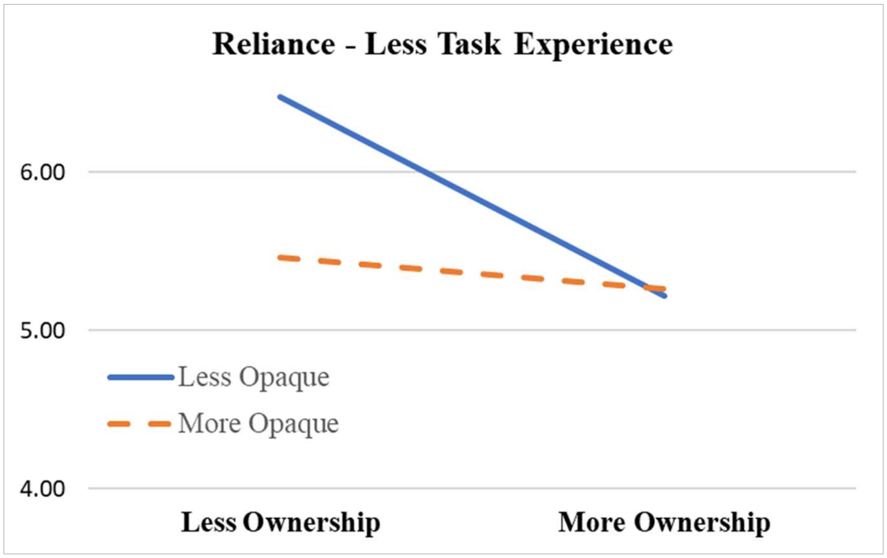

Figure 4-3 – Plot of observed means of dependent variable measuring participants' reliance on the independent expectation, across experimental conditions, for participants who report less task experience

4.4 Tests of Hypotheses – More Task Experience group

Since participants who report some task experience are most appropriately matched to my experimental setting, my remaining analyses focus on the More Task Experience group.[12]

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[12] Participants who report a 0, 1, 2, or 3 (4 or greater) on an 11-point scale are included in the Less Experience (More Experience) group. Note that inferences remain unchanged if I include participants who report a 3 in the More Experience group rather than the Less Experience group. Inferences also remain unchanged if I use a reduced sample and exclude participants who report a 0 or 1, instead of the More Experience group

For the Less Experience group, the ANOVA indicates no effect of opacity ($F_{1,87} = 0.873$, $p = 0.353$) or ownership ($F_{1,87} = 1.971$, $p = 0.164$) on reliance on the independent expectation or an interaction of the variables ($F_{1,87} = 1.045$, $p = 0.309$), all untabulated. Note that I conduct a contrast test for the More Experience group; the pattern of means indicated by the contrast codes used in my analysis do not match the observed data for the Less Experience group.

4.4.1 *Results of ANOVA (Opacity x Ownership) – More Task Experience group*

Table 4-2, Panel B report the means and standard deviations and

Table 4-2, Panel C reports the ANOVA results for the More Task Experience group. For the More Experience group, the ANOVA indicates no effect of opacity ($F_{1,57} = 2.119$, $p = 0.151$) on reliance on the independent expectation, although results are directionally consistent with H1. I do not find a significant interaction of opacity and ownership ($F_{1, 57} = 2.239$, $p = 0.309$) on participants' reliance, although the pattern of means aligns with H2.

Table 4-2, Panel B – Descriptive statistics for reliance on the independent expectation, across experimental conditions (mean, (standard deviation)) (*More Task Experience* group)

	Psychological Ownership		
Opacity	*Less Ownership*	*More Ownership*	*Overall*
Less Opaque	5.69 (2.09) n = 16	5.35 (2.29) n = 17	5.52 (2.17) n = 33
More Opaque	4.08 (2.09) n = 12	5.38 (2.29) n = 16	4.82 (2.06) n = 28
Overall	5.00 (2.09) n = 28	5.36 (2.18) n = 33	

