

...have like terms:

Model:

For store i

$$y_i = X_i \beta_i + e_i \quad e_i \sim N(0, \sigma_i^2)$$

X_i is an $n_i \times 4$ matrix where n_i is the number of observations from store i .

The first column is identically one to fit an intercept. The second is $\log(\text{Price})$. The third is disp . The fourth is $\log(\text{Price}) \times \text{disp}$

Priors

$$\beta_i \sim N(\mu, \Sigma^{-1}) \quad \sigma_i^2 \sim \frac{1}{\sigma_i^2} \quad (\text{Jeffrey's Prior})$$

Conditionals

$$P(\beta_i | n_i, \sigma_i^2) \propto P(y_i | \beta_i, \sigma_i^2) P(\beta_i | \sigma_i^2)$$

$$\propto \exp \left[-\frac{1}{2} \left([y_i - X_i \beta_i]^T \left[\frac{1}{\sigma_i^2} I \right] [y_i - X_i \beta_i] \right. \right.$$

$$\left. + [\beta_i - \mu]^T [\Sigma] [\beta_i - \mu] \right]$$

$$= \exp \left[-\frac{1}{2} \left(y_i^T \left[\frac{1}{\sigma_i^2} I \right] y_i - 2 \beta_i^T X_i^T \left[\frac{1}{\sigma_i^2} I \right] y_i + \beta_i^T X_i^T \left[\frac{1}{\sigma_i^2} I \right] X_i \right. \right. \\ \left. \left. + \beta_i^T \Sigma \beta_i - 2 \mu^T \Sigma \beta_i + \mu^T \Sigma \mu \right) \right]$$

can drop anything without β_i due to proportionality

Combining like terms:

$$\propto \exp \left[-\frac{1}{2} \left(\beta_i^T \left[x_i^T \left[\frac{1}{\sigma_i^2} I \right] x_i + \mathcal{U} \right) \beta_i - 2 \beta_i^T \left(x_i^T \left[\frac{1}{\sigma_i^2} I \right] y_i + \mathcal{U}_M \right) \right] \right]$$

completing the square:

want form $\underbrace{[\beta_i - M_i^*]^T [K_i^*] [\beta_i - M_i^*]}$

$$= \beta_i^T K_i^* \beta_i - 2 \beta_i^T K_i^* M_i^* + \underbrace{M_i^{*T} K_i^* M_i^*}_I$$

but term I is irrelevant due to proportionality by inspection, $K_i^* = x_i^T \left[\frac{1}{\sigma_i^2} I \right] x_i + \mathcal{U}$

$$K_i^* M_i^* = \left(x_i^T \left[\frac{1}{\sigma_i^2} I \right] y_i + \mathcal{U}_M \right)$$

$$\text{so } M_i^* = K_i^{*-1} \left(x_i^T \left[\frac{1}{\sigma_i^2} I \right] y_i + \mathcal{U}_M \right)$$

Therefore $\underbrace{(\beta_i | y_i, \sigma_i^2 \sim N(M_i^*, K_i^{*-1}))}$

$$P(\sigma_i^2 | y_i, \beta_i) \propto P(y_i | \sigma_i^2, \beta_i) P(\sigma_i^2 | \beta_i)$$

$$\propto \exp \left[-\frac{1}{2} \left([y_i - x_i \beta_i]^T \left[\frac{1}{\sigma_i^2} I \right] [y_i - x_i \beta_i] \right) \right] \left(\frac{1}{\sigma_i^2} \right) \left(\frac{1}{\sigma_i^2} \right)^{n_i/2}$$

$$= \frac{1}{(\sigma_i^2)^{\frac{n_i}{2} + 1}} \exp \left[-\frac{1}{2\sigma_i^2} [y_i - x_i \beta_i]^T [y_i - x_i \beta_i] \right]$$

This is inverse Gamma w/ $a = \frac{n_i}{2}$ and $b = \frac{1}{2} [y_i - x_i \beta_i]^T [y_i - x_i \beta_i]$