Video 19 of 21: Weighting Calibration

Sampling

THE WORLD BANK

MANNHEIM BUSINESS SCHOOL

What is calibration? (I)

- The general idea is to use auxiliary variables to improve the efficiency of estimators (Deville & Särndal, 1992)
- **Auxiliary data**: information available for the entire frame or target population, either for each individual population unit or in aggregate form
  - May come from the frame, administrative records, published statistics or other sources
  - Business survey: the frame might have the number of employees from an earlier time period for each establishment
  - Household survey: counts of persons in groups defined by age, race/ethnicity, and gender may be published from a census or from population projections that are treated as highly accurate

What is calibration? (II)

- Auxiliary variables are typically included in survey questionnaire:
  - Make sure to include variables that are predictive of the survey outcomes
- Among the potential benefits of calibration are:
  - Decrease in sampling variances
  - Bias correction for frame coverage and other frame errors
  - Adjustment for nonresponse
- Generally, most of the standard estimators are special cases of calibrated estimators (e.g. the expansion estimator, ratio estimator, post-stratified estimator, GREG estimator, and raked estimator)
- Main calibration adjustments are implemented in most statistical packages

Post-stratification (I)

- Especially prevalent in household surveys of persons where the auxiliary variables are indicators for demographic groups (age group, gender, and race/ethnicity)
- Implemented within calibration weighting classes formed by crossing all categories of the qualitative variables and constructing weights that reproduce the class-specific population counts in the weighted estimates
- Good way to use auxiliary variables that you think are effective predictors of important variables collected in the survey but cannot be easily used for sample selection

Post-stratification (II)

- For example, post-stratified by gender and educational attainment:
  - Gender (1=Male, 2=Female)
  - Education (1=Less than high school; 2=High school graduate; 3=some college; and 4=Bachelor degree or more)
- Cross-classification leads to G = 8 classes that could be used as post-strata
- Using many important auxiliary variables for post-stratification can reduce bias
- But may result in empty weighting classes or ones with a small number of respondent cases
  - Results in unstable estimates of the population controls and adds unnecessarily variability to the final weights

Post-stratification (III)

- The post-stratification adjustment is computed as

$$a_{g,i} = \frac{N_g}{\hat{N}_g}$$

where N_g is the population count for post-stratum *g* and $\hat{N}_g = \sum_{s_g} d_i$ is its estimate using the input weights d_i

- The final post-stratified weight for unit *i* in post-stratum *g* is then computed as

$$w_i = d_i \times a_{g,i}$$

Post-stratification (IV)
Example

Gender	Age	N_g	$\hat{N}_g$	$a_{g,i}$
Male	18-34	16,516,047	13,138,357	1.25708
Male	35-44	9,722,899	6,149,134	1.58118
Male	45-54	10,928,639	9,911,012	1.10267
Male	55-64	8,488,197	14,837,247	0.57208
Male	65+	8,540,787	12,204,434	0.69981
Female	18-34	17,200,469	9,210,347	1.86751
Female	35-44	10,343,299	14,061,085	0.73559
Female	45-54	11,485,779	15,893,681	0.72266
Female	55-64	9,334,197	18,086,949	0.51607
Female	65+	11,055,919	25,539,782	0.43289

Raking (I)

- Raking is an adjustment procedure in which estimates are controlled by marginal population totals
  - Implicitly assumes that the interactions between the calibration variables are not important to explain the survey variable(s)
- The main advantage of raking over post-stratification is that raking potentially allows the use of more auxiliary information (only needs the marginal totals not the cross-classified categories totals)
- Also decreases issues of sparse or empty weighting cells
- In the next example, with raking only the marginal sex and age control counts are needed

Raking (II)
Example (iteration 1)

Gender	N_g	$\hat{N}_g$	$a_{g1,i} = N_g/\hat{N}_g$
Male	54,196,569	56,240,183	0.96366
Female	59,419,663	82,791,843	0.71769

- Update weight by computing $d_i^{(1)} = d_i \times a_{g1,i}$
- Use updated weights to compute $\hat{N}_g$ below

Age	N_g	$\hat{N}_g$	$a_{g2,i} = N_g/\hat{N}_g$
18-34	33,716,516	19,271,206	1.74957
35-44	20,066,198	16,017,324	1.25278
45-54	22,414,418	20,957,760	1.06950
55-64	17,822,394	27,279,096	0.65333
65+	19,596,706	30,090,847	0.65125

- Update weight by computing $d_i^{(2)} = d_i^{(1)} \times a_{g2,i}$
- Start new iteration and keep doing until weights converge

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