National Cancer Institute

Small Area Estimation for Measures Related to Tobacco Use and Policies Using the Tobacco Use Supplement to the Current Population Survey

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Disclaimer

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Outline

- Background of TUS-CPS and research goal
- SAE models and inferences
- Simulation studies to decide on a model and inference approach
- Implementation of the chosen model and evaluation of the model-based estimates
- Demonstration of final results
- Summary and discussion

TUS-CPS Background

- NCI sponsored survey (partially sponsored by CDC, FDA)
- Key source of U.S. national and state level data on tobacco use and tobacco control policy
- Supplement to the BLS' Current Population Survey (CPS) conducted by the Census Bureau
  - uses a national complex probability address-based sample of households
  - is conducted monthly, uses panel design for sampling efficiency
  - detailed stats on demography, labor force & unemployment
- TUS fielded about every two to four years since 1992
  - 240,000 civilian individuals aged 15+(now 18+)
  - 70% by phone & 30% in-person visit interview
  - translated into Spanish

http://riskfactor.cancer.gov/studies/tus-cps

Research Goal

- Model-based county level estimates for the following key measures (for population aged 18+):
  1. Percent of population currently smoking
  2. Percent of population that has ever smoked
  3. Percent of population that has quit for 24+ hours, among those who have smoked within the past year
  4. Percent of population governed by a smoke-free workplace policy
     - (Workplace has an official smoking policy: Smoking Not allowed in ANY public areas and work areas)
  5. Percent of population governed by a smoke–free home rule
     - (No one is allowed to smoke anywhere INSIDE YOUR HOME)

✓ Important to the Tobacco Control Research Branch

Notations

y_{ik} : a binary response for unit *k* in county i;

s_i : the set of sampled units in county i;

n_i : the sample size in county i;

w_{ik} : the sampling weight for unit *k* in county i;

$\mathbf{x}_i$: the vector of auxiliary variables;

$$k = 1, \ ..., \ N_i; \quad i = 1, \ ..., \ m$$

- Parameters of interest are the population proportions:

$$P_i = \sum_{k=1}^{N_i} y_{ik} / N_i$$

Direct Estimates of P_i and Associated Variances

- Direct estimates (design-unbiased):

$$p_{iw} = \frac{\sum_{k \in s_i} w_{ik} y_{ik}}{\sum_{k \in s_i} w_{ik}}, i = 1, \ldots, m$$

- Variances of the direct estimates:

$$VAR_{st}(p_{iw}) = \frac{P_i(1-P_i)}{n_i} * DEFF_i, \; i = 1, \ldots, m.$$

Where $DEFF_i$ is the design effect reflecting the complex design (Kish 1965).

- Problem of p_{iw}: Variance too large (imprecise estimates) for small sample sizes n_i
- Small area estimation techniques to address imprecise estimates

Commonly Used Area Level Model: Fay-Herriot Model

The well known Fay-Herriot model (Fay & Herriot 1979):

- Sampling model: $p_{iw}|P_i \sim N(P_i,\ D_i)$;
  - D_i is the sampling variance and is assumed known
- Linking model: $P_i = X_i'\beta + v_i$; where $v_i \sim N(0, A)$;

- Several transformations proposed to stabilize sampling variance D_i:
  - Fay and Herriot (1979): $\hat{\theta}_i = \log(p_{iw})$
  - Efron and Morris (1975): $\hat{\theta}_i = \sqrt{n_i}\arcsin(2p_{iw} - 1)$
  - Carter and Rolph (1974): $\hat{\theta}_i = \arcsin\left(\sqrt{p_{iw}}\right)$

Fay-Herriot Model with C&R Arcsin Transformation

Let $z_i = \arcsin\left(\sqrt{p_{iw}}\right)$; (Carter & Rolph, 1974 JASA)

- Sampling model: $z_i|\theta_i \sim N\left(\theta_i, \frac{DEFF_i}{4n_i}\right)$;
- Linking model: $\theta_i = X_i'\beta + v_i$; where $v_i \sim N(0, A)$

→ Goal: To estimate $P_i = sin^2(\theta_i)$

!! Extensive simulation study conducted to decide the model to use

SAE Model: Empirical Bayes Predictor (EBP)

Empirical Bayes estimator for P_i, $i = 1, \ldots, m$:

$$\hat{P}_i^{EB} = (1 - \hat{b}_i)p_{iw} + \hat{B}_i X_i' \hat{\beta}, \text{ where } \hat{B}_i = \frac{D_i}{\hat{A} + D_i}.$$

- $\hat{\beta}$: can be obtained using maximum likelihood estimation (MLE)
- $\hat{A}$: restricted maximum likelihood estimation (REML)
- MSE estimation of $\hat{P}_i^{EB}$ using Delta method (Datta and Lahiri 2000):

