SAMPLE LESS, DISCOVER MORE

Cherry Bekaert's journey to more efficient audits

An in depth look at how a top accounting firm generates significant return on investment through reliance on data driven techniques.

Who is MindBridge

MindBridge allows you to build and execute a data-driven risk assessment strategy for every engagement. That means you can use our AI auditing software to complement your existing procedures through every phase of an audit.

From planning and fieldwork through to audit completion, you'll be able to leverage MindBridge to analyze 100% of transactions, and immediately identify errors, potential fraud, and non-compliance issues with a focus on results to uncover valuable insights for your client. You'll also be able to create comprehensive audit plans and reports with visual graphs and annotations to take discussions with your clients further.

MindBridge commissioned a first-of-a-kind algorithm audit from University College London Consulting (UCLC) who are renowned experts in algorithm audit and safety. The algorithm audit provides independent assurance that MindBridge's algorithms operate as expected. This audit demonstrates MindBridge's commitment to transparency in building explainable, credible artificial intelligence.

The MindBridge team knows what it takes to deliver this type of change within your organization. We have developed best practices and have helped a wide range of firms adopt and see value from a data-driven auditing process. We know what it takes from identifying the right resources, planning the project implementation, to managing the communication and training requirements. MindBridge is here to lead, support, and provide guidance every step of the way.

For innovation and methodology leaders

While many have been hesitant to rely on artificial intelligence (AI) and audit data analytics in place of traditional procedures, firms like [Cherry Bekaert] are confidently innovating and reaping the benefits. **Adopting MindBridge firm-wide in 2020**, this top accounting firm has focused their analytics strategy on specific innovative technologies having the most impact on their day-to-day audit activities.

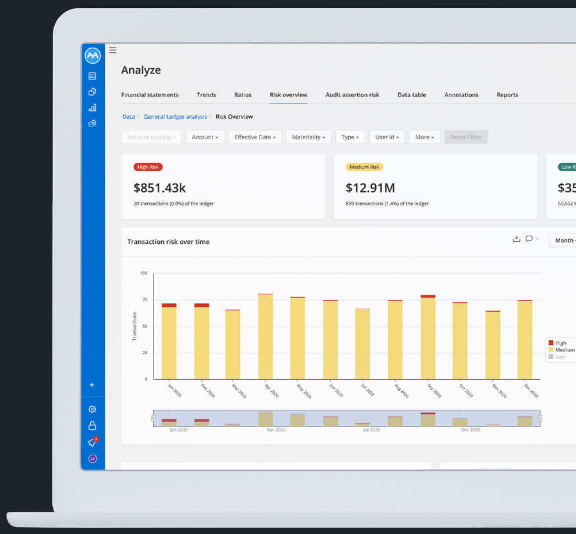
Their first achievement: the use of data analytics to reduce sample sizes and increase audit efficiency.

This methodology case study walks through Cherry Bekaert's audit data analytics implementation process and provides a detailed explanation of how they combined revisions to their audit risk model with the MindBridge platform to achieve game-changing reductions in sample sizes.

ROI

This case study was developed for methodology teams, firms' leaders, and innovation leaders who want to understand how AI fits into the standards, and realize ROI from implementing AI technologies in audit. It is accompanied by a discussion of the change management strategies that Cherry Bekaert used to successfully deploy AI across their practice.

For moderate risk of material misstatement in an illustrative client, Cherry Bekaert demonstrated a reduction in sample size from 384 to 252. At $200 per hour and 10 minutes per sample, that's a $4.4k saving on sampling, balanced against the cost of loading data and performing procedures in MindBridge.



The theory of improving audit efficiency

1. Defined audit risk model and established desired audit risk
2. Quantified risk of material misstatement (RMM)
3. Reduced RMM by using ADA to identify higher risk items
4. Tested controls
5. Defined and quantified procedures that made up other components of detection risk
6. Eliminated arbitrary minimums and determined new sample sizes based on the audit risk model

Risk-based sampling in today’s audit

Cherry Bekaert’s AI-enabled approach helps the auditor focus on the higher-risk transactions and tends to reduce the sample sizes necessary to achieve reasonable assurance.

