# Hybrid BRR and Parametric-Bootstrap Variance Estimates for Small Domains in Large Surveys 

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## Disclaimer

This report is released to inform interested parties of ongoing research and to encourage discussion of work in progress. The views expressed are the author's and not necessarily the Census Bureau's.

## Voting Rights Act Section 203(b) Mandate

States \& political subdivisions (Counties, MCDs, American Indian Areas) must provide voting materials in a language other than English for members of Language Minority Groups (LMGs) according to specific rules based on population fractions.

Census Bureau Director makes the determinations based on (Decennial Census \& Amer. Commun. Survey) data, 263 in 2016

Press release Dec. 5, 2016 links to data files and determinations:
https://www.census.gov/newsroom/press-releases/2016/cb16-205.html
https://www.census.gov/rdo/pdf/1 FRN_201628969.pdf

## Terminology

US Voting Age persons (2014 5-yr American Community Survey)
partitioned into States; also Jurisdictions (Counties \& MCDs)
American Indian Alaska Native pop'n partitioned into AIAs
68 Language Minority Groups: Race self-ID and National Origin (16 Asian, 51 American Indian Alaska Native, plus Hispanic)

CIT : Voting Age Citizen population
LEP : CIT \& Limited English-Proficient (Foreign Language spoken in home, English spoken not 'Very well')

ILLIT : LEP CIT with < 5th grade education

## Scope of Data Example in this Talk

Restrict to Hispanic LMG within ( $\approx$ 7600) Jurisdictions

Rule for Determinations: \{ LEP (Jur,Hisp) count $>10,000$ or (Jur,Hisp) count LEP $>5 \%$ (Jur,Hisp) CIT count \} and (Jur,Hisp) ILLIT / (Jur,Hisp) LEP $>$ national illit. rate

Must estimate $\quad N_{j}^{C}, N_{j}^{L}, N_{j}^{I}, \quad N_{j}^{L} / N_{j, \text { tot }}^{C}, \quad N_{j}^{I} / N_{j}^{L}$
Direct Survey Estimates and Ratios available: ACS ‘special tabulation' from sample sizes $n_{j}$ and person-weights $w_{i}$, e.g.,

$$
\widehat{N}_{j}^{C}=\sum_{i \in(j, \mathrm{Hisp})} w_{i} \cdot I_{[i \in \mathrm{CIT}]}
$$

## Abstract Setting

Sample survey with sampled subjects $i \in \mathcal{S}$, weights $w_{i}$

Disjoint subdomains $C_{j k}, \quad k=1, \ldots, K$, partitioning larger areas $D_{j}, \quad j=1, \ldots, m: \quad D_{j}=\cup_{k=1}^{K} C_{j k}$

Survey-weighted counts $\hat{N}_{j}=\sum_{i \in \mathcal{S} \cap D_{j}} w_{i}, \hat{N}_{j k}=\sum_{i \in \mathcal{S} \cap C_{j k}} w_{i}$
Regard $n_{j}=\left|\mathcal{S} \cap D_{j}\right|$ as fixed, along with design-based estimators $\hat{N}_{j}, j=1, \ldots, m$, of $N_{j}$

Target proportions: $\underline{\pi}_{j}=\left(\pi_{j k}, k=1, \ldots, K\right), \pi_{j k}=N_{j k} / N_{j}$

## Two-Level Small Area Estimation Model

Define $\quad \underline{Y}_{j} \equiv\left(Y_{j k}, k=1, \ldots, K\right), \quad Y_{j k} \equiv n_{j} \hat{N}_{j k} / \hat{N}_{j}$
Data Model: $\quad \underline{Y}_{j} \sim \operatorname{Multinom}\left(n_{j}, \underline{\pi}_{j}\right)$
Parametric Linking Model: $\quad \underline{\pi}_{j} \sim f\left(\underline{\pi}, \theta, \mathbf{X}_{j}\right)$
Assume $\quad\left\{\hat{N}_{j}\right\}_{j=1}^{m} \quad$ indep. of $\quad\left\{\underline{\pi}_{j}, \underline{Y}_{j}\right\}_{j=1}^{m}$
Shared parameter $\theta$ allows borrowing strength
Estimate $\theta$ by combined MLE $\hat{\theta}$ : how to estimate Variances
of Predictors $\quad \tilde{N}_{j k}=Y_{j k}+\left.\left(\hat{N}_{j}-n_{j}\right) \cdot E_{\theta}\left(\pi_{j k} \mid \underline{Y}_{j}\right)\right|_{\theta=\hat{\theta}}$ ?