  MSE($\hat{P}_i^{EB}$)=$g_{1i}(\hat{A}, \hat{\beta}) + g_{2i}(\hat{A}, \hat{\beta}) + 2g_{3i}(\hat{A}, \hat{\beta})$, normal confidence interval can be computed using $\hat{P}_i^{EB}$ and MSE($\hat{P}_i^{EB}$).
- Parametric bootstrap prediction interval (Chatterjee, Lahiri and Li 2008)
  - Step 1: Generate R bootstrap samples using distributions: $P_i^* \sim N(x_i'\hat{\beta}, \hat{A})$ and $p_{iw}^* \mid P_i^* \sim N(P_i^*, D_i), i = 1, \ldots, m, \hat{\beta}$ and $\hat{A}$ obtained from the original sample.
  - Step 2: For each of the R bootstrap samples, obtain $\hat{A}^*$,$\hat{B}_i^*$, and $\hat{\beta}^*$
  - Step 3: For each bootstrap sample, compute $t_i^* = (P_i^* - \hat{P}_i^{EB*}) / \sqrt{D_i(1 - \hat{B}_i^*)}$
  - Step 4: Locate the two equal-tail $\alpha/2$ cut-off points (t_1, t_2) using the B pivot values computed in step 3.
  - Step 5: Construct the parametric bootstrap prediction interval for small area i as follow:

$$PI_i = \left[\hat{P}_i^{EB} + t_1\sqrt{D_i(1 - \hat{B}_i)}, \hat{P}_i^{EB} + t_2\sqrt{D_i(1 - \hat{B}_i)}\right]$$

Hierarchical Bayes (HB) Estimator

- Prior assumptions:
  - Flat prior for β, i.e., $f(\beta) \propto 1$
  - Uniform prior for A, i.e., $A \sim unif(0, L)$, where L is a large number.
- Multiple (3) independents chains for each run, Burn-ins of 10,000 samples and 10,000 after burn-in, thinning=2
- Posterior mean and percentiles obtained from the 15,000 MCMC samples (3 chains of 5,000 independent samples)
- 95% credible interval for $\hat{P}_i^{HB}$ is $\left(\hat{P}_{i,2.5}^{HB}, \hat{P}_{i,97.5}^{HB}\right)$

Model-based Simulation study: Data Generation

- Step 1: Obtain β and A using the 2002 Natality public-use data;
  - Parameter of interest is: $P_i = P(weight\ at\ birth < 3{,}345\ grams) \in [40.2\%, 58.5\%]$, where 3,345 grams was the 2002 national median birthweight.
  - Five auxiliary variables were chosen (percent of births with mother being non-Hispanic, percent of births being first live child in family, etc)
  - Fit the model $\hat{P}_i = x_i'\beta + v_i$; where $v_i \sim N(0, A)$ to obtain estimate of β and A.
- Step 2: Generate one set of θ_i from $\theta_i \sim N(x_i'\hat{\beta}, \hat{A})$, $i = 1, \ldots, 51$.
- Step 3: Generate 1,000 sets of observed data p_{iw} using three approaches:
  - Approach a: Generate p_{iw}based on level 1 of the Fay-Herriot model $p_{iw} \sim N(\theta_i, D_i)$
  - Approach b: Generate binary y_{ij} using Poisson distribution, $y_{ij} \sim Pois\left(\frac{n_i\theta_i}{DEFF_i}\right)$ and then compute $p_{iw} = \frac{\sum_j y_{ij}}{n_i/DEFF_i}$
  - Approach c: Generate binary y_{ij} using binomial distribution $y_{ij} \sim Bin\left(int\left(\frac{n_i}{DEFF_i}\right), \theta_i\right)$ and then compute $p_{iw} = \frac{\sum_j y_{ij}}{int(n_i/DEFF_i)}$

Model-based Simulation Study: SAE Models and Estimators

- Two modeling approaches (with five covariates)
  - Fay-Herriot model
  - Fay-Herriot model with arcsin transformation
- Three estimators:
  - EBP Parametric Bootstrap
  - EBP-REML-Delta method
  - HB method