Jessica Everage Helms, CPA, Senior Manager in the Audit Professional Practices Group at Cherry Bekaert explains, “What auditors do now is very manual in terms of understanding the client’s financial state and identifying areas of risk. It takes time to do things manually which means there’s never enough time to evaluate all the different factors that could help determine the highest-risk financial entries. MindBridge uses AI to automate and pinpoint what to look for, turning this random process into something targeted and efficient.”

This approach is based on the idea that risk-based sampling offers a clearer identification of significant items and reduces the residual risk in the remaining population. Such an approach often allows engagement teams to spend less effort in key sections of the audit, significantly reducing the manual, repetitive testing that auditors typically perform to gain assurance on lower risk transactions.

Audit data analytics “can enhance the auditor’s ability to efficiently and effectively analyze larger volumes of data, and in more depth, than when using manual audit techniques alone”[1]. Platforms like MindBridge take this one step further to score and report risk for every financial transaction, based on a set of business rules, statistical methods, and machine learning criteria. These scores are then aggregated for key account balances or business processes.

> *[...] MindBridge automates and pinpoints what to look for, turning this random process into something targeted and efficient.”*
>
> — Jessica Everage Helms

High Risk

$851.43k

20 transactions (0.0%) of the ledger

Medium Risk

$12.91M

859 transactions (1.4%) of the ledger

Low Risk

$35.01M

60,652 transactions (98.6%) of the ledger

[1]Data and Technology Research Project Spotlight, PCAOB

A focus on the weakest elements of the accounts has also been present in sampling since the 1940s, with auditors often performing 'random testing with special emphasis on vulnerable aspects'.[2] It has long been known that by focusing the sample on where the risk is likely to lie, auditors can most quickly gain assurance that the accounts are free from material misstatement.

Leveraging risk scoring to drive sample selection represents a combination of two long-standing trends in sampling within audit. The introduction of Monetary Unit Sampling was done in part to drive efficiency in the audit process. One of the key advantages of Monetary Unit Sampling is the idea that the auditor can select a smaller number of transactions to gain greater coverage of the 'monetary units' (i.e., the total number of dollars) in the population.

Cherry Bekaert's use of risk-based sampling combines themes from both of these traditional schools of thought. By using risk scoring techniques to stratify the population, the auditor can select transactions which are both high value and contain a high likelihood of material misstatement. Such risk scoring also allows for automated and robust definition of the lower risk transaction sets.

These techniques are also related to the audit risk model itself, and the judgements that the auditors make when selecting their sample size. With the concepts of risk scoring introduced in the AICPA's Audit Evidence Standard (SAS 142[3]) and spectrum of risk introduced in risk assessment standards (ISA 315 Revised 2019, SAS 145), it is clear the audit industry is continuing its move towards risk based auditing.

[2] A History of Auditing: The Changing Audit Process in Britain from the Nineteenth Century to the Present Day, 2013, Derek Matthews
[3] See Exhibit A

This combination of audit data analytics at both the risk assessment and response stage allows audit firms to maximize the efficiency of their auditors, and minimize the potential for over-auditing.

> *As [technologies allowing for interrogation of 100% of the transactions within a population] become widespread in use, stretching beyond journal testing, they will clearly have an impact on the cost of audit (less human checking) and on the depth of testing that will be possible.*
>
> — Assess, Assure and Inform: Report of the Independent Review into the Quality and Effectiveness of Audit, Sir Donald Brydon CBE, September 2019

> *Some audit firms believe that the use of technology-based tools, in certain instances, provides more persuasive evidence than traditional audit techniques.*
>
> — Data and Technology Research Project Update, May 2021, PCAOB

Assurance based on selecting samples and testing documents has been the mantra of auditors for decades. Realizing the efficiency gains from the shift to risk-based samples and audit data analytics requires firms to look at their audit methodology, and in particular how they sample and how sampling interacts with the audit risk model.

