MATHEMATICA Policy Research

WSS Conference on Non-Probability Samples

Exploration of Methods for Blending Unconventional Samples with Traditional Probability Samples

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Offices of Mathematica-MPR
1101 First Street NE, 12th Floor
Washington DC 20002

1:05 – 1:30pm

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Outline

- **Re-Introduce Concept of Blended Designs**
- **Methods**
  - **Review Naïve, calibrated, and model-based procedures**
  - **Explore Blending probability and nonprobability samples via composite estimation**
- **Present Simulation Results**
- **Discussion**

Potential Benefits of Blending

- **Augment existing probability sample based study to**
  - **Increase overall precision**
  - **Increase sample sizes for hard-to-reach populations**
  - **Produce more timely or interim estimates (in-between cycles)**
  - **Save data collection costs**
    - Savings could be used to enhance existing study response rates, equalize the propensity to respond, conduct more in-depth follow-up of nonrespondents.
- **Validate large-scale unconventional sample or panel study**

Goals

- **Develop an approach evaluating the fitness of use of a nonprobability sample alone or in combination with a probability sample.**
- **Explore RMSE and cost tradeoffs for various estimation methods via simulation.**
- **Suggest future research and pilot efforts.**
- **Gain insights from other speakers and audience**

Blended Designs

Setup: Conceptual Situation

- **Two samples from same population:**
  - **One from a probability sample (P)**
  - **One from a non-probability sample (NP) / Panel**
  - **Corresponding list of the complement of cases that make up the sampling frame or target population from each**

- **Both have:**
  - **Same survey instrument**
  - **Sampled at same time or use same reference period**
  - **Survey responses (Y)**
  - **Auxiliary variables (X_s), s=1,…,S**
    - ➢ In aggregate or for each individual.
    - ➢ Known for all units in the population.

Study Dimensions

	II. Level of Bias in Non-Probability Sample	
I. Use of Non-Probability Sample	High	Low
1. Non-Probability Component to Augment Conventional Design n large for both samples	**A**	**C**
2. Probability Sample Validates Larger Non-Probability Based Study n small for probability sample n large for non-probability sample	**B**	**D**

III. Ability of the Covariates to Correct for Bias

IV. Probability Sample — Cost — Non- Probability Sample

Probability Sample – Offers Sufficient Coverage, Essentially Unbiased

History of Blending

- **For Decades Limited Interest /Market**
- **Traditional Polar Opposite Needs /Limited Middle Ground**
  - Clients that expected probability sampling:
    - Government: scientifically valid results; willing to pay
    - Unwilling to accept added complexity and face-value issues
  - Clients that accepted non-probability samples:
    - Business/Polling: fast, low price, good enough
    - Not willing to pay extra for validation
- **But Landscape May be Changing?**
  - Greater acceptance of non-traditional data sources
  - Cost differential widening
    - Probability sample threatened: increasing costs, lower response rates, untimely and insufficient data/ depth of analysis.
  - May 2015 AAPOR: Gordon Willis, National Cancer Institute:
    - Suggested exploring combination approaches rather than substitution

Estimation Methods

Three Classes of Estimators

1. **Sample-Based**
   - **Uses only Y values from sample**

Design Based

2. **Model-Assisted**
   - **Uses Y values from sample and related variables, x, for which we have values <u>for the entire population</u>**

Improved Precision

3. **Model-Based**
   - **Combines sample total with predicted total for rest of cases in population**
     - ➢ Predicted values for non-sampled cases are based on model created from sample data

Design vs. Model-Based Estimation

Design Based

- **Established procedure**
- **Inference depends on sample design**
  - Relies on randomness of probability samples and the properties of repeated sampling to yield unbiased estimates and to describe the sampling error
- **Risks**
  - Chance of skewed sample => poor inference
  - Insufficient sample – too high sampling error
  - Nonresponse bias – increases as response propensities vary
- **Analytical file limited to sample/ responding cases**
- Requires use of weights and sample design information
- Need a list of population units to sample from
- **Covariate information on population nice to have but not necessary for estimation**

Model-Based

- **Creates data for full population / full population estimate (No weights)**
- **Sample source and design are irrelevant as long as model holds**
  - Relies on the ability to generate an accurate prediction model(s) from the data available.

May be benefit for application to NP samples

- **Risks**
  - Available panel data does not "cover" population of interest
  - Covariates do not accurately predict variable of interest.
- **May be considered cumbersome to apply to many survey variables**
- **Need covariate information for each record in observed sample**
- **At least need aggregate covariate data for all cases in the population less the observed sample**

Model-Based Composite Estimation

Step 1
Create model(s) to predict survey variable Y from auxiliary factors (X) for both samples

Step 2
Apply model(s) in step 1 to non-sampled cases (or aggregate data) for both samples, to create model-based estimates of Y

Step 3
Calculate predicted statistic of interest (T) based on each model (e.g., sum or mean)

Step 4
Blend the two estimates (weighted by expected variance and bias).

