Deriving Decision Uncertainty Associated With Calibration Target Data: A Value of Information Approach

EE507

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INTRODUCTION

Model calibration in health economics adjusts model parameters to ensure outputs align with empirical data. **Calibration targets**—empirical data from studies—are crucial for this process but are often imperfect due to **differences in population demographics**, **biases from observational studies,** or **outdated information**. Such imperfections introduce uncertainties and potential biases into models, leading to **suboptimal** or **incorrect** cost-effectiveness **recommendations**.

Value of Information (**VOI**) analysis offers a solution by quantifying the **value of obtaining better or additional data**.

OBJECTIVES

We aim to demonstrate how VOI analysis can be integrated into model calibration. We estimate the:

- Expected Value of Partial Perfect Information (EVPPI) to assess the *benefit* of **eliminating uncertainty in the calibration target** data.
- Expected Value of Sample Information (EVSI) to determine the *worth* of **conducting a study that provides information on the calibration target** data (if we had none).
- EVSI for **acquiring extra data to decrease uncertainty in the calibration targets**.

METHOD

Priors: $X \sim N(\mu, \Sigma);\ X = (x_1, x_2, x_3)$

Model: $z = x^\top m_1,\ INB = x^\top m_2.\ \ m_1 = (1,1,0)^\top,\ m_2 = (1,0,1)^\top$

No Calibration Target data

Target data: $\text{mean} = b$, $\text{variance} = \tau^2$

Bayesian updating

$$p(INB|b) \sim N(\mu_p^\top m_2, m_2^\top \Sigma_p m_2).\ \Sigma_p = \left(\Sigma^{-1} + \frac{m_1 m_1^\top}{\tau^2}\right)^{-1}, \mu_p = \left(\frac{b m_1^\top}{\tau^2} + \mu^\top \Sigma^{-1}\right)\Sigma_p$$

Truncated Normal Properties

$$\left(\mu^* + \sigma^* \frac{\phi(\alpha)}{1-\Phi(\alpha)}\right)(1-\Phi(\alpha)) - \max(\mu^*, 0)$$

EVSI$_{bb}$

$$\mu^* = \mu_p^\top m_2,\ \sigma^* = \Sigma_p - \left(\Sigma_p^{-1} + n_{bb}\frac{m_1 m_1^\top}{v_{bb}}\right)^{-1}$$

SIR

$$Likelihood:\ (b|z) \sim N(z, \tau^2)$$

$$\widehat{EVSI}_{bb} = \frac{1}{N}\sum_{n=1}^{N} \max\{\hat{g}(INB_p(T(bb)^{(n)})), 0\} - \max\{\frac{1}{N}\sum_{n=1}^{N} \hat{g}(INB_p(T(bb)^{(n)})), 0\}$$

PSA using prior distribution

$$p(INB|X) \sim N(\mu^\top m_2, m_2^\top \Sigma m_2)$$

Truncated Normal Properties

$$\left(\mu^* + \sigma^* \frac{\phi(\alpha)}{1-\Phi(\alpha)}\right)(1-\Phi(\alpha)) - \max(\mu^*, 0)$$

$$\widehat{EVPPI}_z = \frac{1}{N}\sum_{n=1}^{N} \max\{\hat{g}(INB(z^{(n)})), 0\} - \max\{\frac{1}{N}\sum_{n=1}^{N} \hat{g}(INB(z^{(n)})), 0\}$$

EVSI$_b$

$$\mu^* = \mu^\top m_2,\ \sigma^* = \Sigma - \left(\Sigma^{-1} + n_b \frac{m_1 m_1^\top}{v_b}\right)^{-1}$$