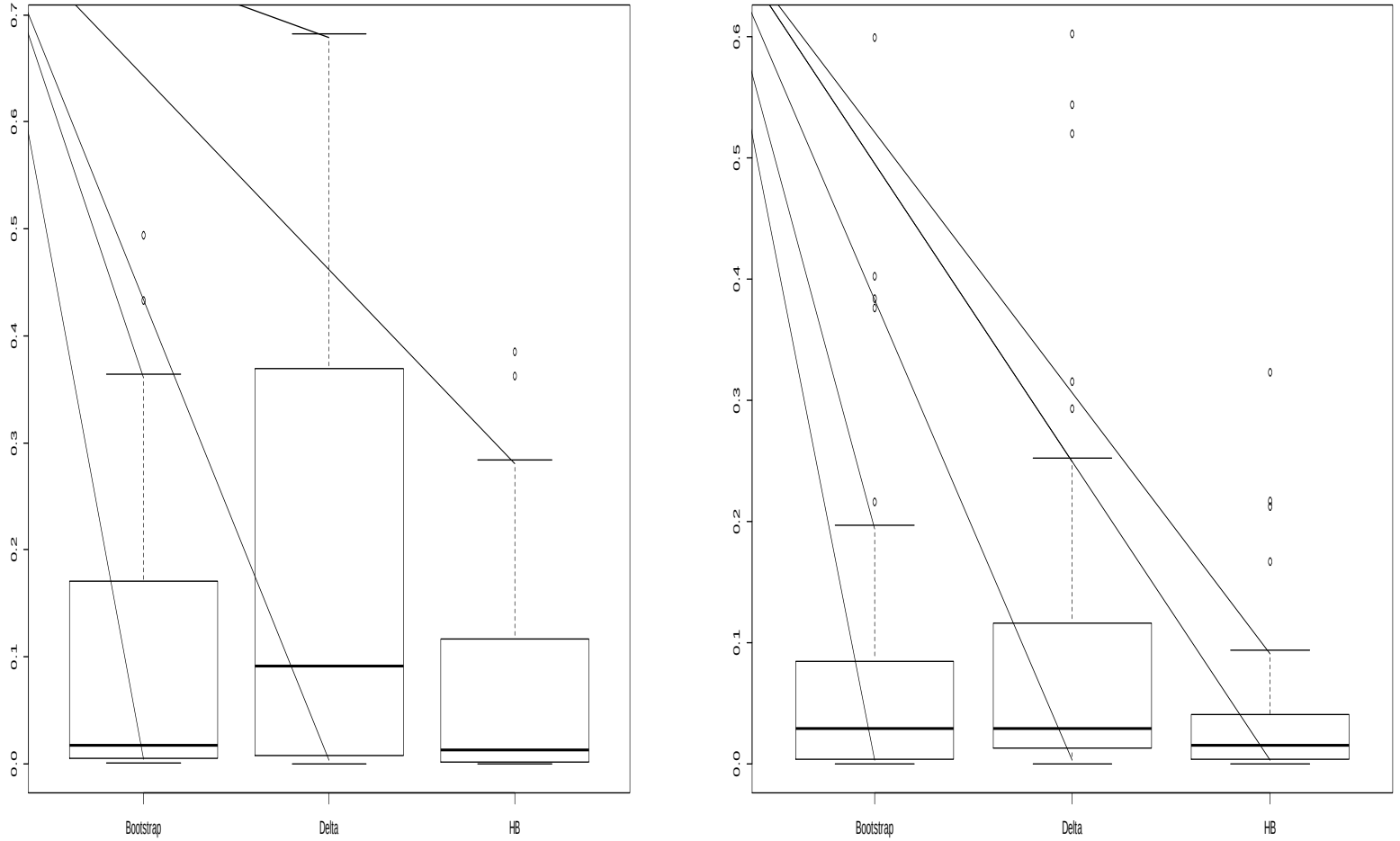
Simulation Results: Summary on 95% Confidence Interval Non-Coverage Rates and MC Errors

Data generation approach	State sample size n	Fay-Herriot Model			Fay-Herriot with arcsin transformation		
		EBP Parametric Bootstrap	EBP REML-Delta	HB	EBP Parametric Bootstrap	EBP REML-Delta	HB
Approach A	overall	4.9 (0.09)	6.9 (0.1)	3.9 (0.08)	4.5 (0.09)	6.4 (0.1)	4.1 (0.09)
	50<=n<60 (24 states)	4.9 (0.13)	6.2 (0.15)	3.0 (0.11)	4.6 (0.13)	5.8 (0.14)	3.6 (0.12)
	60<=n<100 (15 states)	5.6 (0.18)	8.5 (0.21)	4.7 (0.16)	5.2 (0.17)	7.9 (0.2)	4.5 (0.16)
	100<=n<=690 (12 states)	3.9 (0.17)	6.2 (0.2)	4.7 (0.19)	3.6 (0.16)	5.8 (0.2)	4.7 (0.19)
Approach B	overall	4.5 (0.09)	6.3 (0.1)	3.7 (0.08)	4.2 (0.08)	6 (0.1)	3.6 (0.08)
	50<=n<60 (24 states)	3.2 (0.11)	3.9 (0.12)	2 (0.09)	3 (0.11)	3.7 (0.12)	2.1 (0.09)
	60<=n<100 (15 states)	4.9 (0.17)	7.3 (0.2)	3.6 (0.15)	4.5 (0.16)	6.7 (0.19)	3.2 (0.14)
	100<=n<=690 (12 states)	6.5 (0.2)	10.1 (0.24)	7.1 (0.22)	6.1 (0.2)	9.6 (0.24)	7 (0.22)
Approach C	overall	6.7 (0.11)	8.6 (0.12)	9.3 (0.13)	4.2 (0.08)	10 (0.13)	10.6 (0.14)
	50<=n<60 (24 states)	6.0 (0.15)	7.2 (0.17)	7.7 (0.17)	3.0 (0.11)	8.6 (0.18)	9.2 (0.19)
	60<=n<100 (15 states)	6.9 (0.2)	8.5 (0.23)	9.2 (0.23)	4.5 (0.16)	10.2 (0.24)	10.7 (0.25)
	100<=n<=690 (12 states)	7.7 (0.24)	11.5 (0.29)	12.5 (0.3)	6.1 (0.2)	12.5 (0.3)	13.3 (0.31)