Note: P assumed unbiased; bias of NP is the difference

Step 1 (Details)

- Create a model to estimate Y separately for each sample:

  (1) P: $\hat{Y}_i^P = \hat{\alpha}^P + x_i \hat{\beta}^P$

  (2) NP: $\hat{Y}_i^{NP} = \hat{\alpha}^{NP} + x_i \hat{\beta}^{NP}$

Example

- Y: How many times did you take your daily medication last week?

- x_1: Number of physician visits in the last year.
- x_2: Total health expenditures for the last year

Administrative / Program Data

Steps 2 and 3 (Detail)

- **For each sample, estimate Y for the non-sampled subjects in** remaining non-sampled portion **by applying the model (1) or (2) to the non-sampled cases, then calculate predicted summary statistic (T)**

- **Example:** $\boldsymbol{T} = \sum_i \boldsymbol{Y}_i$

  (3) P: $\widehat{\boldsymbol{T}}^P = \sum_{i \in P} Y_i + \sum_{i \notin P} \widehat{\boldsymbol{Y}}_i$

  (4) NP: $\widehat{\boldsymbol{T}}^{NP} = \sum_{i \in NP} Y_i + \sum_{i \notin NP} \widehat{\boldsymbol{Y}}_i$

Includes unsampled subjects and non-responders

Also May Use Prob Model to Create Model Based Estimate for NP

- **Aside:**

  For linear regression models, aggregate x data sufficient:

$$\sum_{i \notin S} \widehat{\boldsymbol{Y}}_i = \sum_{i \notin S}\left(\widehat{\boldsymbol{\alpha}} + \boldsymbol{x}_i \widehat{\boldsymbol{\beta}}\right) = \widehat{\boldsymbol{\alpha}}(\boldsymbol{N} - \boldsymbol{n}) + \widehat{\boldsymbol{\beta}}\left(\sum_i \boldsymbol{x}_i - \sum_{i \in S} \boldsymbol{x}_i\right)$$

  For nonlinear (e.g. logistic) models, individual data is needed

  - Imputable?

Step 4: Composite Estimation (Detail)

- **Blend P and NP estimates using the approach of Elliot and Haviland (2007):**

$$\hat{T}^{C} = \frac{w_P \hat{T}^{P} + w_{NP} \hat{T}^{NP}}{w_P + w_{NP}}$$

where

$$w_P = 1/\hat{\sigma}_P^2$$
$$w_{NP} = 1/\left(\hat{\sigma}_{NP}^2 + \hat{\epsilon}_{NP}^2\right)$$

- **Bias of NP sample ($\hat{\epsilon}_{NP}$) is estimated by $\hat{T}^{NP} - \hat{T}^{P}$**
- **Assume variances ($\hat{\sigma}_P^2, \hat{\sigma}_{NP}^2$) may be robustly estimated by replication methods (bootstrap, jackknife, etc.)***

*See REPORT OF THE AAPOR TASK FORCE ON NON-PROBABILITY SAMPLING, June 2013, and de Munnik, Daniel, David Dupuis, and Mark Illing. 2009. “Computing the Accuracy of Complex Non-Random Sampling Methods: The Case of the Bank of Canada’s Business Outlook Survey.” Bank of Canada Working Paper 2009–10, March 2009.

A Simulation Study

Composite Estimation

Simulation Setup

- **Application/Setting:**

  Blend a probability sample for a health survey with a nonprobability sample of visitors to a health related website

- **Population: 2013 National Health Interview Survey (NHIS) sample adult public use file (33K observations)**
  - **Selected 3 outcome variables:**
    - **Diabetes (ever been told you have)**
    - **Hypertension**
    - **Asthma**
  - **Two Levels of Covariates:**
    - **Base: gender, age, marital status, race and ethnicity, work status**
    - **Deep: Base + Use and frequency of use of internet (two items)**

Sampling

	Level of Bias in Non-Probability Sample	
Use of Non-Probability Sample	High	Lower
1. Non-Probability Component to Augment Conventional Design	**A** $n_{PS} = 5000$ $n_{NPS} = 5000$	**C** $n_{PS} = 5000$ $n_{NPS} = 5000$
2. Probability Sample Validates Larger Non-Probability Based Study	**B** $\boldsymbol{n_{PS} = 800}$ $n_{NPS} = 5000$	**D** $\boldsymbol{n_{PS} = 800}$ $n_{NPS} = 5000$

- **PS: Use SRS**
- **NPS: Used PPS methods where MOS set to skew sample toward younger, employed, single, male, white, non-Hispanic and high internet users**
- **Assumed Cost differences:**
  - **$400 per interview for probability sample completes**
  - **$50 for non-probability sample completes**

Sample Differences High vs Lower Bias

Covariates		Frame Mean	Expected Non-Probability Sample (Scenario A/B)	Bias (High)	Expected Non-Probability Sample (Scenario C/D)	Bias (Lower)
SEX	Sex (1= Male, 2=Female)	1.5565	1.4274	-0.1291	1.5275	-0.0291
sexr	Male	44.3%	57.3%	12.9%	47.3%	2.9%
oldage	Age 65+	22.8%	6.3%	-16.5%	14.8%	-8.0%
nevmarr	Never Married	29.1%	39.5%	10.4%	34.8%	5.7%
hispr	Non-Hispanic	17.2%	27.5%	10.3%	19.8%	2.5%
white	White	75.0%	87.2%	12.2%	79.7%	4.6%
workr	Working for pay at a job or business last week	54.8%	74.3%	19.4%	63.0%	8.2%
INT_USE	Do you use the Internet?	71.2%	95.7%	24.4%	84.6%	13.4%
HIGH_INT	Use internet more than once per day	56.5%	88.2%	31.7%	72.4%	15.9%