## Why Small-Area Estimation ?

Many samples \& VOTAG counts $n_{j}, \hat{N}_{j}$ are small ( $<10$ ) only $3671 j$ 's with $\hat{N}_{j}^{L}>0$ and 6837 with $\hat{N}_{j}>0$

Most, direct-method (SDR) CV's are very large.
Fractions of 3671 Jur's with sampled LEP citizens in which direct- and model-based estimates of CV fall within ranges.

| Range | $0-.2$ | $.2-.3$ | $.3-.4$ | $.4-.5$ | $.5-.61$ | $.61-1$ | $>1$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Direct | .168 | .104 | .089 | .089 | .093 | .317 | .140 |
| Model | .234 | .151 | .141 | .111 | .108 | .221 | .034 |

64\% Direct CV's > 0.4, vs. 47\% Hybrid BRR-Model-based

## Remarks about Model \& Estimation

$n_{j}$ Hisp voting-age persons deemed fixed (analyses conditional)
$\widehat{N}_{j}, \widehat{N}_{j, \text { tot }}^{C}$ design-based: random selected weights within Jur. $j$

Ratios $\quad \underline{\omega}_{j}=\left(N_{j}-N_{j}^{C}, N_{j}^{C}-N_{j}^{L}, N_{j}^{L}-N_{j}^{I}, N_{j}^{I}\right) / N_{j}$ modelled as Dirichlet-distributed target Jur random effects.

Data $n_{j}^{A}, \widehat{N}_{j}^{A}$ (for $A=C, L, I$ ) on occurrence of CIT, LEP and ILLIT persons within Hispanic VOTAG in $j$ : modelled only through ratio-scaled sample sizes $Y_{j}^{A}=n_{j}\left(\widehat{N}_{j}^{A} / \widehat{N}_{j}\right)$

## Predictive Covariates $X$ for SAE Model

Proportion Foreign-Born - within Jur or (Jur, Hisp)<br>Average years in US for Foreign-Born<br>Proportion < High-School Educ - within Jur or (Jur, Hisp)<br>State proportion CIT (within Hisp)<br>State proportion LEP (within Hisp)

Model selection and validation discussed in companion paper Ashmead \& Slud, JSM 2017 earlier in this session.

## Model for Borrowing Strength within LMG

Treat $\widehat{N}_{j}, \widehat{N}_{j, \text { tot }}^{C}$ via direct survey-weighted ACS estimators
Dirichlet-Multinomial model for C,L,I proportions and counts

$$
\begin{gathered}
\underline{\omega}_{j} \equiv \frac{1}{N_{j}}\left(N_{j}-N_{j}^{C}, N_{j}^{C}-N_{j}^{L}, N_{j}^{L}-N_{j}^{I}, N_{j}^{I}\right) \\
\sim \operatorname{Dirichlet}\left(\tau \sqrt{n_{j}},\left(1-\mu_{j}, \mu_{j}\left(1-\nu_{j}\right), \mu_{j} \nu_{j}(1-\rho), \mu_{j} \nu_{j} \rho\right)\right) \\
\text { CIT-rate } \mu_{j}=\frac{\exp \left(\beta^{\prime} \mathbf{X}_{j}\right)}{1+\exp \left(\beta^{\prime} \mathbf{X}_{j}\right)}, \quad \text { LEP-rate } \nu_{j}=\frac{\exp \left(\gamma^{\prime} \mathbf{X}_{j}\right)}{1+\exp \left(\gamma^{\prime} \mathbf{X}_{j}\right)} \\
\left(n_{j}-Y_{j}^{C}, Y_{j}^{C}-Y_{j}^{L}, Y_{j}^{L}-Y_{j}^{I}, Y_{j}^{I}\right) \sim \operatorname{Multinom}\left(n_{j}, \underline{\omega}_{j}\right) \\
\text { where } \quad Y_{j}^{A}=\left(n_{j} / \widehat{N}_{j}\right) \hat{N}_{j}^{A}, \quad A=C, L, I
\end{gathered}
$$

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## Predictor Formulas (like Beta-Binomial)

