$Y_1, ..., Y_n$  are exchangeable

 $\Rightarrow$ 

 $Y_1, ..., Y_n | \theta$  are conditionally i.i.d.,  $\theta \sim \pi(\theta)$  (de Finetti)

$$p(\tilde{Y} = \tilde{y}|Y_1 = y_1, ..., Y_n = y_n) = \frac{p(\tilde{y}, y_1, ..., y_n)}{p(y_1, ..., y_n)}$$
(1)

$$= \frac{\int p(\tilde{y}, y_1, ..., y_n | \theta) \pi(\theta) d\theta}{\int p(y_1, ..., y_n | \theta) \pi(\theta) d\theta}$$
(2)

$$= \frac{\int p(\tilde{y}|\theta)p(y_1, ..., y_n|\theta)\pi(\theta)d\theta}{\int p(y_1, ..., y_n|\theta)\pi(\theta)d\theta}$$
(3)

$$= \frac{\int p(\tilde{y}|\theta)p(\theta|y_1, ..., y_n)p(y_1, ..., y_n)d\theta}{\int p(y_1, ..., y_n|\theta)\pi(\theta)d\theta}$$
(4)

$$= \frac{p(y_1, \dots, y_n) \int p(\tilde{y}|\theta) p(\theta|y_1, \dots, y_n) d\theta}{p(y_1, \dots, y_n)}$$
 (5)

$$= \int p(\tilde{y}|\theta)p(\theta|y_1, ..., y_n)d\theta \tag{6}$$

## Explanation:

- 1. The conditional density of  $\tilde{y}$  is the quotient of the joint density  $\tilde{y}, y_1, ..., y_n$  with the marginal joint density of  $y_1, ..., y_n$  (definition of conditional density)
- 2. The joint densities in both the numerator and denominator can be thought of as marginal joint densities, and written as integrals (with respect to something—here we conveniently choose  $\theta$ ) of products of conditional joint densities (conditional on  $\theta$ ) with the density of  $\theta$
- 3. Conditional independence of the  $y_i$ s with respect to  $\theta$  enables us to express the conditional joint density in the numerator as a product of densities
- 4. Pairing the second and third factor in the integrand of the numerator, we apply Bayes' rule (p(A|B)p(B) = p(B|A)p(A))
- 5. Now the last factor in the integrand of the numerator does not depend on  $\theta$ , and can be pulled out of the integral, while the denominator just reverts back to the original joint density from line 1 (clearly it was not necessary to change it in the first place), and these two quantities conveniently cancel out
- 6. We now have the Bayesian Predictive Inference format we're aiming for

[Showing here that it is indeed a NB distribution]

$$\theta \sim NB(\alpha, \beta) \Rightarrow p(\theta) = \begin{pmatrix} \theta + \alpha - 1 \\ \alpha - 1 \end{pmatrix} \left( \frac{\beta}{\beta + 1} \right)^{\alpha} \left( \frac{1}{\beta + 1} \right)^{\theta}$$

$$\tilde{y} \sim NB\left(\alpha + \sum y_i\right), \beta + n\right) \Rightarrow p(\tilde{y}) = \begin{pmatrix} \tilde{y} + \alpha + \sum y_i - 1 \\ \alpha + \sum y_i - 1 \end{pmatrix} \left(\frac{\beta + n}{\beta + n + 1}\right)^{\alpha + \sum y_i} \left(\frac{1}{\beta + n + 1}\right)^{\tilde{y}}$$

$$= \frac{(\alpha + \sum y_i + \tilde{y} - 1)!}{(\alpha + \sum y_i - 1)! (\tilde{y})!} \left(\frac{\beta + n}{\beta + n + 1}\right)^{\alpha + \sum y_i} \left(\frac{1}{\beta + n + 1}\right)^{\tilde{y}}$$

$$= \frac{\Gamma(\alpha + \sum y_i + \tilde{y})}{\Gamma(\alpha + \sum y_i) \Gamma(\tilde{y} + 1)} \left(\frac{\beta + n}{\beta + n + 1}\right)^{\alpha + \sum y_i} \left(\frac{1}{\beta + n + 1}\right)^{\tilde{y}}$$

, for which

$$E\left[\tilde{Y}|y_1,...,y_n\right] = \frac{a+\sum y_i}{b+n} = E\left[\theta|y_1,...,y_n\right];$$

$$\operatorname{Var}\left[\tilde{Y}|y_1,...,y_n\right] = \frac{a+\sum y_i}{b+n} \frac{b+n+1}{b+n}$$

$$= \operatorname{Var}\left[\theta|y_1,...,y_n\right] \times (b+n+1)$$

$$= E\left[\theta|y_1,...,y_n\right] \times \frac{b+n+1}{b+n}$$

we obtain the posterior

$$p(\theta|Y_1, ..., Y_n) = \frac{p(Y_1, ..., Y_n|\theta)\pi(\theta)}{\int p(Y_1, ..., Y_n|\theta)\pi(\theta)d\theta}$$

$$= \frac{\theta^d e^{-\theta n\bar{y}} \cdot \frac{\gamma^{\delta}\theta^{\delta-1}e^{-\gamma\theta}}{\Gamma(\delta)}}{\int \left(\theta^d e^{-\theta n\bar{y}} \cdot \frac{\gamma^{\delta}\theta^{\delta-1}e^{-\gamma\theta}}{\Gamma(\delta)}\right)d\theta}$$

$$= \frac{\frac{\gamma^{\delta}}{V(\delta)} \left(\theta^{d+\delta-1}e^{-\theta(\gamma+n\bar{y})}\right)}{\frac{\gamma^{\delta}}{V(\delta)} \int \left(\theta^{d+\delta-1}e^{-\theta(\gamma+n\bar{y})}\right)d\theta}$$

$$= \frac{\frac{(\gamma+n\bar{y})^{d+\delta}}{\Gamma(d+\delta)} \left(\theta^{d+\delta-1}e^{-\theta(\gamma+n\bar{y})}\right)d\theta}{\frac{(\gamma+n\bar{y})^{d+\delta}}{\Gamma(d+\delta)} \int \left(\theta^{d+\delta-1}e^{-\theta(\gamma+n\bar{y})}\right)d\theta}$$

$$= \frac{(\gamma+n\bar{y})^{d+\delta}\theta^{d+\delta-1}e^{-\theta(\gamma+n\bar{y})}}{\Gamma(d+\delta)}$$

with the  $\operatorname{Gamma}(d+\delta,\gamma+n\bar{y})$  density in the next to last step integrating to 1.