Sample Differences High vs Lower Bias

Covariates		Frame Mean	Expected NPS (Scenario A/B)	Bias (High)	Expected NPS (Scenario C/D)	Bias (Lower)
DIBEVr	Diabeties	12.1%	7.1%	-5.1%	9.6%	-2.5%
HYPEVr	Hypertension	33.0%	21.8%	-11.1%	27.4%	-5.5%
AASMEVr	Asthma	11.9%	7.5%	-4.4%	10.5%	-1.4%

Diabetes and Hypertension – well predicted by covariates

Asthma – Bias cannot be corrected by covariates available
Missing not at random (MNAR).

Estimation

Drew repeated P and NP samples (1,000 each). For each pair:

- **Naïve Estimation**
  - **Unweighted mean values for binary outcomes**
- **Calibrated Estimation**
  - **Using Sudaan WTADJX procedure and calibrate procedure in R**
- **Model-Based Estimation**
  - **Fit logistic regression models to each outcome from sampled cases and applied models to non-sampled cases**
- **Composite Estimation**
  - **Combined using standard methods and Elliot and Haviland (2007)**

Scenario A

Results for Scenario A, 1000 Iterations (5,000 in each Sample)

			Diabetes				Hypertension				Asthma			
Level	Calibration	Type	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE
Uncalibrated		Population		12.15%				32.97%				11.94%		
		PS	0%	12.16%	0.01%	0.42%	0%	32.95%	0.00%	0.64%	0%	11.93%	-0.02%	0.42%
		NPS	100%	7.09%	-5.05%	5.06%	100%	21.82%	-11.13%	11.13%	100%	7.55%	-4.39%	4.41%
Base	Design-Based	PS	0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100%	10.34%	-1.81%	1.87%	100%	29.65%	-3.30%	3.36%	100%	7.79%	-4.16%	4.20%
		Composite - BS	6.5%	12.06%	-0.08%	0.42%	3.8%	32.83%	-0.12%	0.61%	1.3%	11.88%	-0.07%	0.43%
	Model-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	10.52%	-1.63%	1.70%	100%	29.73%	-3.22%	3.29%	100%	7.78%	-4.17%	4.21%
		Composite - BS	7.5%	12.06%	-0.08%	0.42%	4.0%	32.83%	-0.12%	0.61%	1.3%	11.88%	-0.07%	0.43%
Deep	Design-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	11.71%	-0.43%	0.99%	100%	31.83%	-1.12%	1.59%	100%	7.43%	-4.51%	4.56%
		Composite - BS	12.8%	12.12%	-0.02%	0.39%	12.8%	32.87%	-0.08%	0.56%	1.1%	11.88%	-0.06%	0.43%
	Model-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	12.20%	0.06%	1.02%	100%	32.17%	-0.78%	1.42%	100%	7.40%	-4.54%	4.59%
		Composite - BS	11.1%	12.15%	0.01%	0.39%	13.2%	32.89%	-0.06%	0.56%	1.1%	11.88%	-0.06%	0.43%
						-7.56%				-12.46%				1.40%

