DATA RESEARCH meetup by MagIC

2nd EDITION

Optimized Audit with Risk-based Sampling

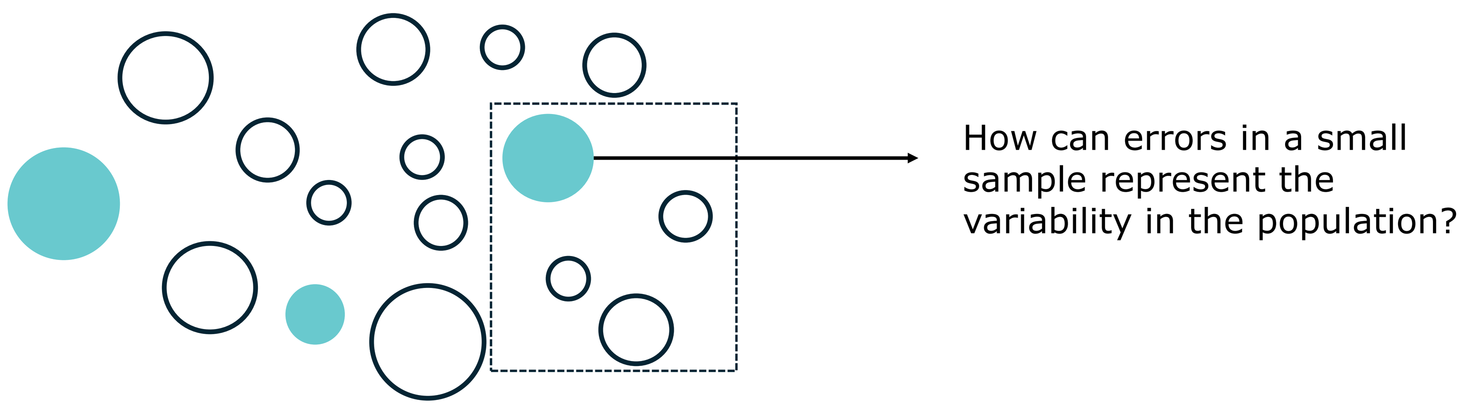
Isabel Dias

NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Campus de Campolide, 1070-312 Lisboa, Portugal

INTRODUCTION

Auditors aim to detect and quantify errors in financial statements, but the large volume of data makes full review impractical. Sampling is used instead, often through Monetary Unit Sampling (MUS), where items are selected with probability proportional to their value, reflecting that high-value items are more likely to carry significant error.

Audit populations typically contain many items with no error and a small subset with highly variable errors [1]. Estimating total error becomes difficult when these non-zero errors are rare. Incorporating auxiliary information, such as historical risk assessments, can improve sampling precision [2]. Prior work has used such data to assess risk or refine error bounds [3, 4], but less attention has been given to using it at the sample selection stage.



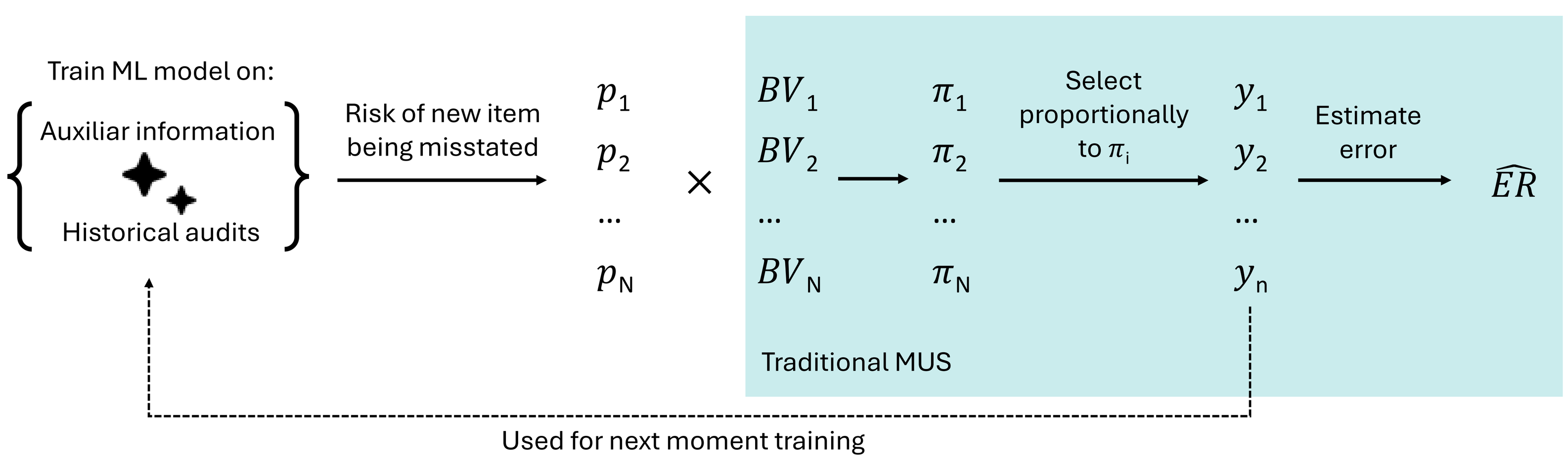
This study proposes a sampling method that integrates historical audit data to assign risk scores, allowing for risk-weighted selection. The goal is to better represent the error structure of the population and improve the accuracy of error estimates.

