

cheese

- 88 stores
- weekly: sales Q , price, P , α/β where product was advertised (1 or 0)

Estimate, for each store, the effect of displaying ads on the demand curve:

$$\log(Q) = \log(\alpha) + \beta \log(P), \quad \leftarrow \text{log-log scale}$$

$\beta \equiv$ price elasticity of demand

- consider 1 in $\alpha \lesssim \beta$
- consider $|Q|$ somehow
- does β vary store-by-store? Is it worth estimating separate β for each store?
- do $\alpha \lesssim \beta$ look similar store-by-store? (list of $\alpha \lesssim \beta$ post fit)
- Do we see any fitting problems?

model store "j"

$$\log(Q_t) \sim N(\log(\alpha_t) + \beta_t \log(P_t), \sigma^2)$$

conjugate $\sigma^2 \sim \text{IG}(100, 0.01)$ weekly homogenous error term

$$\log(\alpha_t) = a + b \mathbb{1}(x_t=1)$$

: a is intercept for $\log(Q_t)$
: b is incremental effect on $\log(Q_t)$ when advertising w/o change in price (?)

not conjugate $a \sim \text{Gamma}(\alpha_a, \beta_a)$ (should be non-negative) (2nd bullet point)

conjugate $b \sim N(0, \sigma_b^2)$

$$\beta_t = c + d \mathbb{1}(x_t=1)$$

conjugate $c \sim N(0, \sigma_c^2)$

conjugate $d \sim N(0, \sigma_d^2)$

Interpretation

$$\log(Q_t) \sim N(a + b \mathbb{1}(x_t=1) + (c + d \mathbb{1}(x_t=1)) \log(P_t), \sigma^2)$$

- a is global intercept
- b is the shift in demand curve when advertising
- c is PED w/o advertising
- d is the marginal increase/decrease in PED when we advertise
- σ^2 is global homogenous error

σ^2 global \equiv week-by-week per store

full-conditionals

$$[\sigma^2 | \cdot] \propto \prod_{t=1}^T [\log(Q_t) | \sigma^2, \dots] [\sigma^2]$$

$$\propto \prod_{t=1}^T N(\log(\alpha_t) + \beta_t \log(P_t), \sigma^2) (\sigma^2)^{-\frac{1}{2}} \exp(-\frac{\sigma^2}{2})$$

$$\propto (\sigma^2)^{\frac{T}{2} + a - 1} \exp \left\{ -\frac{1}{\sigma^2} \left(b + \sum_{t=1}^T \frac{[\log(Q_t) - \log(x_t) - \beta_t \log(P_t)]^2}{2} \right) \right\}$$

$$\Rightarrow [\sigma^2 | \cdot] = \text{IG} \left(a + \frac{T}{2}, b + \frac{1}{2} \sum_{t=1}^T [\log(Q_t) - \log(x_t) - \beta_t \log(P_t)]^2 \right)$$

$$[b | \cdot] \propto N \left(\log(\alpha_0) \middle| a + b \mathbb{1}(x_t=1) + (c + d \mathbb{1}(x_t=1)) \log(P_t), \sigma^2 \right)$$

$$\times \text{Normal}(b | 0, \sigma_b^2)$$

$$\propto \exp \left\{ -\frac{1}{2\sigma^2} \left[\log Q_t - a - b \mathbb{1}(x_t=1) - (c \log P_t + d \mathbb{1}(x_t=1) \log P_t) \right]^2 \right\}$$

$$\times \exp \left\{ -\frac{1}{2\sigma_b^2} b^2 \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[\frac{1}{\sigma^2} \left(-2 \left(\log Q_t \mathbb{1}(x_t=1) - a \mathbb{1}(x_t=1) - c \log P_t \mathbb{1}(x_t=1) - d \mathbb{1}(x_t=1) \log P_t \right) b \right. \right. \right.$$

$$\left. \left. \left. + b^2 \mathbb{1}(x_t=1) \right) \right. \right]$$

$$+ \frac{1}{\sigma_b^2} b^2 \right]$$

$$\propto \exp \left\{ -\frac{1}{2} \left[-2 \left(\frac{b(\log Q_t \mathbb{1}(x_t=1) - a \mathbb{1}(x_t=1) - (c+d) \log P_t \mathbb{1}(x_t=1))}{\sigma^2} \right) b + b^2 \left(\frac{\sum \mathbb{1}(x_t)}{\sigma^2} + \frac{1}{\sigma_b^2} \right) \right] \right\}$$

b*

$$\Rightarrow [b] \equiv N(A^{-1}b, A^{-1})$$

$$[c] \propto \exp \left\{ -\frac{1}{2\sigma^2} \left[\log Q_t - a - b \mathbb{I}(x_t=1) - c \log P_t - d \mathbb{I}(x_t=1) \log P_t \right]^2 \right\}$$

$$\times \exp \left\{ -\frac{1}{2\sigma_c^2} c^2 \right\}$$

$$\begin{aligned} & \propto \exp \left\{ -\frac{1}{2} \left[-2 \left(\frac{\sum (\log Q_t \log P_t - a \log P_t - (b+d) \log P_t \mathbb{I}(x_t=1))}{\sigma^2} \right) \right. \right. \\ & \quad \left. \left. + c^2 \left(\frac{\sum (\log P_t)^2}{\sigma^2} + \frac{1}{\sigma_c^2} \right) \right] \right\} \end{aligned}$$

$$\Rightarrow [d] \equiv N(A^{-1}b, A^{-1})$$

Likewise, $[d] \equiv N(A^{-1}b, A^{-1})$, where

$$A^{-1} = \frac{\sum \mathbb{I}(x_t=1) (\log P_t)^2}{\sigma^2} + \frac{1}{\sigma^2} I$$

$$b = \underbrace{\sum (\log Q_t - a - b - c \log P_t) \log P_t \mathbb{I}(x_t=1)}_{\sigma^2}$$

Non-conjugate update: a

I know this may not be best, but let's just say the proposal for M-H update is the prior, so our M-H ratio simplifies to

$$m_{\alpha}^{h_a} = \frac{[\log Q_t | \alpha^{(+)}, \dots]}{[\log Q_t | \alpha^{(h_a)}, \dots]}$$