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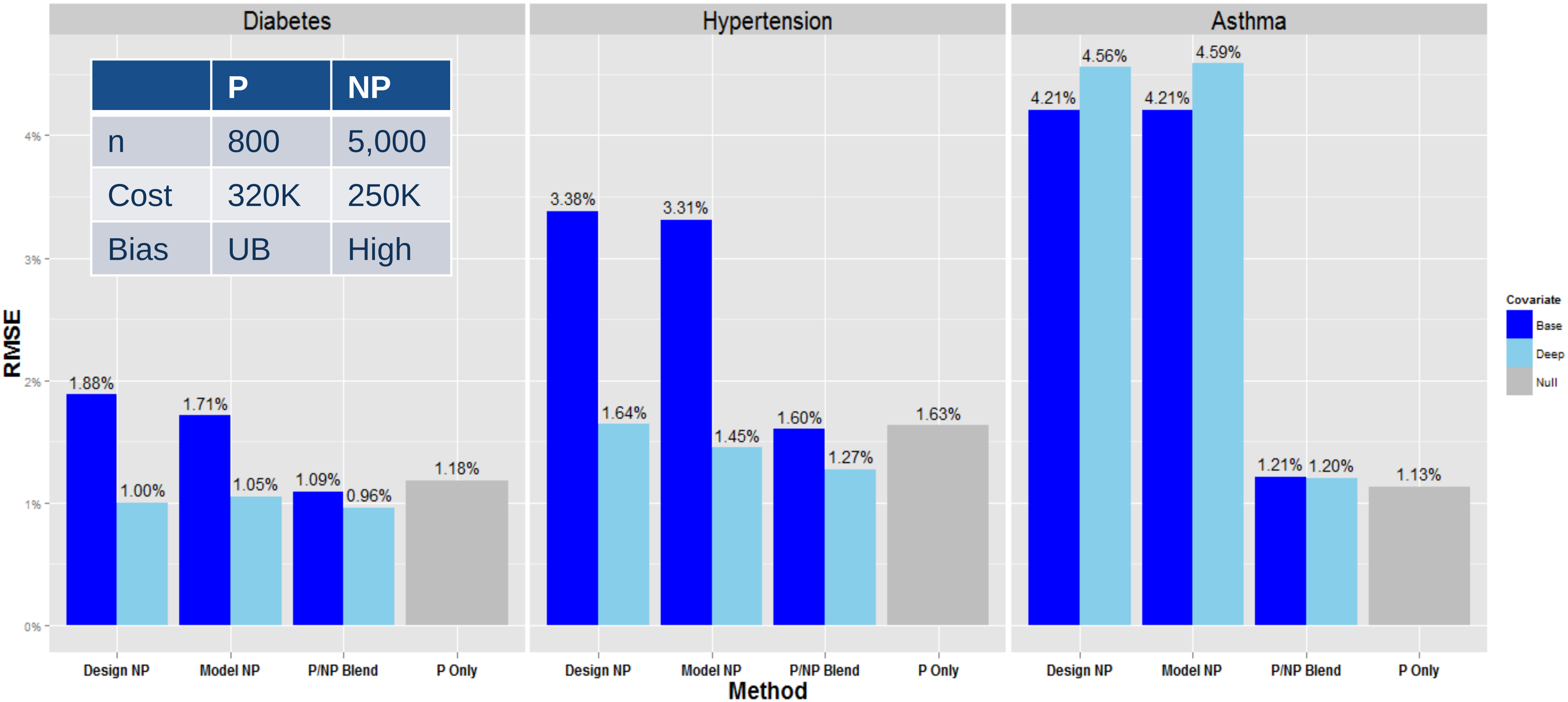
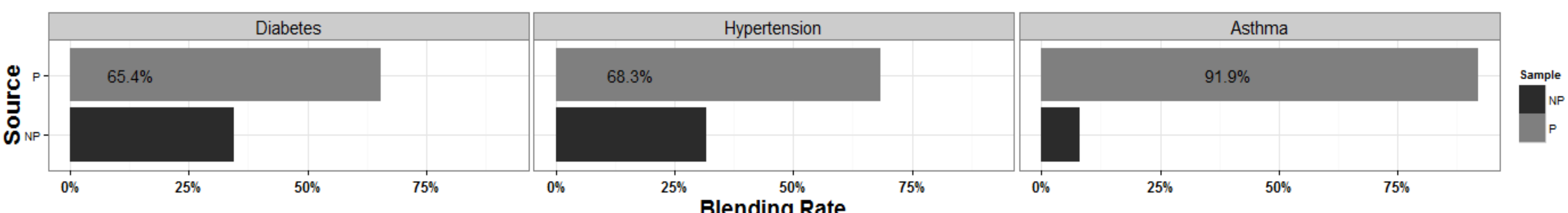
Scenario B

