

Evaluation and Selection of Models for Attrition Nonresponse Adjustment

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Outline

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 - Model-based Adjustments
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 - Adjustment Models
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 - Comparison using Raked vs Raw Weights

Definitions motivated by SIPP

Survey of Income & Program Participation

- Individuals i observed in successive 'Waves'
- Sample \mathbf{s} here denotes Wave-1 **responders**
- Weights w_i are inverse inclusion prob's
re-weighted for Wave-1 response & raked.
- Survey items y_i e.g. socSec income indicator
are **only Wave 1** data values.

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are **only Wave 1** data values.

- $r_i =$ indicator of later-wave (say Wave-4) response
treated as random beyond probability sample
- \hat{p}_i model-based estimator of $p_i = \Pr(r_i = 1 \mid i \in \mathbf{s})$

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Present Methodology – Internal Evaluation

Target $t_y = \sum_{i \in U} y_i$ wave 1 responder total

Estimates initial $\sum_{i \in S} w_i y_i$ (Horvitz-Thompson)

at later wave, adjusted: $\sum_{i \in S} w_i y_i r_i / \hat{p}_i$

Adj. Bias $\sum_{i \in S} w_i y_i \left\{ r_i / \hat{p}_i - 1 \right\}$

SIPP Implemented in Bailey (2004), with
SE calculation in Slud & Bailey (2006).

Model-based Adjustments

- **Cell-based Method:** for i in cell $C \subset \mathcal{U}$,

$$\hat{p}_i = \sum_{j \in C} r_j w_j / \sum_{j \in C} w_j$$

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fitted from weighted ML equation, Wave 1 covariates \mathbf{x}_i
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- **Model comparisons via Subdomain Bias Estimates**

Subdomain Bias & 1st Metric

- **Bias over Subdomain** \mathcal{D} for k 'th survey item

$$\hat{B}_k(\mathcal{D}) = \sum_{i \in \mathcal{D} \cap \mathbf{s}} \left(\frac{r_i}{\hat{p}_i} - 1 \right) w_i y_i^{(k)}$$

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- **Metric def'n**: max Relative Bias over consecutive subsets after random re-ordering $\tau = (\tau(1), \tau(2), \dots, \tau(n))$ of \mathbf{s} : then averaged over permutations τ :

$$m_k = E_{\tau} \left(\max_{1 \leq a \leq n} |\hat{B}_k(\{\tau(1), \dots, \tau(a)\})| \right) / \hat{t}_{y^{(k)}}$$

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- **Monte Carlo Estimate** (over permutations τ_c):

$$\hat{m}_k = \sum_{c=1}^R \max_{1 \leq a \leq n} |\hat{B}_k(\{\tau_c(1), \dots, \tau_c(a)\})| / (R \hat{t}_{y^{(k)}})$$

Whole-Population Bias vs. Bound

- Random permutations ensure one cannot adjust the average maximum bias to 0 !!

$$\begin{aligned}
 |m_k - \frac{|\hat{B}_k(\mathcal{U})|}{\hat{t}_{y^{(k)}}}| &\leq \frac{1.229}{\hat{t}_{y^{(k)}}} \left(\sum_{i \in \mathcal{S}} \left(\frac{r_i}{\hat{p}_i} - 1 \right)^2 \left(\frac{y_i^{(k)}}{\pi_i} \right)^2 \right)^{1/2} \\
 &= \hat{b}_k
 \end{aligned}$$

- **Dominant term** in m_k or \hat{m}_k , when large = $|\hat{B}_k(\mathcal{U})| / \hat{t}_{y^{(k)}}$
- Bound \hat{b}_k on RHS accounts for maximum over subdomains if there is no overall bias.

2nd Metric: Preserving Cells

Subdomain biases are most interesting in cells used in current cell-based adjustment:

- Random permutations σ of indices now permute cells A_j , $j = 1, \dots, J$, and **individuals within** consecutively indexed **cells**:

$$m_k^* \equiv E_\sigma \left(\max_{1 \leq q \leq n} |\hat{B}_k(\{\sigma(1), \dots, \sigma(q)\})| \right) / \hat{t}_{y(k)}$$

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- Monte Carlo estimated version of this metric

$$\hat{m}_k^* \equiv \frac{1}{R} \sum_{r=1}^R \max_{1 \leq q \leq n} |\hat{B}_k(\{\sigma_r(1), \dots, \sigma_r(q)\})| / \hat{t}_{y^{(k)}}$$

Adjustment Models Used in SIPP

- **149 Adjustment Cells** used in SIPP production:
defined in terms of : Education, Income-Level,
Labor-force status, Self-employment,
Race/Hispanic, Assets, ...
- **Logistic regression** using variables:
Renter, race, 'ref-person', education,
poverty, some pairwise interactions, and
Survey Items (AFDC, SocSec, Unemp, ...)