Approach A: Generate p_{iw} based on the Level 1 of the Fay-Herriot model; **Approach B**: Generate y_i using poisson distribution; **Approach C**: Generate y_i using Binomial distribution

Design-based Simulation and Results

- Boxplots of confidence interval non-coverage rates (without-covariate vs five-covariates)



- Sampling frame: 2002 Natality public-use data file;
- Parameter of interest: state level percent of births with weight less than the national median birth weights;
- Repeatedly draw 1000 sets of samples using stratified SRS within states;
- Fit Fay-Herriot model and calculate three estimators

Conclusions from the Simulation Studies

- Design-based study
  - Covariates improved the coverage rates
  - None of the three approaches produced coverage rates close to the nominal rates
  - HB estimator produced more conservative intervals.
- Model-based study
  - Parametric bootstrap approach gave the best coverage rates
  - Parametric bootstrap approach produced coverage rates close to the nominal rates only when data generated from Fay-Herriot model
  - HB approach gave the next best coverage property with often conservative credible/confidence intervals.
  - Not much difference between Fay-Herriot and Fay-Herriot with arcsin transformation.

➢ Fay-Herriot with arcsin transformation and HB approach were chosen for practical reason

TUS-CPS: Estimate Design Effects

Kish's DEFF formula (Kish 1987)

$$DEFF_{kish} = n \frac{\Sigma w_i^2 n_i}{\left(\Sigma w_i n_i\right)^2} [1 + (\bar{b} - 1)\rho]$$

where n_i and w_i denote the # of observations and the weight attached to the ith weight class, $i = 1, \ldots, m$. $n = \sum_i n_{i.}$ $\bar{b}$ is the average cluster size; ρ is the intra-class correlation coefficient.

Steps:

- Use the national DEFF to estimate ρ
- Plug ρ into the Kish's formula to estimate the state level DEFF
- Use the state level DEFF to estimate the county level DEFF

Auxiliary Variables

- The pool of auxiliary variables include:
  - 30 county-level demographic & socio-economic variables obtained from the five-year average of ACS (2005-2009, 2008-2012, , Census 2000 & 2010, and other administrative records;
  - 5 state level tobacco policy data (cigarette taxes, clean air laws, tobacco control funding, Medicaid Coverage for Tobacco-Related Treatment, year in which Quitline service was established)
- Classical model selection procedures are applied to reduce the number of auxiliary variables for each outcome
- Tested forcing in several strong unit level covariates: only worked for current smoking and smoking cessation.

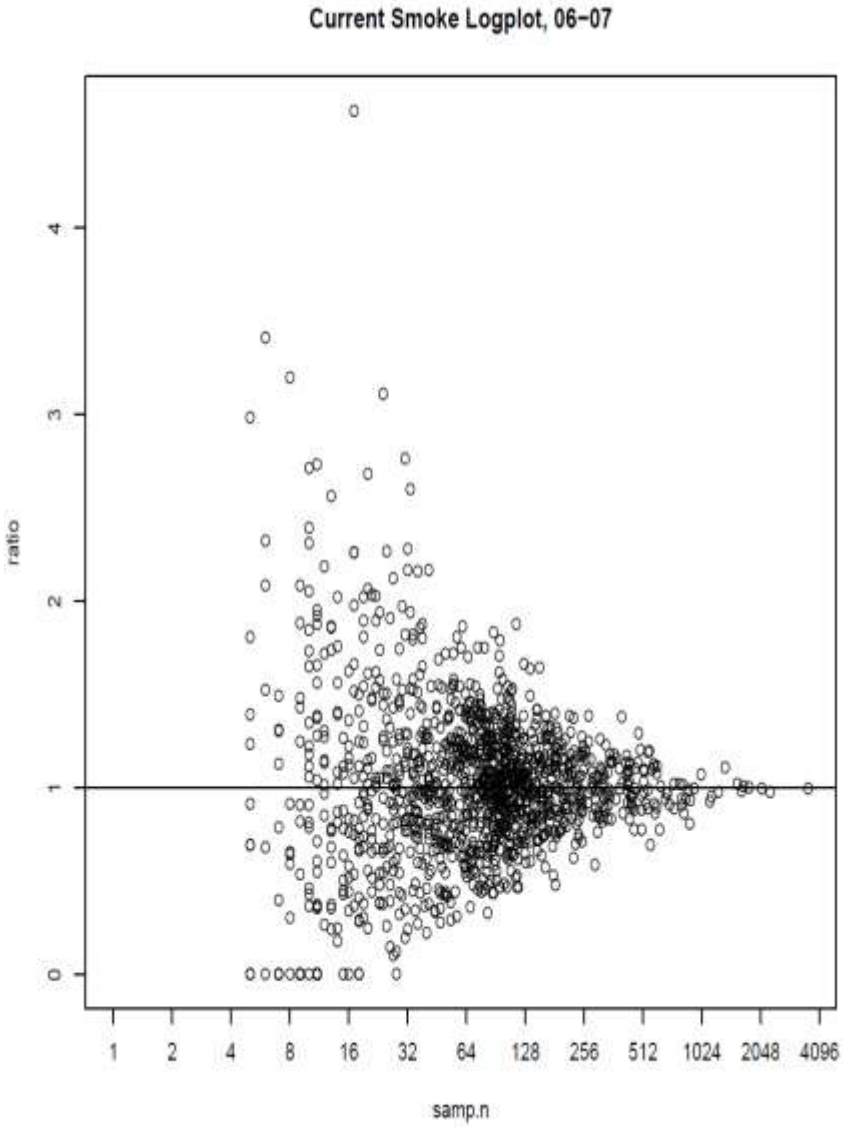
Statistical Inference and Model Diagnosis