	P	NP
n	800	5,000
Cost	320K	250K
Bias	UB	High





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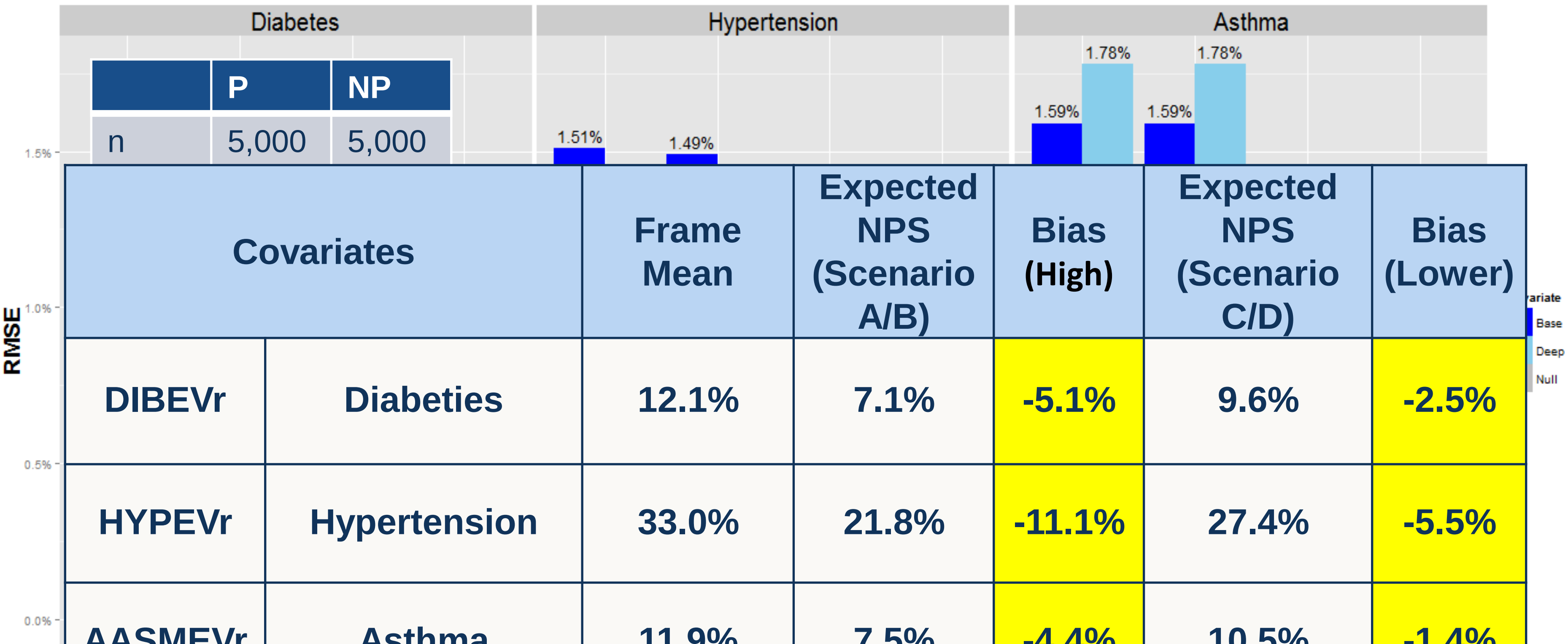
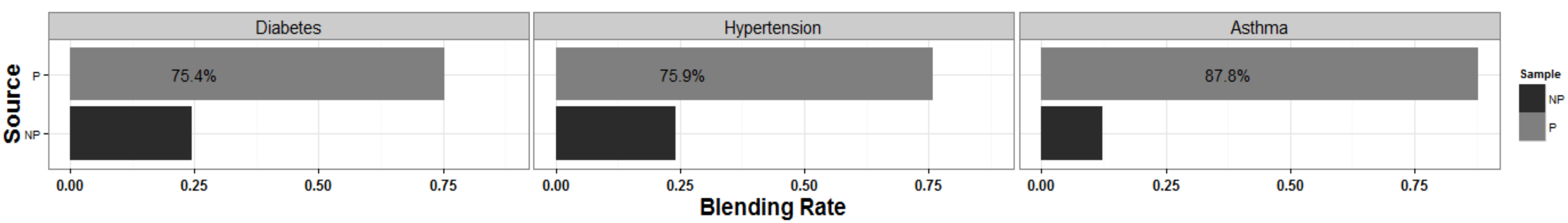
Scenario C



