c. \( X \sim \text{Bin}(\pi, m), \ Y \sim \text{Bin}(\rho, n) \).
   i. "noninformative" "reference" prior on both.
   ii. Likelihood \( \pi^X(1-\pi)^{m-X}\rho^Y(1-\rho)^{n-Y} \)
   iii. Prior \( \pi^{-1}(1-\pi)^{-1}\rho^{-1}(1-\rho)^{-1} \)
   iv. More interesting parameterization
       \( \delta = \pi - \rho \in (-1, 1), \ \tau = \pi + \rho \in (|\delta|, 2 - |\delta|) \)
   v. Posterior \( (\delta + \tau) (1 - \delta - \tau)^{m-X-1}(\tau - \delta)^{n-Y-1} \)
       - The jacobian of the \( (\pi, \rho) \rightarrow (\delta, \tau) \)
         transformation is constant, and will wash out of calculation.

M. Bayesian Hierarchical Models
1. Bayesian alternative to frequentist random effects modeling.
2. Setup:
   \[
   X_{11}, \ldots, X_{1n_1} \sim \text{i.i.d.}\, \mathcal{N}(\theta_1, \sigma^2) \\
   X_{21}, \ldots, X_{2n_2} \sim \text{i.i.d.}\, \mathcal{N}(\theta_2, \sigma^2) \\
   \vdots \\
   X_{k1}, \ldots, X_{kn_k} \sim \text{i.i.d.}\, \mathcal{N}(\theta_k, \sigma^2)
   \]
3. \( \theta_k \sim \text{i.i.d.}\, \mathcal{N}(\mu, \tau^2) \)
4. \( \mu, \sigma \) and \( \tau \) given non-informative prior.
5. Since these are all conjugate priors, one can produce a normal posterior for \( \mu \).
6. Cf. frequentist approach \( X_{ji} = \mu + \eta_j + \epsilon_{ij} \),
   \( \eta_j \sim \mathcal{N}(\sigma^2), \ \epsilon_{ij} \sim \mathcal{N}(\tau^2) \).
7. Results similar.