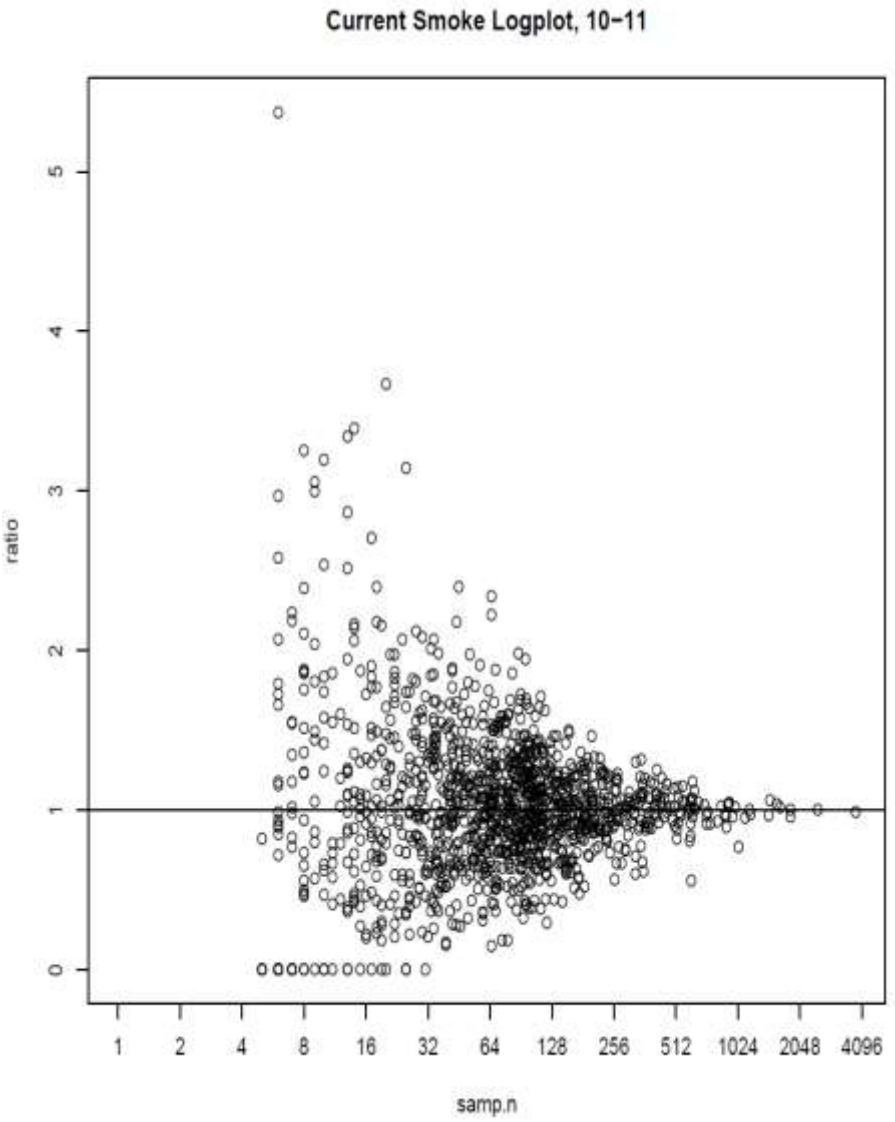
- HB approach through Markov Chain Monte Carlo (MCMC) methods are used to estimate the parameters of the statistical models.

- Extensive model selection and model diagnosis procedures are used to select the final models and assess the goodness of fit for each model.
  - Deviance information criterion (DIC) proposed by Spiegelhalter et al. (2002)
  - Gelman and Rubin's Potential Scale Reduction Factor $\hat{R}$
  - Check the overall fit of the proposed model using method of posterior predictive p –value (Gelman & Meng 1996)