Wave 4, 12 response fitted separately to Wave 1 predictors.

Main Issue. Previously (2006): including `Poverty` mostly removed whole-population adjustment bias for `Poverty`.

- **Subdomain analyses** used to study remaining biases
- add more survey items to logistic model ?

Method based on Metrics.

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Method based on Metrics.

- Items with bad adjustment bias flagged by

$$\hat{m}_k \gg \hat{b}_k$$

- Metric value always of order $\geq \hat{b}_k$.

Logistic Models Compared on SIPP 96

	Df	Variables	Dev
A	7	Wnotsp Renter College RefPer Blk Renter*College Blk*College	76558
B	8	same as A , plus Pov	76545
C	13	same as B , plus Foodst Mdcd Heins UnEmp Div	76299
D	13	same as B , minus Blk*College + Mdcd Heins UnEmp Pov*Heins Mdcd*Heins Heins*College	76242
E	17	same as D + hisp + Famtyp	76017
F	18	C plus Afdc SocSec Emp Mar	76280

Model B vs Adjustment Cell

- Logistic P_{OV} biases small, SocSec, Heins, UnEmp large.
- Bounds \hat{b}_k approx. same for all models.

Item	\hat{m}^{4C}	\hat{m}^{4L}	$\hat{b}_{4,k}$
AFDC	.0067	.0248	.0078
SocSec	.0191	.0116	.0041
Heins	.0085	.0065	.0019
Pov	.0187	.0033	.0047
Emp	.0016	.0017	.0020
UnEmp	.0534	.0594	.0131

Metric for Models A, D, F, Wave 4

- Successive improvement with more Survey-item predictors.

Item	$\hat{m}^{A,A}$	$\hat{m}^{A,D}$	$\hat{m}^{A,F}$	$b_{4,k}^D$
AFDC	.0175	.0067	.0053	.0077
SocSec	.0117	.0125	.0027	.0041
Pov	.0123	.0032	.0032	.0047
UnEmp	.0626	.0095	.0098	.0139

Metrics \hat{m} , all Models

- **1st metric**, averaged over 12 survey items
- Steady improvement in models with more terms

Model	Wave-4	Wave-12
Adj.Cell	0.01228	0.04741
LReg, A	0.01451	0.03942
LReg, B	0.01504	0.03893
LReg, C	0.00426	0.02475
LReg, D	0.00571	0.02812
LReg, E	0.00481	0.02654
LReg, F	0.00342	0.00782

Metrics \hat{m}_k^* Across Models

- **2nd metric**, by single survey item
- Richer models often slightly better,
but now Models C and F virtually tied !!

item	ModB	ModC	ModD	ModF	Adj.Cell
AFDC	.0840	.0728	.0734	.0722	.0697
SocS	.0300	.0305	.0310	.0287	.0332
Pov	.0632	.0574	.0576	.0566	.0572
Emp	.0281	.0263	.0261	.0259	.0227

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- **Low-dimensional Model C as good as Adjustment Cells.**

Metrics in Wave 4 with/without Raking Weights

- Raking was done in SIPP 1996 to 126 demographic cells.
- Compare metric values and models, in Wave 4, with and without raking.

Metric	Raked	ModD	ModF	ModI	ModIII	AdjCel
m_k	No	.0057	.0034	.0039	.0039	.0123
	Yes	.0047	.0057	.0046	.0045	.0083
m_k^*	No	.0065	.0044	.0046	.0045	.0127
	Yes	.0046	.0056	.0046	.0045	.0082

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m_k^*	No	.0065	.0044	.0046	.0045	.0127
	Yes	.0046	.0056	.0046	.0045	.0082

- Raking makes little difference with best models (F,I,III), but helps a lot with poor ones (D, AdjCel).

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- **Internal evaluation** of attrition nonresponse adjustment.
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- Metrics prevent ‘adjusting away’ biases at whole-pop level.
- Metrics rate models **differently from Deviance**: 1st favors greater adjustment. 2nd Metric favors less.
- Re-did metric model-comparisons in SIPP after implementing population-control ‘2nd stage adjustment’ (Raking).

References

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