

Approaches to Small Area Estimation: Multilevel Regression with Poststratification (MRP)

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The general problem

- ▶ Define population U , parameter θ , sample S
- ▶ Suppose U a union of disjoint sub-populations, $U = \bigcup_{j=1}^J U_j$
- ▶ What if we want to estimate θ_j for some U_j ?
 - ▶ If θ = unemployment rate, may be curious about $\theta_{\text{Massachusetts}}$, θ_{Maine} , θ_{Vermont} , etc. in addition to overall θ

The general problem (continued)

- ▶ **Small area estimation** addresses how we can produce estimators for θ_j
- ▶ Could simply use same estimator as with U , but on subset of S belonging to U_j
 - ▶ $n_j < n$, so $\text{Var}(\hat{\theta}_j)$ could be (very) large
- ▶ Want to find “better” $\hat{\theta}_j$, particularly for when $n_j \ll n$

Big Picture: Multilevel Regression with Poststratification

- ▶ Identify categorical respondent attributes x_i in survey that are also available in census data (including area identifiers¹)
- ▶ Gather auxiliary area-level variables (\underline{x}_j) we that may be predictive of y_i
- ▶ Use (bespoke) regression to estimate the effects of individual characteristics (x_i) and area characteristics (\underline{x}_j) on y_i
- ▶ Construct “poststratification table” with cell (row) for every combination such attributes and population size N_c of that cell
- ▶ Calculated predicted value $\hat{\mu}_{yc}$ (estimator of $\mathbb{E}[y_i|i \in U_c]$) for each cell in poststratification table

$$\text{Then we say... } \hat{\mu}_{yj} = \frac{\sum_{c \in j} N_c \hat{\mu}_{yc}}{\sum_{c \in j} N_c}$$

¹Technically can be applied any categorical grouping, not just spatial ones.

Example multilevel logit

- ▶ Assume data follows generating process

$$\Pr(y_i = 1) = \frac{e^{(\alpha_j + \beta_1 x_i)}}{1 + e^{(\alpha_j + \beta_1 x_i)}}, \text{ for observation } i \text{ in group } j$$

- ▶ Try to estimate β and a separate intercept α_j for each group j
 - ▶ **Prior**: α_j 's follow some distribution (often $\alpha_j \sim N(0, \sigma^2)$)
 - ▶ **Posterior**: adjusts for groups with large-enough n_j
 - ▶ For groups with small n_j and outlier y_i distribution, accounts for possibility of sampling variance than outlier α_j

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Opinion polls

How accurate are MRP polls predicting huge Tory losses in next general election?

Firms combine polling and census-type data to predict outcomes but with sometimes differing results

Demonstration:

Question: what do younger adults think of gun control, by state?

- ▶ Largest survey of political attitudes: Cooperative Election Study
 - ▶ 51,550 adults completed both rounds in 2020
 - ▶ Just 6,004 of them under age 30
 - ▶ In individual states, $n_{\text{under-30}}$ very small
- ▶ To see if $n = 6,004$ reasonable for state estimates, can first try estimating something we know: 2020 vote totals

Model (2020 vote)

$y_i = 1$ if voted for Biden, 0 if voted for someone else / didn't vote

Use 'stan_glmr' in *R* to estimate posterior distributions of (weighted) multilevel logit parameters...

α^{state} for every state

α^{race} for every race category

α^{age} for every age category

$\alpha^{education}$ for every education category

$\alpha^{race_education}$ for every race x education interaction

β^{male}

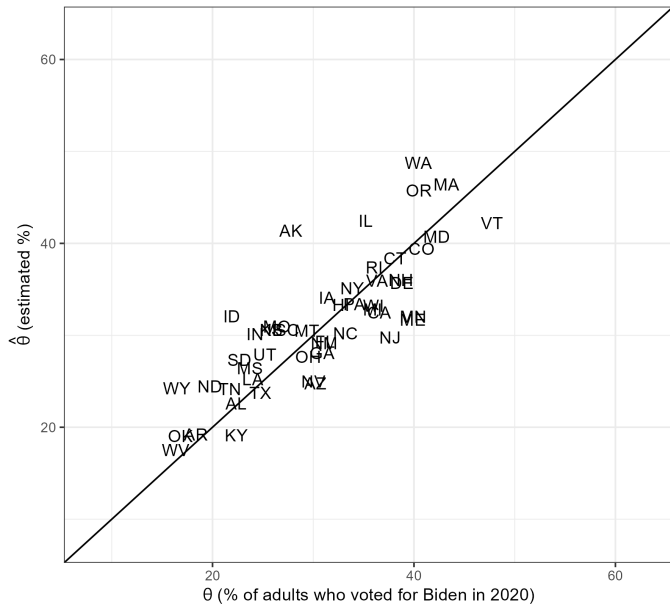
β^{2016_vote}

β^{region} for non-baseline regions (EPA definitions)

Computing estimates

- ▶ Construct poststratification table using Census IPUMS
 - ▶ N_c for each cell $\{\text{state}\} \times \{\text{gender}\} \times \{\text{race}\} \times \{\text{education}\} \times \{\text{age}\}$
 - ▶ 10,200 rows!
 - ▶ Merge in 2016 vote data and add regions
- ▶ Take 4,000 draws of parameter values from posterior distributions, computing every state's mean each time
 - ▶ For each state take mean and quantiles 2.5 and 97.5