$\hat{\theta}=(\hat{\beta}, \hat{\gamma}, \hat{\tau}, \hat{\rho}) \quad \operatorname{MLE} \quad$ from $\left\{n_{j}, Y_{j}^{C}, Y_{j}^{L}, Y_{j}^{I}\right\}_{j}$

$$
\left(\begin{array}{c}
\hat{\omega}_{1 j} \\
\hat{\omega}_{2 j} \\
\hat{\omega}_{3 j} \\
\hat{\omega}_{4 j}
\end{array}\right)=\frac{1}{n_{j}+\hat{\tau}_{j}}\left(\begin{array}{c}
n_{j}-Y_{j}^{C} \\
Y_{j}^{C}-Y_{j}^{L} \\
Y_{j}^{L}-Y_{j}^{I} \\
Y_{j}^{I}
\end{array}\right)+\frac{\hat{\tau}_{j}}{n_{j}+\hat{\tau}_{j}}\left(\begin{array}{c}
1-\hat{\mu}_{j} \\
\hat{\mu}_{j}\left(1-\hat{\nu}_{j}\right) \\
\hat{\mu}_{j} \hat{\nu}_{j}(1-\hat{\rho}) \\
\hat{\mu}_{j} \hat{\nu}_{j} \hat{\rho}
\end{array}\right)
$$

these are the 'random-effect' or target predictors

## Predictors, continued

Then the pop-count predictors $N_{j}^{A}$ (within Hispanic LMG) are

$$
\left(\begin{array}{c}
\tilde{N}_{j}^{C} \\
\tilde{N}_{j}^{L} \\
\tilde{N}_{j}^{I}
\end{array}\right)=\left(\begin{array}{c}
Y_{j}^{C} \\
Y_{j}^{L} \\
Y_{j}^{I}
\end{array}\right)+\left(\widehat{N}_{j}-n_{j}\right)\left(\begin{array}{c}
1-\widehat{\omega}_{1 j} \\
\hat{\omega}_{3 j}+\widehat{\omega}_{4 j} \\
\hat{\omega}_{4 j}
\end{array}\right)
$$

where

$$
\hat{\tau}_{j}=\hat{\tau} \sqrt{n_{j}}, \quad \hat{\mu}_{j}=\frac{\exp \left(\hat{\beta}^{\prime} \mathbf{X}_{j}\right)}{1+\exp \left(\hat{\beta}^{\prime} \mathbf{X}_{j}\right)}, \quad \hat{\nu}_{j}=\frac{\exp \left(\hat{\gamma}^{\prime} \mathbf{X}_{j}\right)}{1+\exp \left(\hat{\gamma}^{\prime} \mathbf{X}_{j}\right)}
$$

Rate predictors: $\tilde{N}_{j}^{L} / \widehat{N}_{j, \text { tot }}^{C}$ and $\quad \tilde{N}_{j}^{I} / \tilde{N}_{j}^{L}$

## Variance Estimation

- for survey-weighted estimators, via Balanced Repeated Replication (BRR) - Successive Difference Replication (SDR) in ACS
- for functions of model parameters, via Parametric Bootstrap
- treat sample sizes $n_{j}$ as fixed, and within $j$ model for $N_{j}^{A} / N_{j}, n_{j} \widehat{N}_{j}^{A} / \widehat{N}_{j}$ has same form regardless of $\widehat{N}_{j}$, so parametric bootstrap loops nest inside BRR replicates


## Balanced Repeated Replication (BRR)

In internal or public-use files for ACS (and other large surveys), responder weights $w_{i}$ are provided along with replicate weights $w_{i}^{(r)}=w_{i} \cdot f_{i, r}, r=1, \ldots, R \quad$ (40 sampled $r$ 's)

- $f_{i, r}$ constant over $i$ in pseudo-strata defined in ACS by sort order $\bmod \mathrm{R}$ with respect to specific variables $(R=80)$
- $R^{-1} \sum_{r=1}^{R} f_{i, r} \approx 1 \quad, \quad(4 / R) \sum_{r=1}^{R}\left(f_{i, r}-1\right)^{2} \approx 1$
- $\operatorname{Var}\left(\sum_{i} w_{i} z_{i}\right) \approx(4 / R) \sum_{r=1}^{R}\left(\sum_{i} w_{i}^{(r)} z_{i}-\sum_{i} w_{i} z_{i}\right)^{2}$