Table 4-2, Panel C – Reliance 2x2 ANOVA (*More Task Experience* group)

Source of Variation	df	MS	F-statistic	p-value
Opacity (**H1**)	1	9.369	2.119	.151
Psychological Ownership	1	3.429	.776	.382
Opacity x Ownership **(H2)**	1	9.899	2.239	.140
Error	57	4.421		

4.4.2 Results of contrast tests – More Task Experience group

I next perform my follow-up contrast testing for the More Experience group, using the same planned contrast codes discussed for my full sample tests (-3 for More Opaque, Less Ownership; +1 for all other conditions). Visual inspection of the predicted pattern (Figure 2-1) and observed data, for the More Task Experience group (Figure 4-2), suggests a fit of the data to the pattern suggested by my theory and contrast codes. Statistical results of the contrast test are reported in

Table 4-2, Panel D. Test results indicate a significant planned contrast ($p = 0.044$) and a non-significant residual between-cells variance ($p = 0.867$), which provides support for a significant interaction. Results (untabulated) further indicate that $q^2 = 0.053$, which indicates that the contrast does not explain 5.3% of the between-cells variance (and does explain the remaining 94.7%).

Table 4-2, Panel D – Contrast and residual between-cells variance test (*More Task Experience* group)

Source	SS	df	MS	F-statistic	p-value
Contrast	18.318	1	18.318	4.252	**.044**
Residual between-cells variance	1.235	2	0.617	0.143	.867
Error	254.161	59	4.308		

4.4.3 Results of simple main effects tests – More Task Experience group

I further test my hypotheses with simple effects tests, reported in Table 4-2, Panel E. I find that when auditors have less ownership of independent expectations, they rely on the expectations less when they use more opaque methods compared to when they use less opaque methods ($t = 2.047$, $p = 0.045$). When auditors have more ownership of independent expectations, I no longer find a statistically significant difference in reliance across level of opacity ($t = 0.137$, $p = 0.892$). This difference in reliance is mitigated because ownership increases reliance for auditors who use more opaque methods ($t = 1.565$, $p = 0.123$). Taken together, these results provide support for my hypotheses.

Table 4-2, Panel E – Simple main effects tests (*More Task Experience* group)

Comparison	Contrast Value	t-statistic	df	p-value
More Opaque (Less Ownership)				
vs Less Opaque (Less Ownership)	1.604	2.047	59	0.045
vs More Opaque (More Ownership)	-1.211	-1.565	59	0.123
vs Less Opaque (More Ownership)	-1.306	-1.707	59	0.093
Less Opaque (More Ownership)				
vs Less Opaque (Less Ownership)	0.299	0.424	59	0.673
vs More Opaque (More Ownership)	0.095	0.137	59	0.892

4.5 Additional Analysis: Effects of Task Experience, by Level of Opacity

To further understand my three-way interaction of opacity, ownership, and task experience, I also examine the effects of ownership and *task experience* on participants' reliance on the independent expectation separately for each of the two levels of opacity. Figure 4-4 and Figure 4-5 plot the means and Table 4-3, Panel A and Table 4-3, Panel C report the means and standard deviations for the More Opaque and Less Opaque conditions, respectively. Table 4-3, Panel B and Table 4-3, Panel D below report the ANOVA results for the More Opaque and Less Opaque conditions, respectively.