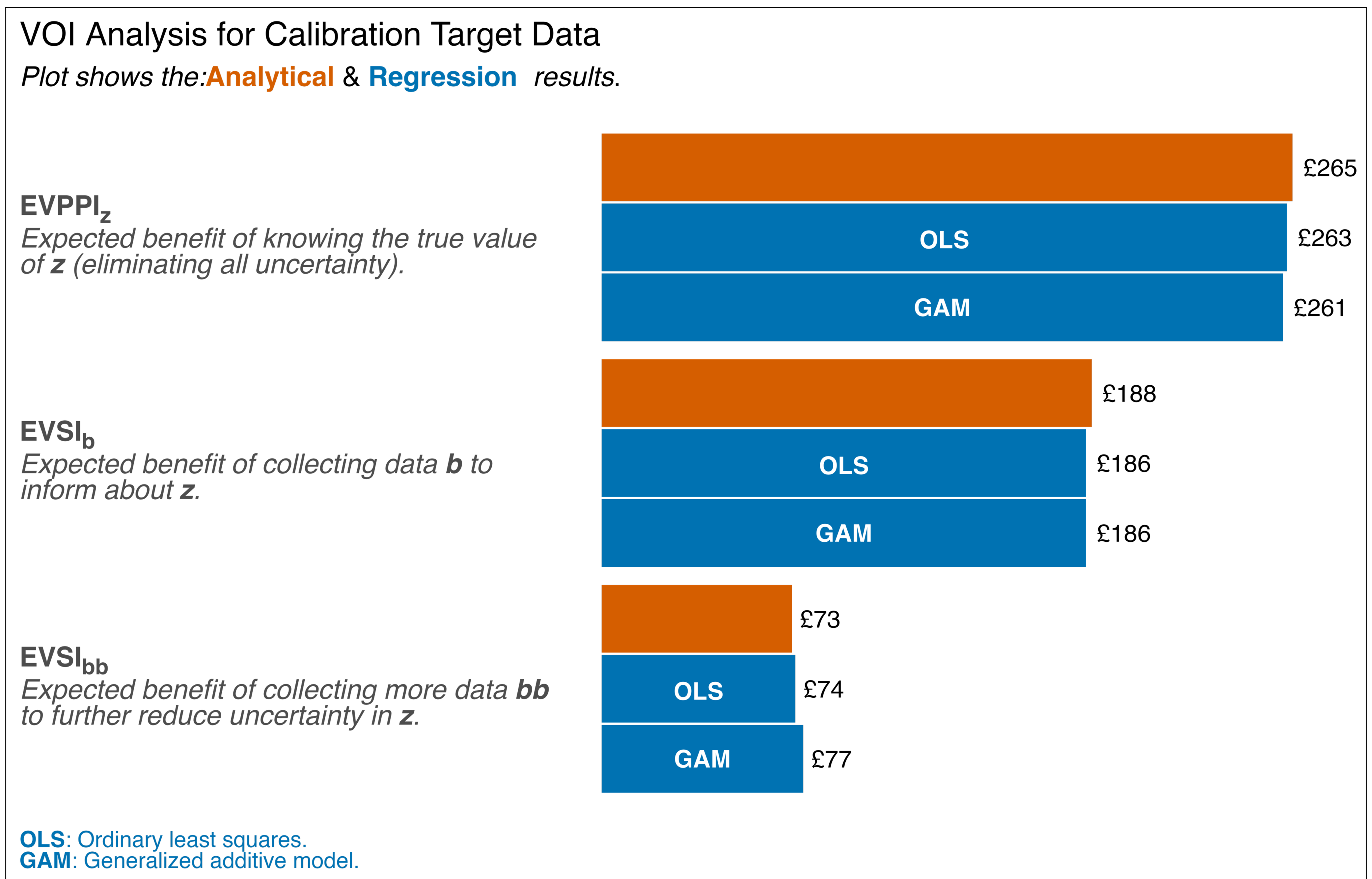
EVPPI$_z$

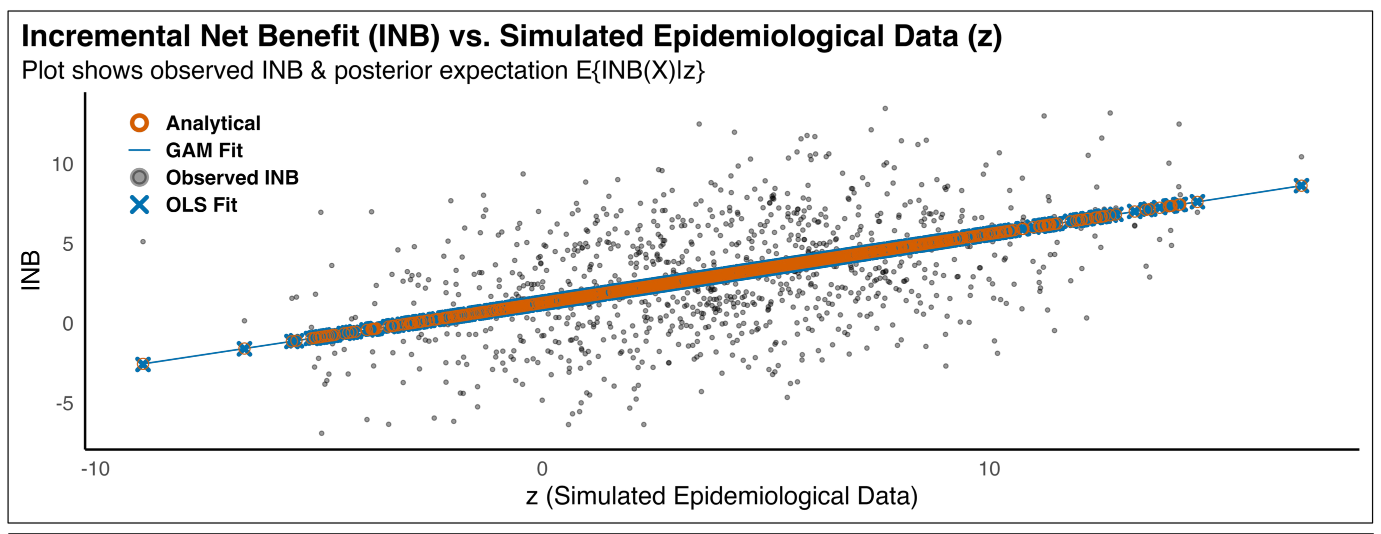
$$\mu^* = \mu^\top m_2,\ \sigma^* = \Sigma - \left(\Sigma^{-1} + \frac{m_1 m_1^\top}{0}\right)^{-1}$$