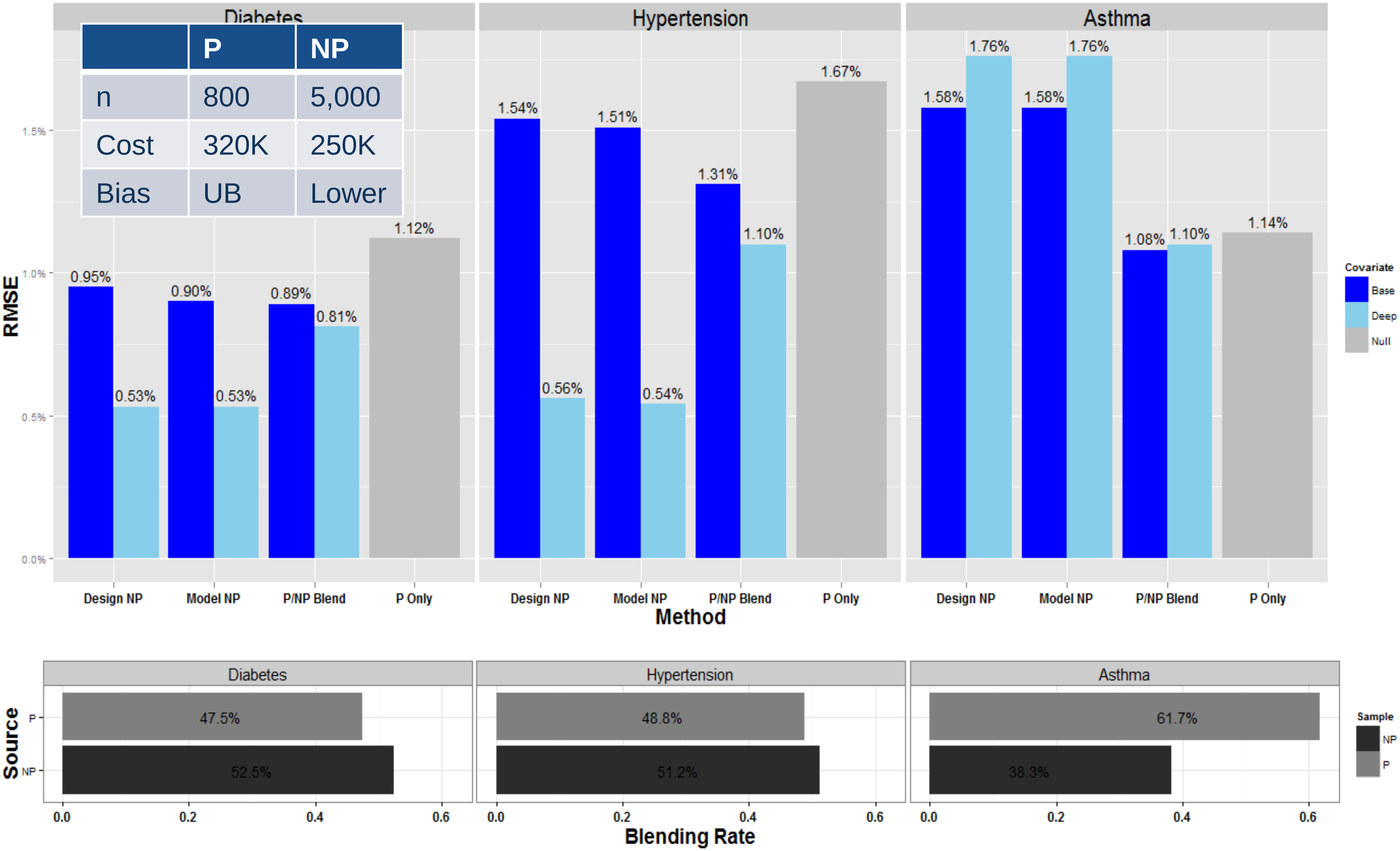
	P	NP
n	5,000	5,000

Covariates		Frame Mean	Expected NPS (Scenario A/B)	Bias (High)	Expected NPS (Scenario C/D)	Bias (Lower)
DIBEVr	Diabeties	12.1%	7.1%	-5.1%	9.6%	-2.5%
HYPEVr	Hypertension	33.0%	21.8%	-11.1%	27.4%	-5.5%
AASMEVr	Asthma	11.9%	7.5%	-4.4%	10.5%	-1.4%



Scenario D

	P	NP
n	800	5,000
Cost	320K	250K
Bias	UB	Lower



Summary

- **Blended methods provide ability to evaluate and leverage unconventional samples appropriately**
  - **High/Uncorrectable Bias and/or large PS:**
    - Leverage as much of PS is possible
    - Gains possible if cost of NPS is low enough to warrant its use
  - **Low/Correctable Bias and/or small PS:**
    - Gains due to blending may be substantial
    - Offers ability to greatly reduce costs
- **Gains/Losses to Depend on Actual Situation**
  - **Differences in the cost of collection (P vs NP) have to great enough to offset “costs” of bias in NP sample**

Comments

- **Best Application:**
  - Agency has existing large scale study based on PS, relative high cost to maintain desired response rate.
  - Able to collect supplemental sample from vendor (website visitors) at low cost
- **Looking for Input**
  - Use of probability sample as verification sample with non-probability sample making up the bulk of combined sample (attractive for hard-to-find populations)
- **Consider an Adaptive Design**
  - Run both P and NP samples in parallel
  - Evaluate costs and bias trade-off on flow basis between samples
  - Expand/Reduce PS/NPS sample sizes per findings
  - Result in "Optimal Use" of available sources of data and resources.

Extensions

- **Explore use of probability sample model on both probability and non-probability non-sampled cases.**
- **Explore application of composite model-based estimation at the individual level**
  – Obtain subject-specific blended estimates, which are then averaged
- **Only aggregate data available**
  – Linear regression for binary outcome (commonly done)
  – Two-stage imputation of individual data (Zangeneh and Little, 2012)
- **Mathematically evaluate break-even outcomes**
- **Variance estimation for unconventional samples.**

References

DiSogra, C, Cobb, C, Chan, E, Dennis JM. “Calibrating Non-Probability Internet Samples with Probability Samples Using Early Adopter Characteristics.” 2011 JSM Proceedings, Survey Methods Section. Alexandria, VA: American Statistical Association. pp. 4501–4515.

Elliott. M and Haviland, A. (2007) Use of a web based convenience sample to supplement a probability sample. Survey Methodology, December 2007 Vol. 33, No. 2, pp. 211-215 Statistics Canada, Catalogue no. 12001X

Guo, S and Fraser, M.W. (2010) Propensity Score Analysis, Statistical Methods and Applications, Thousand Oaks CA, Sage Publications

Horvitz,D. G.; Thompson, D. J. (1952) "A generalization of sampling without replacement from a finite universe", Journal of the American Statistical Association, 47, 663–685, . JSTOR 2280784

Little, R. and Zheng, H. (2007). The Bayesian Approach to the Analysis of Finite Population Surveys. Bayesian Statistics, 8(1):1–20.

Lee, S. (2006). Propensity Score Adjustment as a Weighting Scheme for Volunteer Panel Web Surveys. Journal of Official Statistics, Vol. 22, No. 2, pp. 329–349.

Rao, J.N.K. (2003). Small Area Estimation. New York: John Wiley & Sons, Inc.