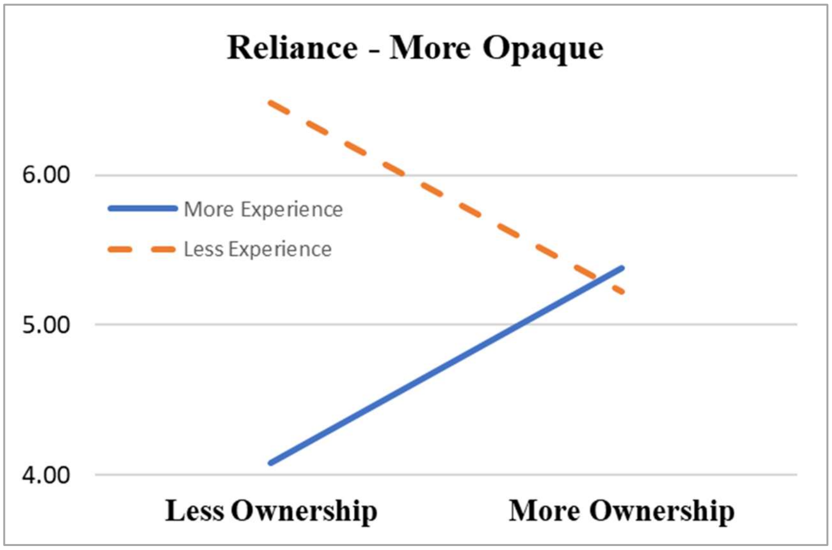

Figure 4-4 – Plot of observed means of dependent variable measuring participants' reliance on the independent expectation, across levels of Ownership and reported levels of Task Experience (*More Opaque* condition)

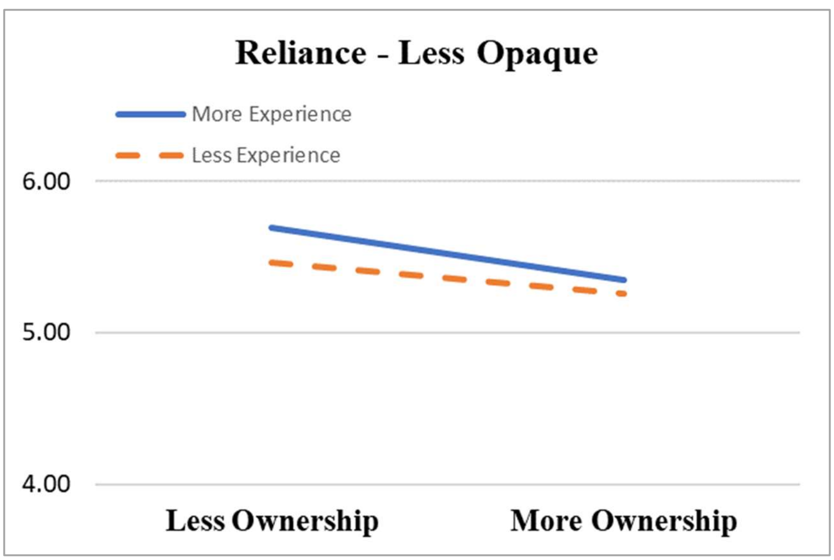

Figure 4-5 – Plot of observed means of dependent variable measuring participants' reliance on the independent expectation, across levels of Ownership and reported levels of Task Experience (*Less Opaque* condition)

For the More Opaque condition, the ANOVA (Table 4-3, Panel B) indicates a significant disordinal interaction of ownership and task experience ($F_{1, 70} = 5.319$, $p = .024$). The plot of means suggests that for auditors with some task experience, ownership appears to increase reliance on the independent expectation, consistent with my theory. Interestingly, for auditors with lower levels of task experience, ownership may reduce reliance on the expectation. The ANOVA further indicates an effect of task experience on reliance. Participants who reported more task experience relied *less* on the independent expectation (mean = 5.20) than those who reported lower levels of task experience (mean = 5.62, $F_{1, 70} = 4.087$, $p = .047$).

Table 4-3, Panel A – Descriptive statistics for reliance on the independent expectation, across levels of Ownership and reported Task Experience (mean, (standard deviation)) (*More Opaque* condition)

	Psychological Ownership		
Task Experience	*Less Ownership*	*More Ownership*	*Overall*
Less Experience	6.48 (2.41) n = 23	5.22 (2.50) n = 23	5.85 (2.51) n = 46
More Experience	4.08 (1.78) n = 12	5.38 (2.13) n = 16	4.82 (2.06) n = 28
Overall	5.66 (2.47) n = 35	5.28 (2.33) n = 39	