MindBridge helps lay the foundation for audit data analytics

With many opportunities to drive audit efficiencies, Cherry Bekaert took a strategic and deliberate approach to introducing and implementing MindBridge across their audit practice. MindBridge delivers a configurable AI powered risk discovery platform designed by experienced engineers and CPAs for auditors. MindBridge goes beyond statistical modeling by using advanced machine learning, identifying anomalies and calculating risk scores on 100% of the entries in core accounting ledgers. This allowed Cherry Bekaert to stay competitive in proposals, and level-up the firm's analytics capabilities with a proven and scalable platform, removing legacy approaches to risk assessment.

"One of the challenges with existing auditing standards is there are no clear guidelines around how much we can use audit data analytics or data usage in general," said Helms. "We first piloted MindBridge to understand how the tool works and determine the best way to apply it to our audits, including a full quality control (QC) review and documentation against the standards to ensure compliance for our specific use cases. In particular, SAS 142 and SAS 145 really opened up what we can do in terms of using analytics within a standards-compliant framework."

As news of the MindBridge project spread throughout the firm's 25 offices, there was excitement around what the platform could do, mixed with hesitation. As with any major technology shift, Cherry Bekaert adopted a change management strategy that educated and supported everyone, starting with practice development at the national level.

"We had to develop a firm-wide policy for everything we use MindBridge on," said Michael Hoose, CPA, Director at Cherry Bekaert and member of the firm's Audit Professional Practices group. "We defined policies for journal entry testing, a policy for identifying high-risk transactions for revenue testing, and another one for "reconciliation of cash received to revenue". We also reperformed every MindBridge control point using test data to ensure it complied with our Firm's quality standards. Using the product's documentation we gained an understanding of the algorithmic settings and how high risk transactions are selected. Overall, we gained a high level of confidence that the risk scoring worked for our Firm's purposes and the knowledge to back it up.

MindBridge is committed to building the confidence and documentation that firms need to place reliance on our techniques. With the upcoming requirements that firms assess vendors present in ISQM1, documentation such as the independent assessment of the MindBridge algorithms, completed by University College London Consulting becomes critical to adoption.

At a high level, the QC process within Cherry Bekaert included:

- Reviewing MindBridge's SOC 2 type 2 report
- Performing an independent calculation of the rules-based and statistical selection criteria
- Explaining MindBridge to national office personnel
- Developing criteria for when use of MindBridge is and is not acceptable
- Identifying senior and manager-level change "champions" who would lead
- Starting implementation efforts and performing quality review of MindBridge outputs

These documents included the technical reasoning behind the use of audit data analytics, the justification that the procedures were appropriate and the actual steps to perform them. "We needed these artifacts so that everyone from a senior partner to a brand-new staffer in any office could get on board with MindBridge," said Hoose.

One key piece to Cherry Bekaert's national rollout of MindBridge was the research and development of a white paper on the evolution of Cherry Bekaert's audit risk model and how it led to a reduction in sample sizes. Created by Hoose, this paper is summarized in the next section, offering a step-by-step roadmap for any firm seeking to understand how MindBridge improves the audit process.

The theory: Six key steps to reduce sample sizes by using risk scoring and analytics

Minimizing sample sizes to maximize audit efficiency requires a detailed understanding of the components of the audit risk model, and how they interact with sample size calculations. There are six key steps in these calculations for firms and engagement teams to consider, laid out below. This section has been written with the technical teams in mind and largely point out changes required to illustrative third-party sample size calculators.

The objective is to determine sample sizes using the *highest* allowable risk of incorrect acceptance by identifying and testing higher risk transactions so that the residual risk of material misstatement is lowered coupled with decreasing the detection risk of other non-sampling procedures.

The steps to reduce samples sizes are as follows:

1. Establish the desired Audit Risk
2. Quantify Risk of Material Misstatement by quantifying its components
3. Reduce Risk of Material Misstatement by using data analytics to identify higher risk items and reduce the "residual" inherent risk
4. Test controls, if appropriate
5. Define and quantify procedures that make up the other components of Detection Risk
6. Eliminate arbitrary minimums and determine sample sizes using the highest allowable risk of incorrect acceptance based on the audit risk model

Cherry Bekaert
Your Guide Forward

Michael Hoose, CPA
Director, Audit Professional Practices group

Michael is a Director in Cherry Bekaert's National Office working on complex accounting matters. He is a licensed Certified Public Accountant with over fifteen years of experience serving both private and publicly-traded companies.