MRP estimates vs. actual % of adults voting for Biden



Estimates calculated using 2020 ACS and sample of 6,004 respondents from 2020 Cooperative Election Study

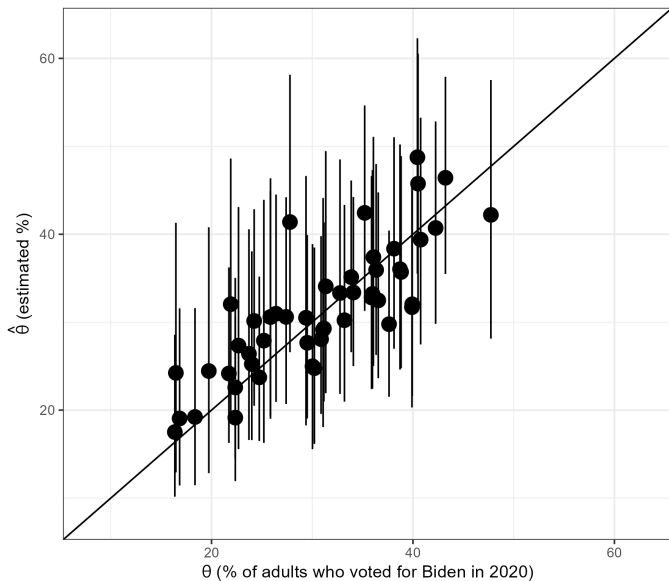
MSE lower than direct estimator

	States	MRP_MSE	Direct_MSE
1	All states	21.48948	77.86618
2	25 largest states	16.92803	28.03674
3	25 smallest states	26.05093	127.69562

- ▶ Much lower MSE than “direct estimator” (weighted mean of ‘biden_vote’ by state)
 - ▶ True even of larger states

MRP estimates vs. actual % of adults voting for Biden in 2020

95% confidence intervals shown



Estimates calculated using 2020 ACS and sample of 6,004 respondents from 2020 Cooperative Election Study

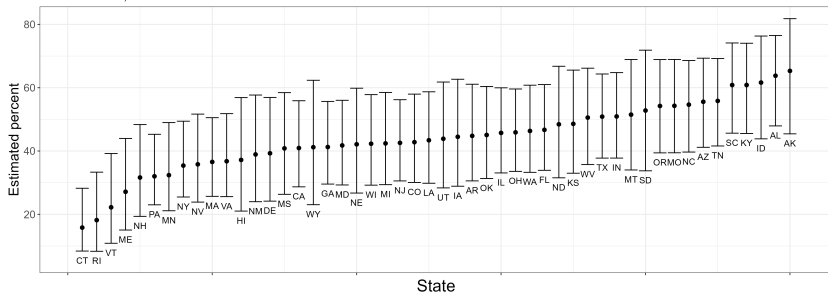
Gun control

Now back to young adults' views of gun control

- ▶ $n = 6,004$ respondents aged 18–29
- ▶ Each asked whether they support policy to “make it easier for people to obtain concealed-carry permit”
- ▶ Run same model using this as y_i , and dropping age parameter

Estimates

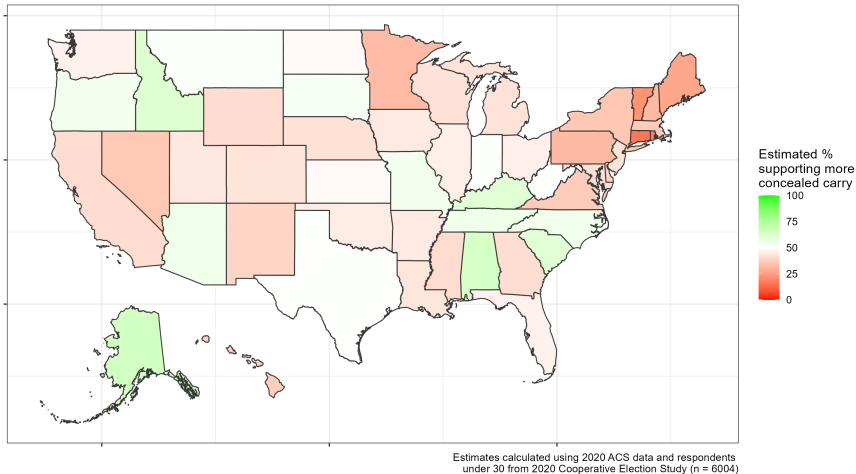
Percent of Americans ages 18–29 who believe it should be easier to obtain a concealed carry permit
MRP estimates, 95% confidence intervals shown



Estimates calculated using 2020 ACS data and respondents under 30 from 2020 Cooperative Election Study (n = 6004)

Best part of small area estimation: maps!

Percent of Americans ages 18–29 who believe it should be easier to obtain a concealed carry permit
Estimated via multilevel regression with poststratification



Further reading:

- ▶ General guides to MRP:
 - ▶ Lopez-Martin et al. (2022), “Multilevel Regression and Poststratification Case Studies”
 - ▶ Alexander (2023), *Telling Stories with Data*, chapter 16
- ▶ On multilevel models:
 - ▶ Gelman and Hill (2007), *Data Analysis Using Regression and Multilevel/Hierarchical Models*
 - ▶ Snijders and Bosker (2012), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*
- ▶ Data this would not have been possible without:
 - ▶ 2020 ACS IPUMS
 - ▶ 2020 Cooperative Election Study