Table 4-3, Panel B – Reliance 2x2 ANOVA (*More Opaque* condition)

Source of Variation	df	MS	F-statistic	p-value
Psychological Ownership	1	.004	.001	.978
Task Experience	1	21.503	4.087	**.047**
Ownership x Task Experience	1	27.989	5.319	**.024**
Error	70	5.262		

These results could indicate that those with more task experience understand enough to question the more opaque independent expectation, but in turn have improved reliance with psychological ownership, as predicted. Alternatively, those with less task experience likely do not understand the underlying estimate or the inputs well enough to scrutinize the more opaque independent expectation, leading to potential "blind" reliance. In this case, ownership could help temper the effect. However, for participants who did not have any required involvement in developing the independent expectation, namely those in the Less Ownership condition, they may not have felt accountability for the judgment made, which could lead to reduced motivation to scrutinize the evidence. For example, auditors in practice would be required to document and explain conclusions to superiors and/or the client. Thus, results may not generalize outside of the experiment, and further research may be warranted to further examine task experience and the potential for blind reliance.

For the Less Opaque condition, the ANOVA (Table 4-3, Panel D) indicates no effect of ownership ($F_{1, 74}$ = .240, p = .625) or task experience ($F_{1, 74}$ = .084, p = .772) on reliance on the independent expectation or an interaction of the variables ($F_{1, 74} = .016$, $p = .901$). My theory suggests that because less opaque methods are easier to understand, psychological ownership of independent expectations would not be critical for reliance. These results are consistent with my theory.

Table 4-3, Panel C – Descriptive statistics for reliance on the independent expectation, across levels of Ownership and reported Experience (mean, (standard deviation)) (*Less Opaque* condition)

	Psychological Ownership		
Task Experience	*Less Ownership*	*More Ownership*	*Overall*
Less Experience	5.46 (2.55) n = 26	5.26 (2.35) n = 19	5.38 (2.44) n = 45
More Experience	5.69 (2.09) n = 16	5.35 (2.29) n = 17	5.52 (2.17) n = 33
Overall	5.55 (2.36) n = 42	5.31 (2.29) n = 36	

Table 4-3, Panel D – Reliance 2x2 ANOVA (*Less Opaque* condition)

Source of Variation	df	MS	F-statistic	p-value
Psychological Ownership	1	1.337	.240	.625
Task Experience	1	.469	.084	.772
Ownership x Task Experience	1	.087	.016	.901
Error	74	5.560		

CHAPTER 5. DISCUSSION AND CONCLUSION

5.1 Summary of results

In this study, I examine auditors' reliance on independence expectations of estimates. I argue that the methods auditors use to generate independent expectations can affect their reliance on expectations. Specifically, I predict that auditors' reliance depends jointly on their use of opaque methods and their psychological ownership of independent expectations. I hypothesize that opacity of audit methods can interfere with reliance on independent expectations because opacity affects understanding. However, I further predict that auditors' psychological ownership of independent expectations improves reliance on expectations developed using more opaque methods because auditors are more likely to rely on their "own" expectations, while ownership is less critical for increasing reliance on independent expectations generated using less opaque methods, since these independent expectations are easier to understand.

Results of an experiment with senior auditors from two Big 4 firms indicate that when auditors generate an independent expectation using a more opaque method, auditor ownership in the expectation affects reliance but that task experience moderates the effects. Specifically, for auditors with some prior familiarity with the audit area, who are best matched to the experimental task, an ordinal interaction of opacity and ownership supports my hypotheses.

5.2 Contributions

This study makes several contributions to the literature. I add to research on auditors' judgments and decision making when auditing estimates. Prior work has examined auditors' professional skepticism, such as improving critical thinking and information processing during the examination of evidence (GHKY 2015; Rasso 2015; Tegeler 2018; Hong 2019), auditors' reliance on specialists' work (Griffith 2018; Estep 2021), and the effect of factors such as subjectivity and uncertainty and the timing of evidence (Griffin 2014; Fitzgerald et al. 2020). However, even when auditors do have disconfirming evidence, they may under-rely on such evidence, and I demonstrate ways to increase reliance on contradictory evidence.