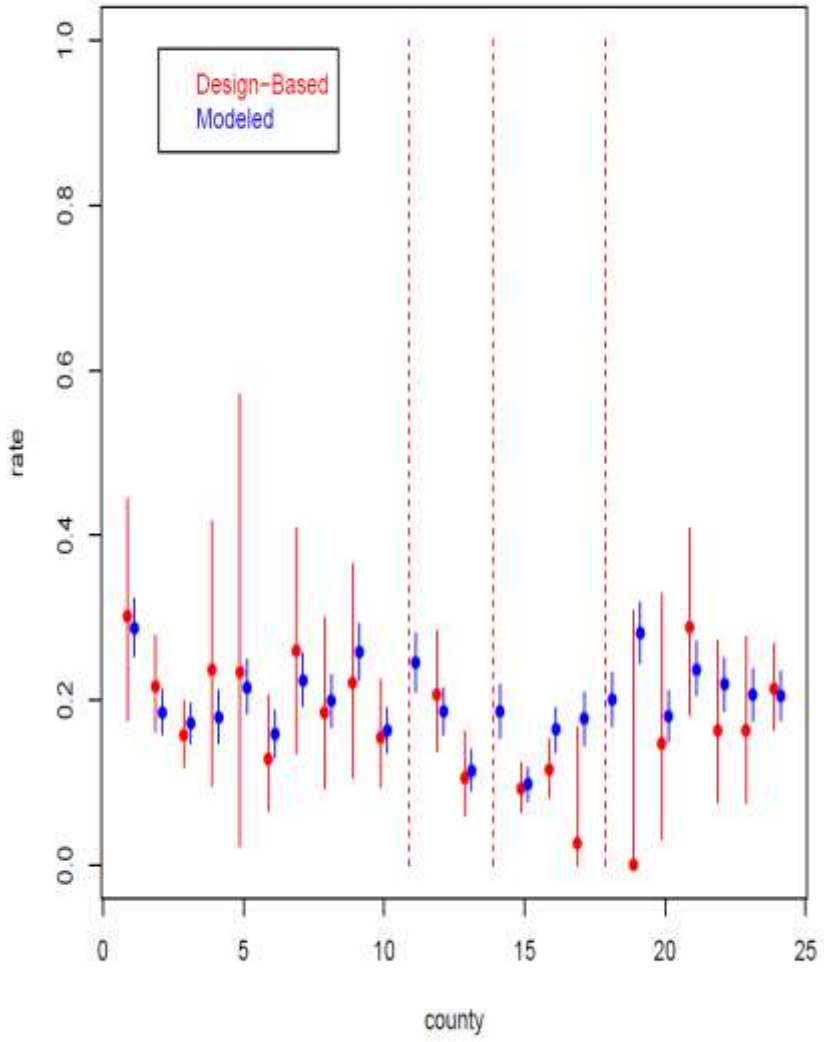
- Modeled estimates are also compared to the available direct estimates. The ratio of the two is expected to converge to 1 as the sample size gets larger.

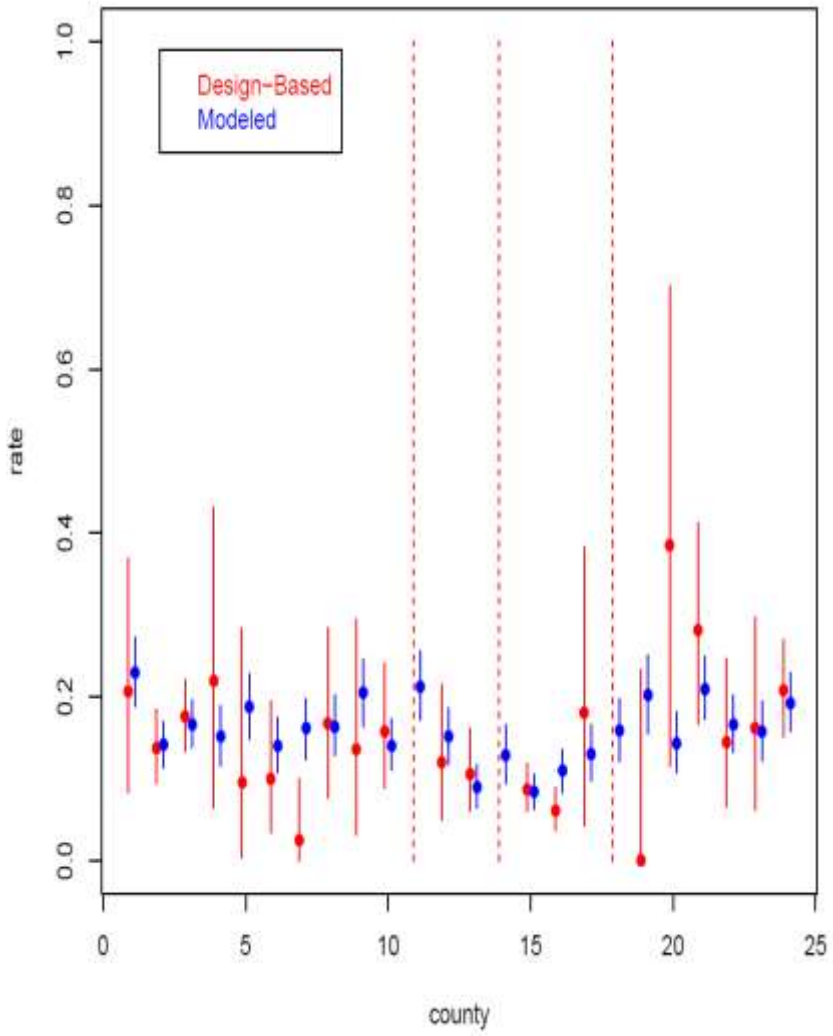
Ratio of the Direct Over the Modeled Estimates for the Current Smoking Prevalence