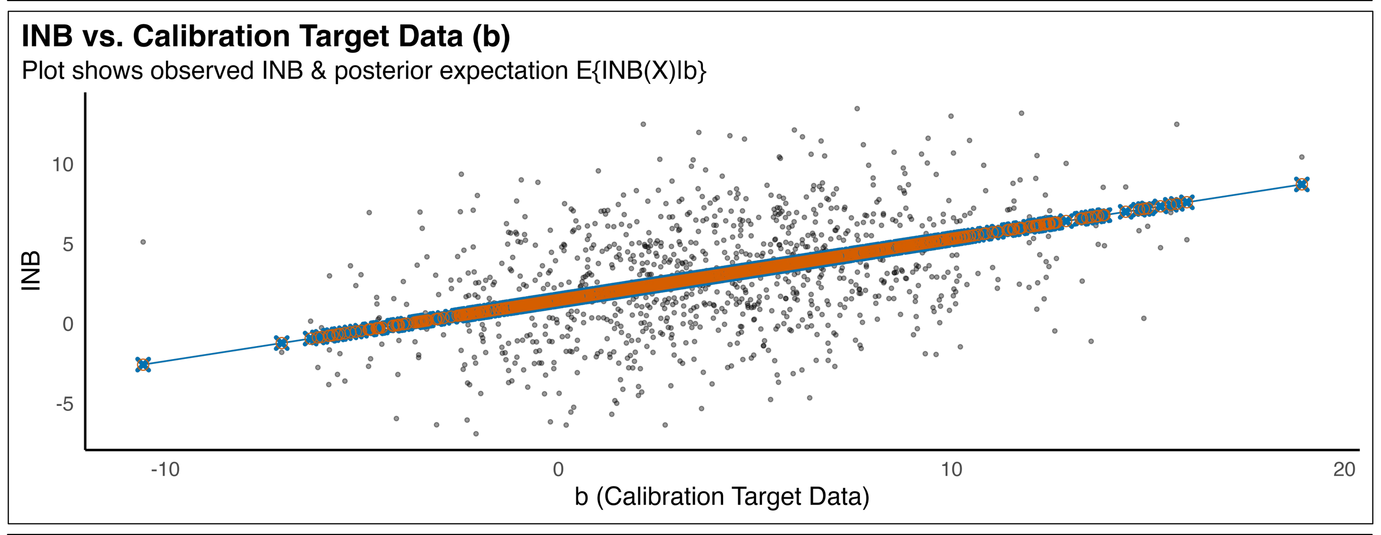
$$\widehat{EVSI}_b = \frac{1}{N}\sum_{n=1}^{N} \max\{\hat{g}(INB(T(b)^{(n)})), 0\} - \max\{\frac{1}{N}\sum_{n=1}^{N} \hat{g}(INB(T(b)^{(n)})), 0\}$$

