Linking Decision Theory and Quantitative Microbial Risk Assessment: Tradeoffs Between Compliance and Efficacy for Waterborne Disease Interventions
Supplemental Material

October 4, 2018

Contents

Appendices

A Extended methods

Maximum utility compliance Here we prove that an individual's compliance probability is given by Equation 10. We seek to maximize Equation 6 with respect to $Pr_i(use)$. The utility function is negative quadratic in this argument, so we need only solve the first order condition

$$\begin{aligned} u_i' &= 2(1 - Pr_i(use) - \Delta x) \\ 0 &= 2(1 - Pr_i(use)^* - \Delta x) \\ Pr_i(use)^* &= 1 - \Delta x \end{aligned} \tag{1}$$

as desired.

Optimal interventions The optimal intervention for a given preference distribution is

$$\hat{x}^* = argmin_{\hat{x}} E[d_i] \tag{2}$$

where

$$E[d] = wv[(1 - E[Pr(use)]) + E[Pr(use)]10^{-\hat{x}}] \tag{3}$$

From Equation 10, the compliance probability is a function of individual preferences x_i, which are normally distributed. As a result, we can compute the expected value of $Pr(use)$ (referred to here as $p(x_i)$ for simplicity) using the following

$$E[p(X)] = \int_{-\infty}^{\infty} p(x) f(x|\mu, \sigma) dx \tag{4}$$

where $f(x|\mu, \sigma)$ is the probability density function of the preference distribution. While an analytical solution to the minimization problem is not straightforward, numerical optimization and integration perform well. Specifically, we use Brent's algorithm for our numerical solutions. This procedure allows our optimal interventions to take the shape of the preference distribution into account.

For our local sensitivity analysis, we compute the partial derivative of $\hat{x}^*$ with respect to the variance σ^2 for each average preference tested. We used a baseline variance of 3.6 for our results in Section 3.

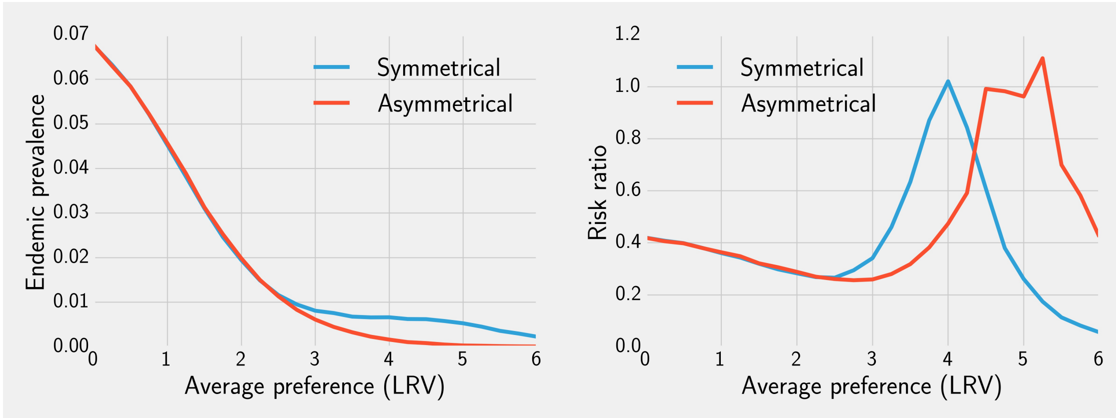
B Game theoretic representation of optimal interventions

The process of selecting an optimal intervention can be framed as an extensive form game between a policymaker and the N individuals in a population. This game has the following structure:

1. A policymaker selects an intervention $\hat{x}$.
2. Next, all individuals independently determine their compliance level $Pr_i(use)$ given their LRV preference x_i.

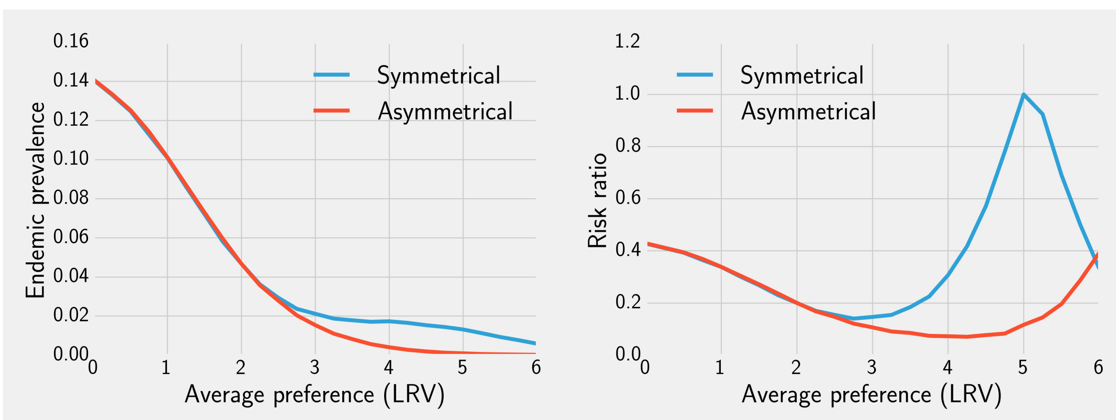
Individual payoffs for compliance are given as in Equation 6 while the payoff for the policymaker is inversely proportional to the population risk of infection. We use backward induction (Fudenberg and Tirole, 1991; Tadelis, 2013) to solve for the subgame perfect Nash equilibrium of this game. To do so, we determine the optimal decision for each player beginning with the last decision node and proceeding backward to the first decision node. For individuals, the maximum utility compliance level is shown in Equation 10. Next, we determine policymaker's optimal decision, i.e., the intervention that minimizes the risk of infection given that individuals will play their optimal compliance strategy. The policymaker's decision is then given by Equation 12.

C Additional figures



(a) (b)

Figure S1: The simulated endemic *E. coli* prevalence when the optimal intervention from Figure 3 is implemented (S1a) and the risk ratio comparing the optimal intervention vs. the current 4 LRV guideline for *E. coli* across a range of LRV preferences (S1b). Results are shown for both an asymmetric and symmetric appeal function. Endemic prevalence was calculated for a simulated population of 10,000 after one year.



(a) (b)

Figure S2: The simulated endemic rotavirus prevalence when the optimal intervention from Figure 3 is implemented (S2a) and the risk ratio comparing the optimal intervention vs. the current 5 LRV guideline for rotavirus across a range of LRV preferences (S2b). Results are shown for both an asymmetric and symmetric appeal function. Endemic prevalence was calculated for a simulated population of 10,000 after one year.

References

Fudenberg, D. and Tirole, J. *Game theory*. MIT Press, 1991.

Tadelis, S. *Game theory an introduction*. Princeton university press, 2013.