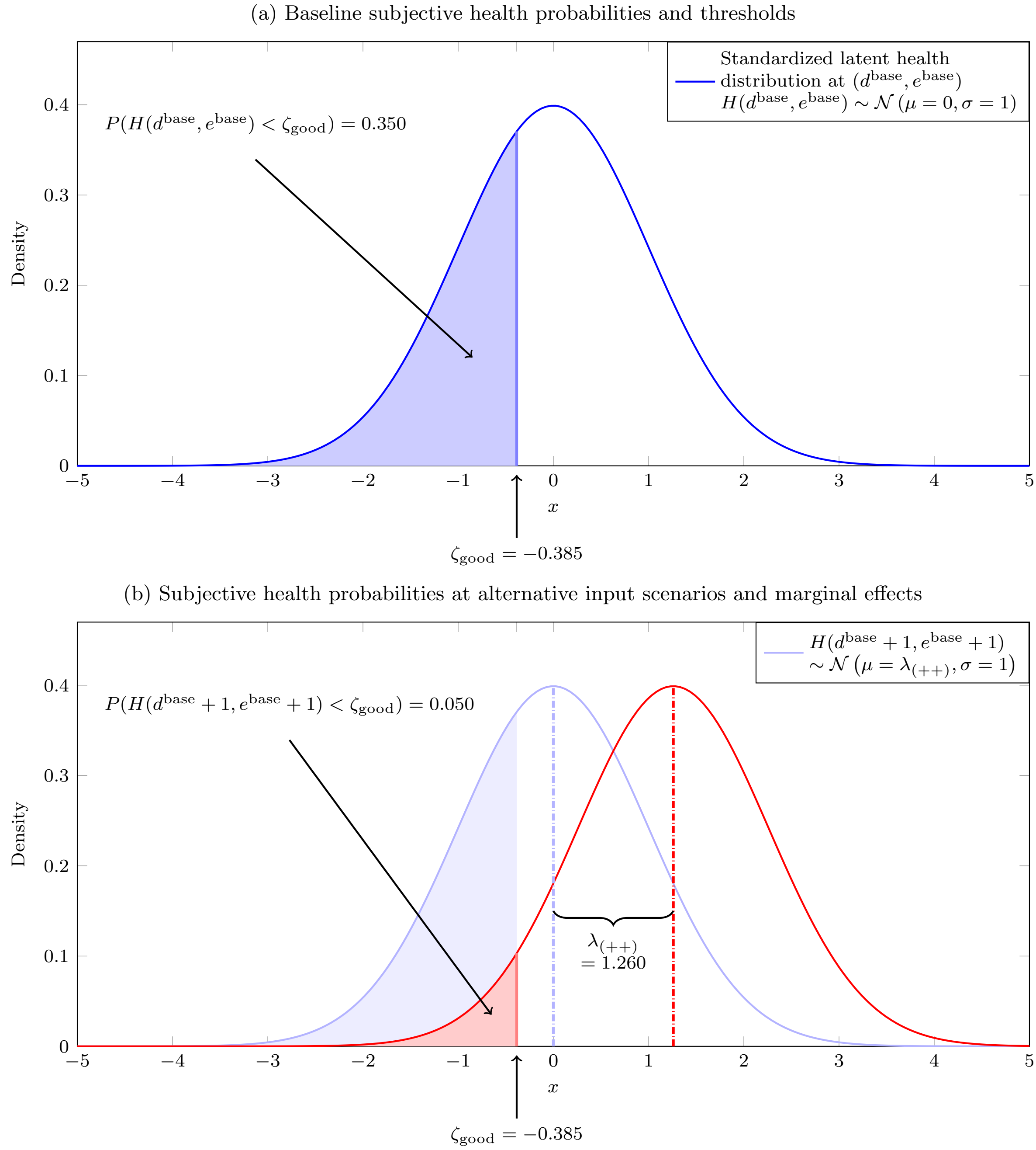
Figure 1: Illustration of the identification of latent health thresholds and marginal effects given elicited subjective health probabilities across input scenarios and health status levels.



Note: Next period latent health is a random variable. The latent health random variable at baseline input levels is $H(d^{\text{base}}, e^{\text{base}})$. The latent health random variable given increases in both input levels is $H(d^{\text{base}} + 1, e^{\text{base}} + 1)$. We elicit subjective probabilities that next period latent health is worse than "good" at the baseline and alternative input scenarios. We assume that latent health is a mixture of normals (in this case one normal). Since the scale and location of latent variables can not be identified, we normalize $H(d^{\text{base}}, e^{\text{base}}) \sim \mathcal{N}(\mu = 0, \sigma = 1)$. The normalized latent threshold for good health, ζ_{good}, can be identified by inverting the survey-elicited cumulative probability of having less than good health: $\Phi^{-1}\left(P\left(H\left(d^{\text{base}}, e^{\text{base}}\right) < \zeta_{\text{good}}\right)\right) = \zeta_{\text{good}}$. The marginal effect of increasing inputs is $\lambda_{(++)}$, where $\lambda_{(++)}$ provides a mean-shift of the baseline latent health random variable: $H(d^{\text{base}} + 1, e^{\text{base}} + 1) = H(d^{\text{base}}, e^{\text{base}}) + \lambda_{(++)}$. The marginal effect can be identified as the difference of inverted cdfs: We have $P\left(H\left(d^{\text{base}} + 1, e^{\text{base}} + 1\right) < \zeta_{\text{good}}\right) = P\left(H\left(d^{\text{base}}, e^{\text{base}}\right) + \lambda_{(++)} < \zeta_{\text{good}}\right) = \Phi\left(\zeta_{\text{good}} - \lambda_{(++)}\right)$, and hence $\lambda_{(++)} = \zeta_{\text{good}} - \Phi^{-1}\left(P\left(H\left(d^{\text{base}} + 1, e^{\text{base}} + 1\right) < \zeta_{\text{good}}\right)\right)$.