I examine variables that can affect reliance on independent expectations that have not been previously examined (Griffin 2014; Fitzgerald et al. 2020). My findings shed additional light on auditors' reliance on independent expectations but can also generalize more broadly to evidence that contradicts management's assertions. Prior research suggests that generating independent expectations of management estimates can mitigate over-reliance on management evidence; however, use of independent expectations does not necessarily lead to full reliance on them. Reliance is subject to judgment—auditors will also compare independent expectations to management evidence, and estimates are inherently subjective.

Given my operationalization of audit method opacity using predictive modeling, a type of data analytics, I also answer a call to conduct research on the behavioral implications of auditors' use of data analytics (Brown-Liburd et al. 2015; Earley 2015). I also add to recent research on the effect of data analytics on accounting judgments. Recent research has examined auditors' and investors' reliance on human versus data analytic advice (Chen et al. 2018; Commerford et al. 2020) and the effect of data visualizations on auditor judgments (Rose et al. 2017 and 2019). I examine auditors' reliance on data analytic methods relative to non-ADA tools. I develop new theory for why individuals may rely less on ADA methods; specifically, my results suggest that attributes of different methods, such as opacity, affect reliance on output from the methods.

This study also has implications for practice. Findings suggest that certain methods are more opaque to auditors. Further, auditor ownership of their work and auditors' task experience are critical considerations when using more opaque methods in practice. Less experienced auditors (e.g., junior staff or new seniors) may be tasked with utilizing certain opaque methods, such as ADA, given their more relevant university education. Outsourcing of simpler audit tasks has also led firms to push more complex tasks, such as the audit of estimates, down to less experienced staff. Less experienced staff may not understand the specific task, such as the type of estimate, very well, and my results indicate that task experience can impact reliance on ADA.

Audit firms may also engage firm specialists to develop ADA because engagement team auditors lack sufficient experience with such tools and methods, suggesting that engagement team auditors should be less involved. Prior research suggests that auditors may not fully rely on specialists' work (Griffith 2018). Engagement team auditors would have client-specific knowledge that would prove useful for fine-tuning analytics that are developed by specialists. Future research could explore whether auditor involvement and ownership could also improve reliance on specialists' work.

5.3 Limitations

This study is not without limitations. Participants did not engage with a real tool or software, which could influence their judgments. However, by not having participants perform a real calculation, I cleanly control for the work done and time spent by participants in the case as well as the output, outside of the level of opacity. Participants also did not have as much information as they would in a real audit to help make choices regarding the factors. Therefore, inferences I make in this study may not generalize to scenarios where auditors have significantly more information.

For participants who reported less task experience, I found no evidence of an effect of opacity or ownership; however, directionally, participants relied more on the independent expectation generated with a more opaque method, with contradicts H1. Prior research finds that individuals can "blindly" rely on recommendations from opaque or "black box" decision tools when they do not know what to question (Parasuraman and Manzey 2010). However, any observed results for participants who reported low task experience may not generalize outside of my experimental setting. In practice, auditors have the ability to gain an understanding of the task or area before completing the work (for example, reading prior year workpapers, speaking with engagement team members, or referencing accounting standards). In my experimental setting, however, participants have limited time and background information to gain sufficient understanding. Future research may be warranted to examine the effects of task experience as a manipulated variable.

In addition, most of my participants were new seniors who had not yet completed a busy season as an in-charge auditor. In addition to an effect on task experience, more experienced auditors may make different judgments if they are more attuned to client pressure or preferences to confirm management's numbers. For example, greater opacity of output and unfamiliarity with more opaque methods could cause more experienced auditors (i.e., experienced seniors or managers) to question the output more. Additional research could examine the effect of experience, aside from task experience, or examine settings where a preference to confirm management's estimate (e.g., a supervisor preference) is salient.

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