Michael serves as a technical resource for Cherry Bekaert's Accounting & Auditing ("A&A") Professional Practices group and is actively involved in quality review and the development of the Firm's A&A technical resources and internal training.

Michael has also taught numerous internal and external courses including for the North Carolina Association of CPAs (NCACPA) covering a wide range of topics from ASC 606 Revenue from Contracts with Customers to Share-based Compensation, Foreign Currency, Analytical Procedures and Accounting Standards Updates.

Using a hypothetical engagement, we can demonstrate the impact on sample sizes:

Gross revenue:

100M

Tolerable misstatement (TM):

500K

Sample sizes for revenue can be reduced as follows:

	Potential sample sizes[1]		
Procedures performed	**Illustrative third-party sampling methodology[2]**	**Cherry Bekaert-tailored**	**Decrease**
Substantive sampling only, unstratified	600	600	N/A
Moderate risk of material misstatement[3] & Moderate other substantive procedure risk[4], unstratified	384	252	132 (34%)
Moderate risk of material misstatement[3] & Low other substantive procedure risk[5], unstratified	288	0	288 (100%)

[1] Using a revenue example assessed as high risk of material misstatement
[2] e.g., off the shelf methodologies like PPC or Knowledge Coach
[3] Through the use of data analytics to identify higher risk items resulting in a moderate "residual" inherent risk
[4] Through the performance of moderate quality analytics
[5] Through the use of data analytics to perform a "reconciliation of cash received to revenue"

The audit risk model

It is worth laying out the audit risk model, and explaining how audit data analytics and risk scoring impact each of these components.

The audit risk model is broken down as follows:	**(AR)** Audit Risk	=	**(RMM)** Risk of Material Misstatement	×	**(DR)** Detection Risk
Where,	**(RMM)** Risk of Material Misstatement	=	**(IR)** Inherent Risk	×	**(CR)** Control Risk
	(DR) Detection Risk	=	**(AP)** Analytical Procedures Risk	×	**(TD)** Test of Details Risk
	(TD) Test of Details Risk	=	**(OSP)** Other Substantive Procedure Risk	×	Sampling Allowable Risk of Incorrect Acceptance

Therefore,

AR = IR × CR × AP × OSP Risk × Sampling Allowable Risk of Incorrect Acceptance

The *lower* the risks are (IR × CR × AP × OSP), the *higher* the allowable risk of incorrect acceptance can be, thus the *smaller* the sample size.

1. Establish the desired Audit Risk (AR)

AR = IR × CR × AP × OSP Risk × Sampling Allowable Risk of Incorrect Acceptance

For the audit risk model, what should audit risk be?

Audit risk is the risk that the auditor expresses an inappropriate audit opinion when the financial statements are materially misstated. For practical reasons and because the objective of an audit is to obtain reasonable but not absolute assurance, acceptable audit risk is never zero. Acceptable audit risk is not prescribed by authoritative guidance; however, the consensus is that audit risk should be no higher than 10%.

It is worth noting that acceptable audit risk does not have to be the same for all engagements. For example, a firm could have a policy that their baseline audit risk is 7% and decrease the audit risk for higher risk engagements to 5%.

Defining what constitutes higher risk engagements is a matter of professional judgment. One approach might be to require a certain subset of engagements (e.g., public entities) use a lower audit risk or require those engagements where firm policy requires an engagement quality review use a lower audit risk.

2. Quantify Risk of Material Misstatement (RMM) by quantifying its components

AR = **IR** × **CR** × AP × OSP Risk × Sampling Allowable Risk of Incorrect Acceptance

(RMM) = Inherent Risk (IR) × Control Risk (CR)

By quantifying the components of Risk of Material Misstatement (Inherent Risk and Control Risk), the auditor can mathematically determine the other inputs required in the audit risk formula, including sampling risk of incorrect acceptance.

