

Discussion on “Using Models to Estimate Hog Production”

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In Consultation with Dr. Eric Slud
US Census Bureau
A CNSTAT Workshop
May 15, 2019
Washington, DC

Fay-Herriot Model: A Popular Model for Area-Level Data

- 1 Goal is to estimate θ_i , hog production for state i , $i = 1, \dots, m$
- 2 State summary Y_i based on state sample *directly* estimates θ_i
- 3 Direct estimates are often not reliable
- 4 To develop reliable SAE, Fay and Herriot (1979) proposed a model for to “borrow strength” from other data source
- 5 **Sampling model:** $Y_i = \theta_i + e_i$, $e_i \stackrel{ind}{\sim} N(0, D_i)$, $i = 1, \dots, m$
- 6 Known sampling variances D_i : $D = \text{Diag}(D_1, \dots, D_m)$
- 7 Fay-Herriot model connects θ_i to covariate x_i by a
- 8 **Linking model :** $\theta_i = x_i^T \beta + v_i$, $v_i \stackrel{ind}{\sim} N(0, \sigma_v^2)$, $i = 1, \dots, m$
- 9 The predictors x_i do not fully explain θ_i by linear regression
- 10 Random term v_i is the model error

Benchmarking of SAE Predictions

- SAE usually considers explicit use of models.
- These model-based estimates can differ widely from the direct estimates, especially for areas with very low sample sizes.
- One potential drawback of the model-based estimates is that when aggregated, the overall estimate for a larger geographical area may be quite different from the corresponding direct estimate, the latter being usually believed to be quite reliable.
- The problem can be more severe in the event of model failure.
- An overall agreement with the direct estimates at an aggregate level: often a political necessity to convince the legislators of the utility of small area estimates.
- A Bayesian benchmarking solution in Datta et al. (2011)



A Bayesian Benchmarking Solution

- Y_1, \dots, Y_m : the direct estimators of the m small area means $\theta_1, \dots, \theta_m$. Let $\mathbf{Y} = (Y_1, \dots, Y_m)^T$, $\boldsymbol{\theta} = (\theta_1, \dots, \theta_m)^T$.
- Require estimators $\hat{\boldsymbol{\theta}}^{BM1} = (\hat{\theta}_1^{BM1}, \dots, \hat{\theta}_m^{BM1})^T$ of $\boldsymbol{\theta}$ such that $\sum_{i=1}^m w_i \hat{\theta}_i^{BM1} = t$.
- t : either externally given or equals $\sum_{i=1}^m w_i \hat{\theta}_i$, where w_i are known weights.
- Bayesian approach: Minimize $\sum_{i=1}^m E[(\theta_i - e_i)^2 | \mathbf{y}]$ with respect to e_i 's satisfying $\bar{e}_w = \sum_{i=1}^m w_i e_i = t$.
- $\hat{\theta}_i^B$ is the posterior mean of θ_i , $i = 1, \dots, m$
- $\bar{\hat{\theta}}_w^B = \sum_{i=1}^m w_i \hat{\theta}_i^B$, $L = \sum_{i=1}^m w_i^2$.
- Benchmarked estimator: $\hat{\theta}_i^{BM1} = \hat{\theta}_i^B + L^{-1}(t - \bar{\hat{\theta}}_w^B)w_i$.

(MV) FH Measurement Error Model

$$\begin{aligned} \mathbf{Y}_i &= \boldsymbol{\theta}_i + \mathbf{e}_i, & \boldsymbol{\theta}_i &= \boldsymbol{\beta}\mathbf{x}_i + \boldsymbol{\delta}\mathbf{z}_i + \mathbf{v}_i, \\ \mathbf{X}_i &= \mathbf{x}_i + \boldsymbol{\eta}_i, & & i = 1, \dots, m \end{aligned}$$

- $\mathbf{Y}_i, \boldsymbol{\theta}_i$ s -dimensional. $s = 1$ is univariate
- $s = 4$ to estimate statewide hog production $\boldsymbol{\theta}_i$ for the four weight groups
- **Covariates \mathbf{x}_i are not observed, instead \mathbf{X}_i are observed.** These covariates may be from a survey
- Covariates \mathbf{z}_i are observed with no measurement error.
- $\boldsymbol{\beta}(s \times p)$, $\boldsymbol{\delta}(s \times q)$, and $\Sigma_v(s \times s)$ p.d.
- $\mathbf{e}_i \stackrel{iid}{\sim} N_s(0, \mathbf{D}_i) \perp \mathbf{v}_i \stackrel{iid}{\sim} N_s(0, \Sigma_v) \perp \boldsymbol{\eta}_i \stackrel{iid}{\sim} N_p(0, \mathbf{C}_i)$.
- Variance matrices $\mathbf{D}_i, \mathbf{C}_i$ are known and p.d.

Multivariate Cross-Sectional Time Series SAE Model*

- At time $t(= 1, \dots, T)$, \mathbf{Y}_{it} is an s -dimensional vector of direct estimators of some characteristics θ_{it}
- The problem is to estimate some function of the θ_{it} 's
- One possible MV C-S T-S extension of FH model given by Ghosh et al. (1996)
- $\mathbf{Y}_{it} | \theta_{it} \stackrel{ind}{\sim} N_s(\theta_{it}, \mathbf{D}_{it}), t = 1, \dots, T, i = 1, \dots, m$
- $\theta_{it} = \mathbf{X}_{it}\alpha + \mathbf{Z}_{it}\mathbf{b}_t + \mathbf{v}_{it}$, where $\mathbf{v}_{it} \stackrel{ind}{\sim} N_s(0, \Sigma_v)$
- A Random Walk model for \mathbf{b}_t : $\mathbf{b}_t | \mathbf{b}_{t-1} \sim N(\mathbf{b}_{t-1}, \Sigma_b)$
- An HB model may be based on diffuse priors for α, Σ_v and Σ_b