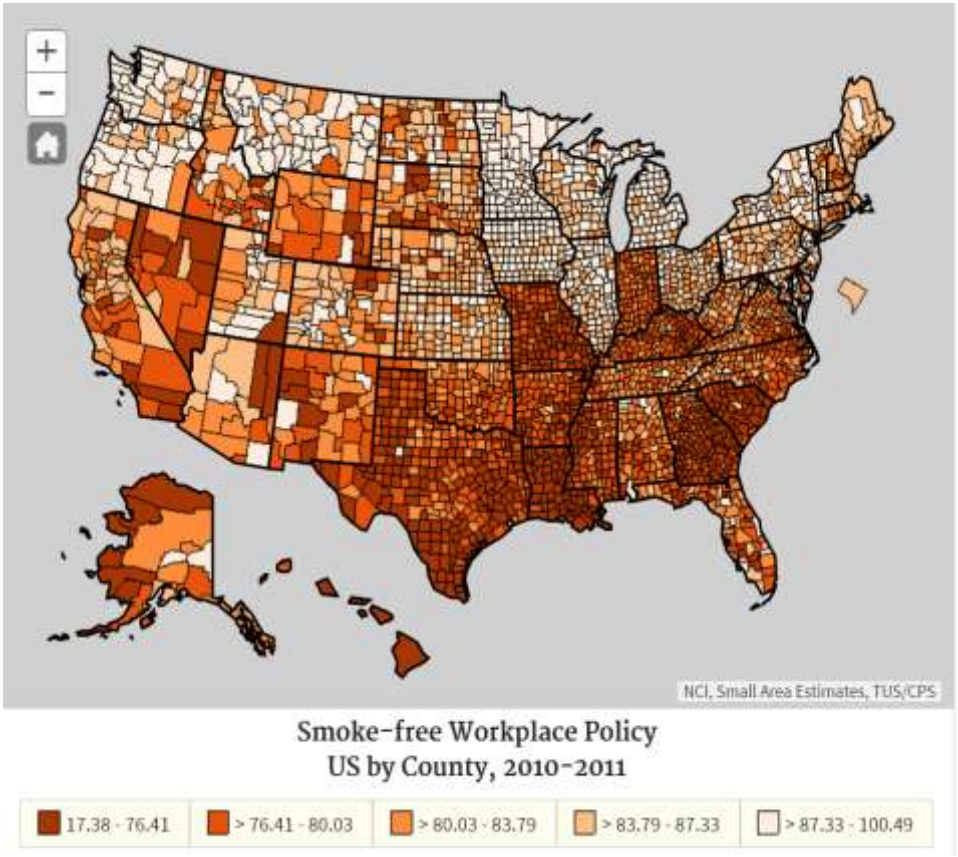
Model-based vs Design Based Estimates for Current Smoking Prevalence –Maryland 2010/11



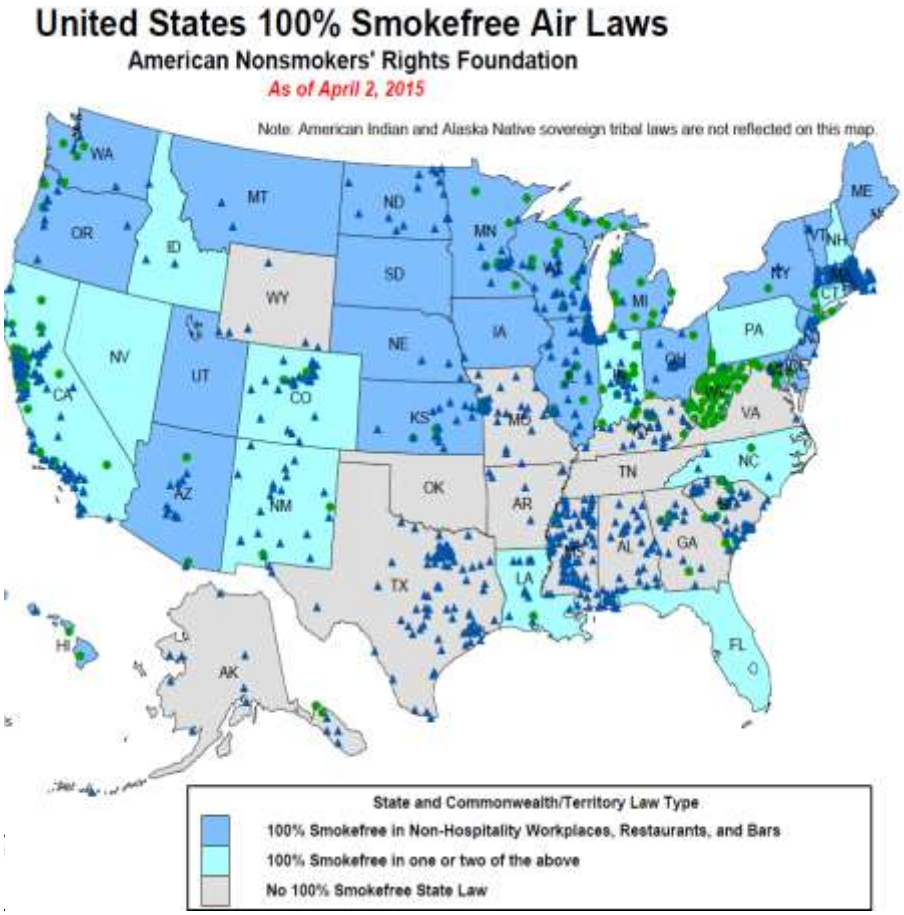


Model-based Estimates for Percent of Population Governed by a Smoke-free Workplace Policy* Among Age 18+: TUS-CPS 10/11