The Risk of Material Misstatement is the risk that the financial statements are materially misstated prior to the performance of any substantive procedures, and is the product of Inherent Risk and Control Risk. Many firms and third-party methodologies use qualitative terms (e.g., high, moderate, or low) to describe these risks.

As the objective is to determine sample sizes using the highest allowable risk of incorrect acceptance, which is a quantified mathematical value, it's necessary to quantify Inherent Risk and Control Risk. Quantifying these risks is a matter of professional judgment, however, one approach might be to assign the following quantitative values to qualitative descriptions:

Qualitative Risk Category	Quantified Risk
High	100%
Moderate	50%
Low	10%

The same quantifications for control risk categories could be used, however, quantifying control risk requires less judgment and is more precise than inherent risk because control sample sizes are generally derived using the binomial probability distribution which quantifies the confidence level achieved through sampling.

The mathematical and Microsoft Excel formulas necessary for this quantification are available in the Technical Notes on the AICPA Audit Guide Audit Sampling. Furthermore, many sampling forms from third-party audit methodologies include the confidence level achieved based on the number of sample items tested and deviations found.

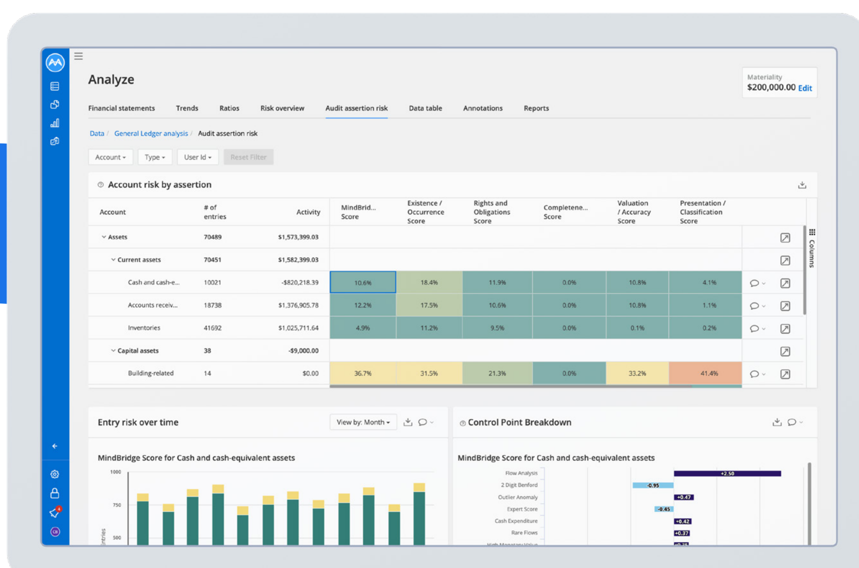
3. Reduce the Risk of Material Misstatement by using data analytics to identify higher risk items and reduce the “residual” inherent risk

$$AR = \mathbf{IR} \times CR \times AP \times \text{OSP Risk} \times \begin{matrix}\text{Sampling Allowable Risk} \\ \text{of Incorrect Acceptance}\end{matrix}$$

Traditionally, auditors have used a quantitative threshold for determining higher-risk items to exclude from the sample population and test individually, often called “Individually Significant Items” (ISI). This may include some qualitative criteria such as related party transactions.

By using data analytics to apply more quantitative, statistical, and even machine learning approaches to identify Individually Significant Items, an auditor may be able to reduce the residual Inherent Risk that exists in the sample population.

Reducing “residual” Inherent Risk decreases the risk of material misstatement, which also reduces the level of assurance needed through Control Risk, Analytical Procedures, Other Substantive Procedures, and sampling. Importantly, the amount of effort required to reduce residual Inherent Risk is generally significantly less than the amount of effort required to achieve the same level of assurance.