## Parametric Bootstrap

Within all Jur's $j$, for fixed $n_{j}, \hat{N}_{j}, \mathbf{X}_{j}$ in each
Variance of function $q\left(n_{j}, \hat{N}_{j}, Y_{j}^{C}, Y_{j}^{L}, Y_{j}^{I}, \hat{\theta}\right)$ estimated by
$\begin{array}{cl}\text { - generating many indep. replicate samples } & \underline{\omega}_{j}^{*(b)}, Y_{j}^{*(b) A} \\ \text { across all } j=1, \ldots, m, \quad b=1, \ldots, B & (\mathrm{~B}=30)\end{array}$

- estimating MLE $\hat{\theta}^{*(b)}$ from data $\left\{Y_{j}^{*(b) A}, n_{j}, \mathbf{X}_{j}\right\}_{j, A}$
- for each $j$, calculating sample variance across $b=1, \ldots, B$ of $\quad q\left(n_{j}, \hat{N}_{j}, Y_{j}^{*(b) C}, Y_{j}^{*(b) L}, Y_{j}^{*(b) I}, \widehat{\theta}^{*(b)}\right)$


## Hybrid BRR \& Parametric Bootstrap

To estimate Mean Squared Prediction Error

$$
\operatorname{MSPE}=E\left(\tilde{N}_{j}^{A}-\omega_{j}^{A} N_{j}\right)^{2} \quad \text { for } \quad \mathrm{A}=\mathrm{C}, \mathrm{~L}, \mathrm{I}
$$

decompose using independence of $\hat{N}_{j}$ and $\left(\underline{Y}_{j}, \hat{\theta}\right)$ :
$\mathrm{MSPE}=E\left(\widetilde{N}_{j}^{A}-\hat{N}_{j} \omega_{j}^{A}\right)^{2}+\operatorname{Var}\left(\widehat{N}_{j}\right) E\left(\left(\widehat{\omega}_{j}^{A}\right)^{2}-\left(\omega_{j}^{A}-\widehat{\omega}_{j}^{A}\right)^{2}\right)$

Get MSPE from squared residuals nested $b$ within $r$ :

$$
\tilde{N}_{j}^{*(r, b) A}-\widehat{N}_{j}^{(r)} \omega_{j}^{*(r, b) A}, \quad \widehat{\omega}_{j}^{*(r, b) A}-\omega_{j}^{*(r, b) A}
$$

## Components of MSPE

Decompose mean-square residuals (of 2 types) into pieces
$E\left(e_{j}\right)^{2}=E\left(e_{j}-E\left(e_{j} \mid \widehat{N}_{j}\right)\right)^{2}+E\left(E\left(e_{j} \mid \hat{N}_{j}\right)-E\left(e_{j}\right)\right)^{2}+\left(E\left(e_{j}\right)\right)^{2}$
Within, Between, Bias-Sq terms respectively estimated by

$$
\sum_{r=1}^{R} \sum_{b=1}^{B} \frac{\left(e_{j}^{*(r, b)}-\bar{e}_{j}^{*(r+)}\right)^{2}}{R(B-1)}, \quad \frac{4}{R} \sum_{r=1}^{R}\left(\bar{e}_{j}^{*(r+)}-\bar{e}_{j}^{*(0+)}\right)^{2},\left(\vec{e}_{j}^{*(0+)}\right)^{2}
$$

where $r=0$ denotes original sample and

$$
\bar{e}_{j}^{*(r+)}=B^{-1} \sum_{b=1}^{B} e_{j}^{*(r, b)}
$$

Scatterplot of MSPE/SDRvar [log10 scale] vs log10(SDRvar) for 3671 Jurisdiction Hispanic LEP totals


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## Summary of Data Results

- Jur's with large variances tend to have large estimates, with relatively smaller improvements of MSPE over SDR Variance
- Great majority of Jur's with intermediate variance have MSPEs much smaller (note log scale!) than SDR Variances, but those which also have smaller sample sizes tend to have MSPE notably worse than SDRvar.
- Jur's with very small sample size (or overall LEPcount estimate) have very small ratios of MSPE over SDR variance.

Ratios of Quantiles of Hybrid-Method MSPEs vs. SDR For Hispanic LEP totals, all Jur's and by sampsize classes


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## Further Research on this Topic

- Using independence to remove necessity for double looping (b within r)
- Generalizing model to allow dependence between modeled targets and $\hat{N}_{j}$ and perhaps
to model $n_{j k}=\sum_{i \in \mathcal{S}} I_{\left[i \in C_{j k}\right]}$ jointly with other variables


## References

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## Thank you!

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