Individual Self-Reported



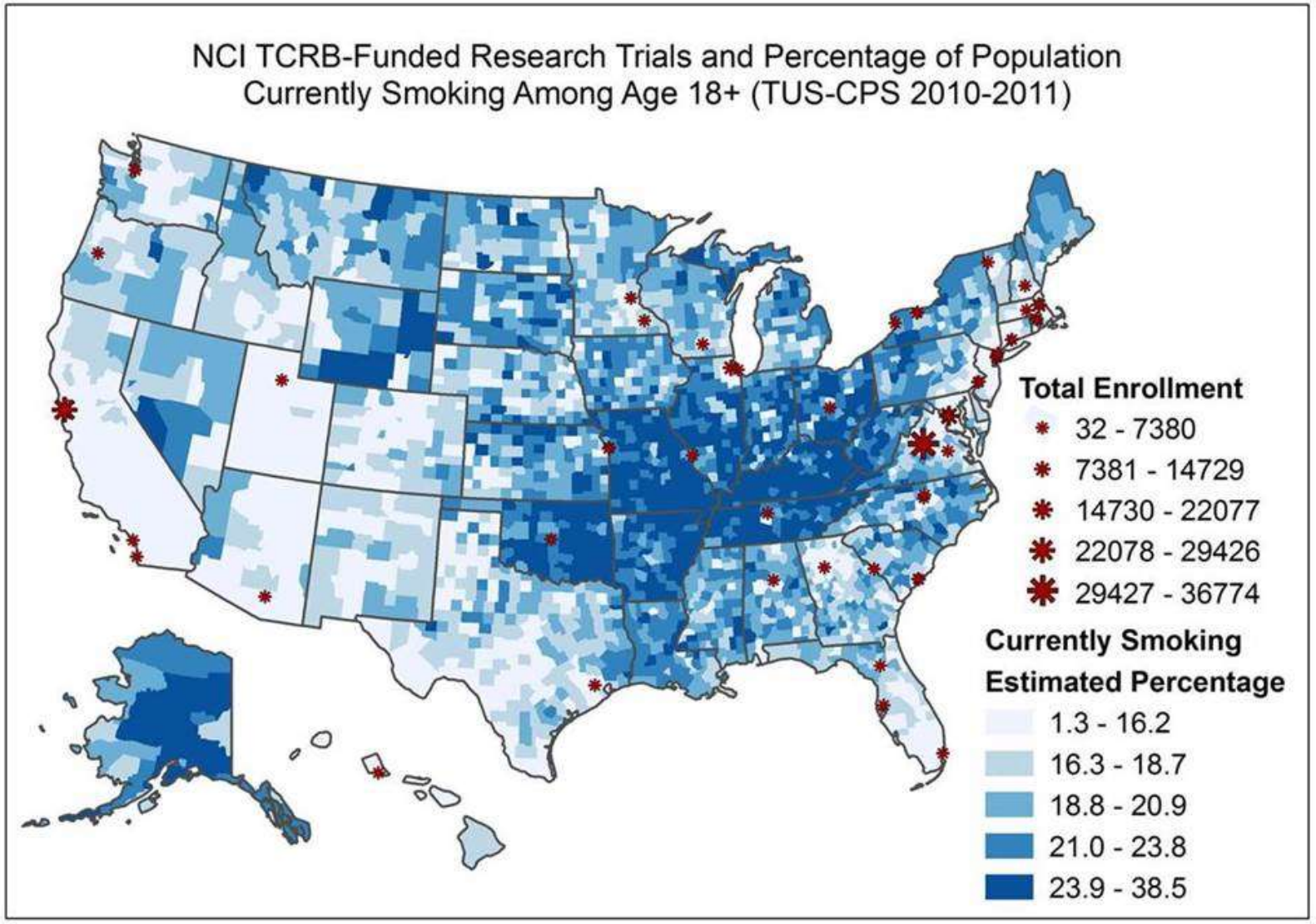
Law Legislations



*Workplace has an official smoking policy: Smoking Not allowed in ANY public areas and work areas

https://sae.cancer.gov/tus-cps/

Applications of the SAE maps



Summary and Discussion

- More details and results are available at https://sae.cancer.gov/tus-cps/.
- The model-based SAE techniques represent an effective means of generating estimates where there is small (or zero) state or county sample.
- The SAE results, which are released and disseminated at several NCI's websites provide a useful resource for the broad cancer surveillance society to fulfill multiple needs.
- We are currently working on estimates for the 2014/2015 data cycle.

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Any Questions?

Thank you!

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