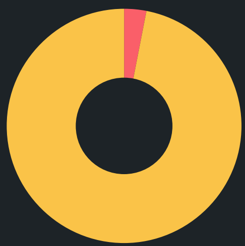
Significant Account

Traditional Sampling Approach

Revenue: $100M

Tolerable Misstatement: $500K

Total Sample Size: 311



- **Individual Significant Items**

Value: $3M
Count: 15
Sample: 15

- **Remaining Population** (Risk unknown)

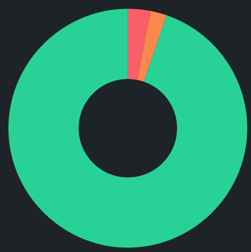
Value: $97M
Count: 2K
Sample: 296

Risk-based Sampling Approach

Revenue: $100M

Tolerable Misstatement: $500K

Total Sample Size: 161



- **Individual Significant Items**

Value: $3M
Count: 15
Sample: 15

- **Risky Transactions** (Presence of risk)

Value: $2M
Count: 15
Sample: 15

- **Remaining Population**

Value: $95M
Count: 2K
Sample: 131

For example, audit data analytics can more effectively and efficiently identify transactions displaying [characteristics which are indicative of a risk of misstatement](). This could include rules-based techniques and statistical methods such as Benford's analysis, or identifying transactions that are unusually complex (e.g., transactions that flow into and out of the same account or have many lines). AI and machine learning techniques help identify transactions that have unusual amounts, debits and credits, or frequencies relative to other transactions. MindBridge has a number of powerful machine learning indicators, such as Outlier Anomaly and Unusual Amounts.

Such data analytics platforms often allow the auditor to turn such indicators of risk on or off based on their judgement. However, it would be ineffective and impractical to test every transaction that contains any indication of risk. Instead, each risk indicator is assigned a "risk score" and the weighted average of all risk scores for an individual transaction is that transaction's total risk score. This is a similar approach to that described in [Exhibit A of SAS142](). Determining what contribution an individual risk indicator should be to the total risk score, and what total risk score constitutes an Individually Significant Item is incumbent on the auditor or audit methodology.

Where a data analytics platform comes with a pre-set risk scoring system or "weighting", a key decision is to what degree the auditor can and should adjust the weighting based on their professional judgement. Audit firms should develop protocols for assisting engagement teams in this determination. Across MindBridge's clients, a variety of approaches have been taken. This includes allowing engagement teams full discretion to adjust the weightings, to completely pre-determining weightings on behalf of the engagement teams.

After identifying the Individually Significant Items, if the population can be distilled into a group of homogeneous transactions with lower risk profiles, the residual inherent risk of the sample population can be assessed lower than the overall Inherent Risk of the account balance. For example, if the starting Inherent Risk is qualitatively assessed as "high", then the residual Inherent Risk might be "moderate" after identifying the Individually Significant Items using data analytics.

This reduction in Inherent Risk generally results in significantly fewer Item transactions tested than if the auditor achieved a similar level of assurance through substantive sampling. For example, using the previously mentioned hypothetical engagement, to achieve a risk reduction of 50%, the auditor would have to sample approximately 140 randomly selected sample items. It's highly unlikely this reduction in sample size would be fully offset by an increase in the number of Individually Significant Items tested.

4. Test controls, if appropriate

AR = IR × **CR** × AP × OSP Risk × **Sampling Allowable Risk of Incorrect Acceptance**

There are opportunities to drive further efficiency by using controls-based testing, as control sample sizes are not one-for-one relative to substantive sample sizes to achieve the same assurance.

A 50% reduction to control risk is treated the same as a 50% Sampling Allowable Risk of Incorrect Acceptance. However, the number of sample items required to reduce Control Risk to 50% is significantly lower than the number of sample items required to achieve a 50% Sampling Allowable Risk of Incorrect Acceptance due to the binary nature of controls and the mathematical formula used to determine control sample sizes.

5. Define and quantify procedures that make up the other components of Detection Risk (DR)

AR = IR × CR × **AP** × **OSP Risk** × Sampling Allowable Risk of Incorrect Acceptance

The use of audit data analytics as a component of the response to assessed risk is a key part of the reduction of sample sizes. By defining and quantifying the procedures that make up the other components of Detection Risk (Analytical Procedures and Other Substantive Procedures), auditors can simultaneously increase consistency across the firm and mathematically solve for the Sampling Allowable Risk of Incorrect Acceptance.