METHODS AND MATERIALS

This study builds on the Customised Monetary Unit Sampling method endorsed by EU Audit Guidance [5], offering advantages such as simplicity, improved precision, and a solid theoretical basis.

Rather than relying solely on book values (BV), the proposed method combines BV with risk scores (p) derived from historical audits and auxiliary data. A classification model is trained to estimate the probability of error for each item.

For a new audit population, predicted risk scores are multiplied by BV to calculate inclusion probabilities (π). Sampling is then performed proportionally to this product. Audited (true) values (y) are used to estimate error rate, and the results feed back into the model for continuous improvement.



Using real data from audits of the ERDF/CF and ESF funds over the years of 2015/2016 until 2021/2022. An artificial population was created with the last year, and the remaining data was used to train the classification model. Given the disparate characteristics of both funds, they were tested separately.

A simulation study was conducted, where 5000 independent samples were selected with Customised MUS and MRS. Then, the precision and estimator error were calculated for each sample, and the variability of the estimator was compared.

ACKNOWLEGEMENTS

This study is co-authored with Professor Pedro Simões Coelho (NOVA IMS) and Professor Bruno Damásio (NOVA IMS).

This work was supported by national funds through FCT (Fundação para a Ciência e a Tecnologia), under the project - UIDB/04152 - Centro de Investigação em Gestão de Informação (MagIC)/NOVA IMS.

NOVA Information Management School, 10 July 2025

RESULTS & DISCUSSION

The simulations produced very similar outcomes for both funds. Both sampling methods produce similar projected errors. On the other hand, the MRS shows significant improvement in precision, in relation to the MUS approach.

In the ERDF/CF we can say that, for the same sample size, the precision of the MRS approach has a 21% improvement in precision, in comparison to the MUS approach. This translates into being capable of reducing the sample size by 38%, to achieve the same precision level.

In the ESF fund, there is an improvement of 28% in precision for the same sample size. Alternatively, it is possible to achieve a 52% sample reduction for the same precision level.

In short, the new sampling design can produce significant improvements in the precision of estimates, while maintaining an unbiased estimate of the error.

	ESF			ERDF/CF		
	Projected Error	**Precision**	**Estimate Variability**	**Projected Error**	**Precision**	**Estimate Variability**
Monetary Unit Sampling (MUS)	1.35%	0.61%	3.50×10^{-5}	3.45%	1.88%	3.31×10^{-4}
Monetary Risk Sampling (MRS)	1.32%	0.44%	1.80×10^{-5}	3.44%	1.48%	2.03×10^{-4}

CONCLUSION

The results show this is a promising research avenue. It was proven that the incorporation of a risk score can improve the precision of estimation. By using a classification model to predict the occurrence of error, a risk score can be assigned to new items and more informed samples can be selected.

This has strong implications for the practice of auditing. In the context of periodic audits, accumulation of information from historical records can help target the error items better. This means that the sample sizes can be reduces, leading to the decrease in workload and costs associated.

Future research can focus on different combinations of the risk and amount of error. Specifically, take into consideration the actual amount of error predicted to have error [2]. Given both the amount and error rate are of interest, the space for improvement is vast and dependent on what is most prioritised.

REFERENCES

[1] Higgins, H. N., & Nandram, B. (2009). Monetary unit sampling: Improving estimation of the total audit error. Advances in Accounting, 25(2), 174–182. https://doi.org/10.1016/j.adiac.2009.06.001
[2] Marazzi, A., & Tillé, Y. (2017). Using past experience to optimize audit sampling design. Review of Quantitative Finance and Accounting, 49(2), 435–462. https://doi.org/10.1007/S11156-0160596-7
[3] Miller, T. C., Cipriano, M., & Ramsay, R. J. (2012). Do auditors assess inherent risk as if there are no controls? Managerial Auditing Journal, 27(5), 448–461. https://doi.org/10.1108/02686901211227931
[4] Godfrey, J., & Neter, J. (1984). Bayesian bounds for monetary unit sampling in accounting and auditing. Journal of Accounting Research, 22(2), 497. https://doi.org/10.2307/2490661
[5] European Commission. (2017). Guidance on sampling methods for audit authorities.

ONLINE VERSION