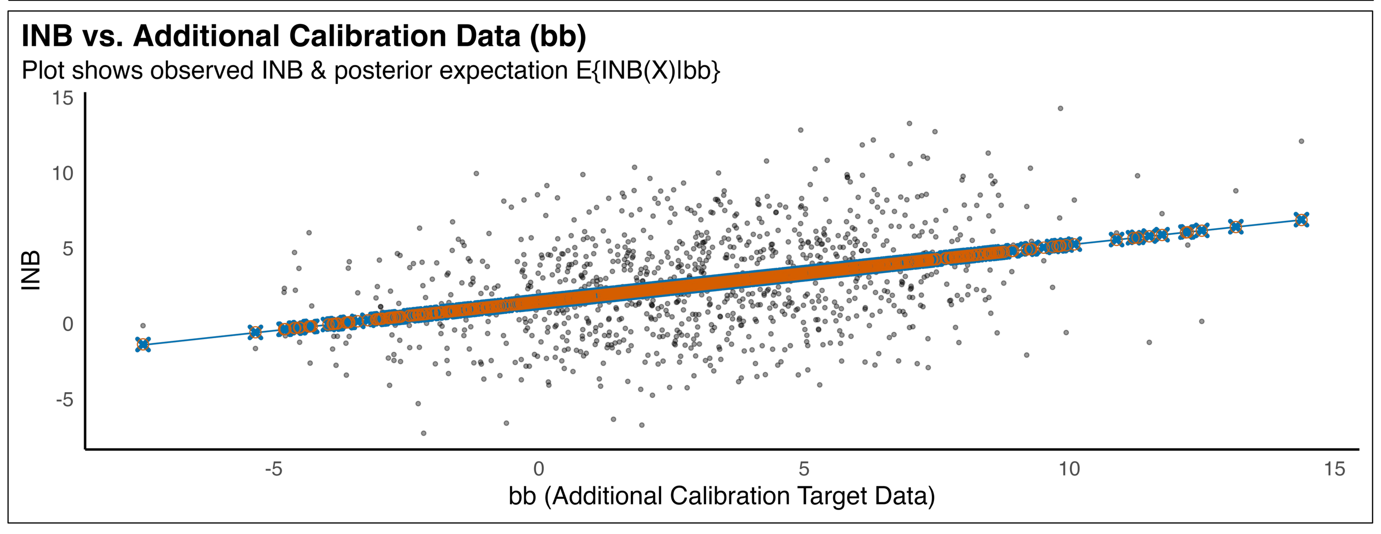
SIR: Sampling importance resampling.

RESULTS









CONCLUSIONS

This simulation study underscores the potential benefits of integrating VOI analysis into the model calibration process. While the presented analytical solutions are limited by restrictive assumptions, the regression approach is more flexible and generalisable to real-world models.

By illustrating the methodology and demonstrating how uncertainties in calibration targets can be quantified, we provide a foundation for future studies to apply these techniques with real-world data. Consequently, such integration could better inform the prioritisation of data collection efforts and resource-allocation decision-making.

REFERENCES

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