Most firms and third-party audit methodologies use qualitative descriptions of analytical and other substantive procedures risk (e.g., high, moderate, or low). Moreover, few define what constitutes a high, moderate, or low quality analytic or other substantive procedure. This exercise presents an opportunity to improve what constitutes a high, moderate, and low-quality analytic to avoid the inconsistent application of qualitative descriptions that often result in widely varying sample sizes.

Defining what constitutes a high, moderate, or low quality analytic is a matter of professional judgment beyond the scope of this case study. Quantifying the level of assurance achieved by performing each is also a matter of professional judgment, however, one approach might be to assign the following quantitative values to qualitative descriptions:

Qualitative Description of Analytics	Detection Risk Achieved*
High	20%
Moderate	50%
Low	80%

* The lower the detection risk, the higher the assurance provided, the higher the sampling risk of incorrect acceptance can be, and thus reducing the substantive sample size

Firms can create a "menu" of other substantive procedures and quantify the assurance provided by each. The menu of other substantive procedures depends on the account balance and assertions being tested.

For example, a menu for testing revenue might include cut-off testing and alternative procedures over accounts receivable. In addition, a "proof of cash" can provide significant assurance when testing revenue. In Cherry Bekaert's case, auditors can choose to perform a "proof of cash" using either manual techniques, or perform procedures similar to a proof of cash to reconcile cash received to revenue within MindBridge.

A traditional "proof of cash" entails using bank statements to reconstruct revenue by summing all deposits for a period less any deposits not pertaining to revenue such as debt and equity proceeds and comparing the resulting sum to recorded revenue adjusted for changes in accounts receivable. When existence or occurrence is the only significant risk related to revenue (e.g., as-invoiced practical expedient used), a "proof of cash" can provide significant assurance and lower substantive sample sizes.

The use of data analytics makes a material impact on the necessary sample size. Data analytics can perform procedure similar to a proof of cash but they are automated and performed at a far more disaggregated level. For example, a "reconciliation of cash received to revenue" can be performed by a data analytics tool whereby each individual transaction that increases (credits) recorded revenue is matched to the corresponding increase (debit) to cash or accounts receivable. Any increases to recorded revenue not accompanied by an increase to cash or accounts receivable would be flagged and tested.

This procedure combined with cash and accounts receivable testing and cut-off procedures can yield the required level of assurance whilst greatly reducing substantive sample sizes. Given that the auditor is likely to be testing cash, accounts receivable, and performing cut-off testing already, any additional work to perform the "proof of cash", or similar procedure, is likely to be more efficient than achieving the same level of assurance through substantive sampling.

Guidance and protocols should be developed for determining when a "proof of cash" or similar procedure is appropriate and the level of assurance provided by such procedures. One approach might be to assign a level of assurance equal to a moderate quality analytic (e.g., 50% detection risk).

6. Eliminate arbitrary minimums and determine sample sizes using the highest allowable risk of incorrect acceptance based on the audit risk model

AR = IR × CR × AP × OSP Risk × **Sampling Allowable Risk of Incorrect Acceptance**

Many firms and third-party methodologies explicitly or implicitly do not permit the Sampling Allowable Risk of Incorrect Acceptance to fall below an arbitrarily determined percentage (e.g., 40%). However, this can be strengthened by understanding that once Audit Risk, Inherent Risk, Control Risk, Analytical Procedures, and Other Substantive Procedures Risk are determined, the necessary allowable risk for incorrect acceptance is a simple matter of algebra.

For example:

If:

Audit Risk	=	5%
Inherent Risk	=	Moderate or 50% (e.g., due to the use of data analytics, such as MindBridge, in selecting Individually Significant Items)
Control Risk	=	Moderate or 50% due to control testing
Analytical Procedures	=	Moderate or 50% (e.g., due to performing a well-defined "moderate" quality analytic)
Other Substantive Procedures	=	50% due to use of data analytics in performing a "reconciliation of cash received to revenue"

then:

0.05 = 0.50 × 0.50 × 0.50 × 0.50 × Sampling Allowable Risk of Incorrect Acceptance

Or written differently,

Sampling Allowable Risk of Incorrect Acceptance = 80% (0.05 divided by [0.50 × 0.50 × 0.50 × 0.50]).