Valliant, R., Dorfman, A. and Royall, R. (2000) Finite Population Sampling and Inference: A Prediction Approach, New York, Wiley Publications

Wang, W et al., (2014) Forecasting elections with non-representative polls. International Journal of Forecasting. http://www.stat.columbia.edu/~gelman/research/published/forecasting-with-nonrepresentative-polls.pdf

Sahar Z Zangeneh and Roderick J.A. Little (2012) Bayesian inference for the finite population total from a heteroscedastic probability proportional to size sample, Section on Survey Research Methods – JSM 2012.

https://www.amstat.org/sections/SRMS/Proceedings/y2012/Files/305010_74129.pdf
and Sahar Z Zangeneh dissertation at http://deepblue.lib.umich.edu/bitstream/handle/2027.42/96005/saharzz_1.pdf?sequence=1

Thank You

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Appendix

Detailed Findings Scenario A

Results for Scenario A, 1000 Iterations														
			Diabetes				Hypertension				Asthma			
Level	Calibration	Type	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE
Uncalibrated		Population		12.15%				32.97%				11.94%		
		PS	0%	12.16%	0.01%	0.42%	0%	32.95%	0.00%	0.64%	0%	11.93%	-0.02%	0.42%
		NPS	100%	7.09%	-5.05%	5.06%	100%	21.82%	-11.13%	11.13%	100%	7.55%	-4.39%	4.41%
Base	Design-Based	PS	0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100%	10.34%	-1.81%	1.87%	100%	29.65%	-3.30%	3.36%	100%	7.79%	-4.16%	4.20%
		Composite - Text	13.9%	11.95%	-0.19%	0.46%	8.7%	32.70%	-0.25%	0.67%	1.6%	11.87%	-0.08%	0.43%
		Composite - BS	6.5%	12.06%	-0.08%	0.42%	3.8%	32.83%	-0.12%	0.61%	1.3%	11.88%	-0.07%	0.43%
	Model-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	10.52%	-1.63%	1.70%	100%	29.73%	-3.22%	3.29%	100%	7.78%	-4.17%	4.21%
		Composite - BS	7.5%	12.06%	-0.08%	0.42%	4.0%	32.83%	-0.12%	0.61%	1.3%	11.88%	-0.07%	0.43%
		Composite - Ind	21.0%	11.80%	-0.34%	0.51%	16.2%	32.43%	-0.52%	0.79%	5.5%	11.68%	-0.27%	0.51%
Deep	Design-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	11.71%	-0.43%	0.99%	100%	31.83%	-1.12%	1.59%	100%	7.43%	-4.51%	4.56%
		Composite - TB	51.3%	12.03%	-0.11%	0.44%	45.9%	32.66%	-0.29%	0.63%	2.2%	11.84%	-0.11%	0.44%
		Composite - BS	12.8%	12.12%	-0.02%	0.39%	12.8%	32.87%	-0.08%	0.56%	1.1%	11.88%	-0.06%	0.43%
	Model-Based	PS	0.0%	12.15%	0.01%	0.40%	0%	32.94%	-0.01%	0.58%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	12.20%	0.06%	1.02%	100%	32.17%	-0.78%	1.42%	100%	7.40%	-4.54%	4.59%
		Composite - BS	11.1%	12.15%	0.01%	0.39%	13.2%	32.89%	-0.06%	0.56%	1.1%	11.88%	-0.06%	0.43%
		Composite - Ind	30.2%	12.11%	-0.03%	0.37%	31.1%	32.78%	-0.17%	0.53%	5.1%	11.66%	-0.28%	0.52%
						-7.56%				**-12.46%**				**1.40%**

Text or TB – Textbook / Standard methods
BS – Bootstrap

Detailed Findings Scenario B

Results for Scenario B, 1000 Iterations

			Diabetes				Hypertension				Asthma			
Level	**Calibration**	**Type**	**%NPS**	**Mean**	**Bias**	**rMSE**	**%NPS**	**Mean**	**Bias**	**rMSE**	**%NPS**	**Mean**	**Bias**	**rMSE**
Uncalibrated		**Population**		12.15%				32.97%				11.94%		
		PS	0%	12.12%	-0.02%	1.18%	0%	32.96%	0.01%	1.63%	0%	11.94%	0.00%	1.13%
		NPS	100%	7.08%	-5.06%	5.07%	100%	21.79%	-11.16%	11.17%	100%	7.56%	-4.39%	4.41%
Base	**Design-Based**	**PS**	0%	12.12%	-0.02%	1.13%	0%	32.98%	0.03%	1.51%	0%	11.94%	0.00%	1.13%
		NPS	100%	10.32%	-1.82%	1.88%	100%	29.64%	-3.31%	3.38%	100%	7.78%	-4.16%	4.21%
		Composite - TB	11.0%	12.01%	-0.13%	1.12%	7.9%	32.80%	-0.15%	1.52%	1.8%	11.89%	-0.06%	1.14%
		Composite - BS	31.5%	11.77%	-0.37%	1.12%	22.9%	32.47%	-0.48%	1.61%	8.9%	11.64%	-0.30%	1.21%
	Model-Based	**PS**	0.0%	12.12%	-0.02%	1.13%	0%	32.98%	0.03%	1.51%	0%	11.95%	0.00%	1.13%
		NPS	100.0%	10.50%	-1.64%	1.71%	100%	29.72%	-3.23%	3.31%	100%	7.77%	-4.17%	4.21%
		Composite - BS	33.5%	11.79%	-0.35%	1.09%	23.5%	32.47%	-0.48%	1.60%	9.0%	11.65%	-0.30%	1.21%
		Composite - Ind	60.9%	11.22%	-0.93%	1.19%	53.8%	31.42%	-1.53%	1.94%	29.9%	10.73%	-1.22%	1.68%
Deep	**Design-Based**	**PS**	0.0%	12.12%	-0.02%	1.13%	0%	32.99%	0.04%	1.50%	0%	11.94%	0.00%	1.13%
		NPS	100.0%	11.73%	-0.41%	1.00%	100%	31.75%	-1.20%	1.64%	100%	7.44%	-4.51%	4.56%
		Composite - TB	25.2%	12.08%	-0.06%	1.00%	22.3%	32.83%	-0.12%	1.36%	2.4%	11.86%	-0.09%	1.15%
		Composite - BS	39.1%	12.02%	-0.12%	0.95%	38.7%	32.72%	-0.23%	1.30%	7.4%	11.67%	-0.28%	1.20%
	Model-Based	**PS**	0.0%	12.12%	-0.02%	1.13%	0%	32.99%	0.04%	1.50%	0%	11.95%	0.00%	1.13%
		NPS	100.0%	12.22%	0.08%	1.05%	100%	32.09%	-0.86%	1.45%	100%	7.41%	-4.54%	4.59%
		Composite - BS	35.6%	12.12%	-0.02%	0.96%	39.8%	32.79%	-0.16%	1.27%	7.3%	11.67%	-0.28%	1.20%
		Composite - Ind	66.7%	12.07%	-0.07%	0.77%	67.9%	32.49%	-0.46%	1.05%	28.2%	10.62%	-1.33%	1.76%
						-19.04%				**-22.40%**				**5.55%**

