

Not another correlation coefficient: A method to adjust cost-effectiveness acceptability curves in economic evaluations

Objectives

- Illustrate the sensitivity of cost-effectiveness acceptability curves (CEACs) to the correlation between estimated incremental cost (ΔC_i) and effectiveness ($\triangle E_i$) outcomes (hereafter ρ) in health economic evaluations.
- Introduce a method to adjust the empirical joint distribution of incremental cost and effect data in order to vary ρ , while holding first-order estimates constant (e.g., incremental cost-effectiveness ratio, ICER).
- Provide a Stata program which can be used to:
 - 1. Transform data generated in probabilistic sensitivity analysis (PSA) or resampling procedure to adjust $\rho \longrightarrow \rho'$, for $\rho' \in [-1, 1]$
 - 2. Generate *ex-post* confidence intervals for CEACs.
 - 3. Assess the robustness of willingness-to-pay (WTP)-type statistical claims used to inform stakeholder decision-making.

Figure 1: The relationship between the shape of cost-effectiveness acceptability curves (left panel) and the correlation between $\triangle E_i$ and $\triangle C_i$ (right panel).



Case 1: ρ is positively correlated



Case 2: $\rho = 0$, or uncorrelated



Case 3: ρ is negatively correlated

Notice in the left panel of Fig. 1 that the WTP value above which we are 95% confident a new health intervention is cost-effective compared to control (vertical red line) shifts left as $\rho \longrightarrow 1$, and likewise shifts right as $\rho \longrightarrow -1$.

Transformation Matrix

Let $\bar{\lambda} = \Delta C / \Delta E$ and $\bar{\lambda}^{-1} = \Delta E / \Delta C$ be the estimated *ICER* and inverse *ICER* from a health economic evaluation study with a given empirical distribution $\left[\bigtriangleup E_i \ \bigtriangleup C_i \right]^{\perp}$ generated from PSA or resampling procedure. The following piece-wise transformation, $T(\delta)$ is thus defined as,

$$\begin{bmatrix} \triangle E_i' \\ \triangle C_i' \end{bmatrix} = \begin{cases} \begin{bmatrix} (1 - \frac{\delta}{2}) & \frac{\delta}{2}\bar{\lambda}^{-1} \\ \frac{\delta}{2}\bar{\lambda} & (1 - \frac{\delta}{2}) \end{bmatrix} \begin{bmatrix} \triangle E_i \\ \triangle C_i \end{bmatrix}, & \text{for } \rho \to 1 \\ \begin{bmatrix} (1 - \frac{\delta}{2}) & -\frac{\delta}{2}\bar{\lambda}^{-1} \\ -\frac{\delta}{2}\bar{\lambda} & (1 - \frac{\delta}{2}) \end{bmatrix} \begin{bmatrix} \triangle E_i \\ \triangle C_i \end{bmatrix} + \delta \begin{bmatrix} \triangle \overline{E} \\ \triangle \overline{C} \end{bmatrix}, & \text{for } \rho \to -1 \end{cases}$$

Intuition: The above transformation is based on an analytic tool employed in macroeconomics to study equilibrium processes—i.e., phase diagrams. $T(\delta)$ maps all cost and effect pairs, $(\triangle C_i, \triangle E_i)$ to a convex combination between their original value and that of the nearest point corresponding to nullclines (or stable isoclines) of a system of first-order ordinary differential equations described by the matrices in $T(\delta)$, which can be interpreted as a Jacobian matrix.

The saddle path solutions for $\rho \to 1$ and $\rho \to -1$ is given by $\Delta C_i = \bar{\lambda} \Delta E_i$ and $\Delta C_i = -\overline{\lambda} \Delta E_i + 2\overline{\Delta C}$, respectively.

Convergence and linearity: We observe that in both matrix transformations, the determinant of the Jacobian is $-\delta - 1 < 0$, which is strictly less than the squared value of its trace $(2 - \delta)$, for all $\delta \in [0, 1]$. Therefore, the matrix transformations in $T(\delta)$ have real (linear) and distinct roots, and there exists a saddle path convergent sequence in the domain of $\begin{bmatrix} \Delta E_i & \Delta C_i \end{bmatrix}^{\perp}$.

Results: Stata Program Examples

Example 1: Generate *ex-post* confidence intervals for CEACs for varying degrees of uncertainty in estimated $\hat{\rho}$.



Note: Pink shaded areas display the lower $(\rho \rightarrow 1)$ and upper $(\rho \rightarrow -1)$ range of WTP values above which the adjusted empirical distributions, $\left[\triangle E'_i \quad \triangle C'_i \right]$ indicate that a health intervention is cost-effective at a 95% confidence level.

Example 2: Adjust the empirical joint distribution of incremental cost and effect estimates to be more negatively correlated ($\rho \rightarrow -1$).







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Example 3: Adjust the empirical joint distribution of incremental cost and effect estimates to be more positively correlated ($\rho \rightarrow 1$).

Conclusion and Dissemination

• A method to adjust the joint distribution of incremental cost and effect estimates from an economic evaluation study was presented.

• Studies that do not directly observe individual-level cost and effect outcomes, such as decision-analytic or simulation models, may find the Stata program (available via email: alj4004@med.cornell.edu) described in this study useful in addressing uncertainty in $\hat{\rho}$.

• Recommendation: economic evaluation studies should include the estimated value of $\hat{\rho}$ when reporting results.