Going back to our hypothetical engagement, the sample size required to achieve an 80% risk of incorrect acceptance would be 75. Compare that to third-party methodologies that generally limit the risk of incorrect acceptance to 40% that leads to a sample size of 216.

These sample sizes can be further reduced by stratifying sample selections using either traditional methods or using data analytics.

In summary the overall sampling methodology and significant judgments made should be documented, specifically:

- The firm's allowable audit risk
- Quantified values for any qualitative descriptions (e.g., low, moderate, or high)
- What rules-based, statistical-based, or machine-learning-based approaches should be used when utilizing data analytics, the risk score assigned to each, and the total risk score or weighting that constitutes higher risk
- What defines different qualitative categories of analytics and what degree of assurance they provide
- What "menu" of other substantive procedures that can be performed, when it's appropriate to perform them, and what degree of assurance they provide

Documentation like this supports education and training, and for building confidence in audit data analytics. There are also a number of key professional judgements which have been made throughout the six steps detailed above. Firms should consider how to provide authoritative guidance and training to their engagement teams, so that they are comfortable relying on audit data analytics.

Conclusion

We'd like to thank Cherry Bekaert for working with us to talk about how they are driving their sample sizes using MindBridge. By engaging with experts and taking the right expertise and approach, Cherry Bekaert has been able to forge a new way of thinking about sampling and see benefits because of it. We look forward to seeing how Cherry Bekaert's use of MindBridge will continue to evolve in the future.

The use of risk scoring to focus the sample where it matters is just one example of benefits that firms can realize from ambitious applications of AI. With standards like ISA 315, SAS 142, and SAS 145 enabling auditors to rely on audit data analytics for evidence, there are a range of other potential avenues for application, including the use of AI as both a risk assessment and response procedure. Through a strategic and disciplined approach to deploying MindBridge, audit firms are seeing benefits from sampling less, discovering more of their clients. They're able to deliver a better quality audit at less cost because of it.

As MindBridge continues to apply its risk scoring to a wider variety of data-sets, we are excited by the various use-cases where firms can apply AI, and the increasing degree they can rely on data-driven assurance in place of documents and inquiry.

In the end, these material reductions in sample sizes are achieved through understanding of the audit risk model, quantifying any qualitative terms, and the use of audit data analytics to automate and focus risk identification.

"Through a comprehensive and explainable coverage of risk, MindBridge has given us the tools to identify risky transactions and reduce sample sizes, explains Helms. "We use it on clients of any size, any budget, and our experience proves that data analytics is a viable option towards data-driven assurance and risk-based sampling that firms can start using right now."

Special thanks to:

Michael Hoose, CPA
Director, Audit Professional Practices group
Cherry Bekaert

Jessica Everage Helms, CPA
Senior Manager, Audit Professional Practices group
Cherry Bekaert

Talk to our professionals and learn how MindBridge can empower your firm, contact us at info@mindbridge.ai. We'll be happy to schedule a discussion and get you started on a path to leveraging AI to help surface critical data anomalies.

Ranked among the largest accounting and consulting firms in the country, Cherry Bekaert provides guidance and support that helps our clients move forward to reach their organizational goals. We will ignite growth with integrated, forward-looking industry solutions that effectively deliver on our Client Promise, and we will deliver this growth by empowering our people and investing in efficient innovative processes to become the Firm of the Future.

MindBridge, the world's leading financial risk discovery platform, allows you to identify, surface, and analyze risk across broad financial data sets in fewer hours and with less effort. Through the power of human-centric artificial intelligence, helps organizations deliver rapid value to their clients with deeper insights and higher risk assurance for 100% of their data. Used by over 20,000 audit and financial professionals globally, MindBridge unlocks insights into your business-critical data for AI-driven assurance.