Detailed Findings Scenario C

Results for Scenario C, 1000 Iterations														
			Diabetes				Hypertension				Asthma			
Level	Calibration	Type	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE
Uncalibrated		Population		12.15%				32.97%				11.94%		
		PS	0%	12.12%	-0.02%	0.42%	0%	32.94%	-0.01%	0.62%	0%	11.93%	-0.02%	0.42%
		NPS	100%	9.58%	-2.56%	2.58%	100%	27.43%	-5.52%	5.54%	100%	10.48%	-1.46%	1.56%
Base	Design-Based	PS	0%	12.12%	-0.02%	0.40%	0%	32.93%	-0.02%	0.57%	0%	11.93%	-0.02%	0.42%
		NPS	100%	11.30%	-0.85%	0.95%	100%	31.51%	-1.44%	1.51%	100%	10.48%	-1.46%	1.59%
		Composite - TB	25.4%	11.99%	-0.15%	0.42%	21.1%	32.73%	-0.22%	0.61%	13.5%	11.83%	-0.12%	0.44%
		Composite - BS	20.6%	12.01%	-0.13%	0.41%	17.1%	32.77%	-0.18%	0.60%	13.2%	11.82%	-0.12%	0.44%
	Model-Based	PS	0.0%	12.12%	-0.02%	0.40%	0%	32.93%	-0.02%	0.57%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	11.35%	-0.79%	0.91%	100%	31.54%	-1.41%	1.49%	100%	10.48%	-1.47%	1.59%
		Composite - BS	21.7%	12.01%	-0.13%	0.41%	17.7%	32.77%	-0.18%	0.60%	13.1%	11.82%	-0.12%	0.44%
		Composite - Ind	37.0%	11.86%	-0.28%	0.44%	34.5%	32.50%	-0.45%	0.66%	27.8%	11.59%	-0.36%	0.53%
Deep	Design-Based	PS	0.0%	12.12%	-0.02%	0.40%	0%	32.93%	-0.02%	0.57%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	12.00%	-0.14%	0.53%	100%	32.75%	-0.20%	0.55%	100%	10.31%	-1.63%	1.78%
		Composite - TB	40.2%	12.09%	-0.05%	0.34%	40.8%	32.89%	-0.06%	0.46%	12.6%	11.83%	-0.12%	0.44%
		Composite - BS	27.8%	12.10%	-0.05%	0.36%	30.4%	32.90%	-0.05%	0.48%	11.3%	11.83%	-0.12%	0.44%
	Model-Based	PS	0.0%	12.12%	-0.02%	0.40%	0%	32.93%	-0.02%	0.57%	0%	11.93%	-0.02%	0.42%
		NPS	100.0%	12.08%	-0.06%	0.52%	100%	32.82%	-0.13%	0.53%	100%	10.31%	-1.64%	1.78%
		Composite - BS	27.5%	12.11%	-0.03%	0.36%	30.5%	32.91%	-0.04%	0.48%	11.3%	11.83%	-0.12%	0.44%
		Composite - Ind	42.3%	12.09%	-0.05%	0.32%	43.5%	32.89%	-0.06%	0.40%	26.9%	11.55%	-0.40%	0.56%
						-15.33%				**-22.70%**				**3.94%**

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Detailed Findings Scenario D

Results for Scenario D, 1000 Iterations														
			Diabetes				Hypertension				Asthma			
Level	Calibration	Type	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE	%NPS	Mean	Bias	rMSE
Uncalibrated		Population		12.15%				32.97%				11.94%		
		PS	0%	12.13%	-0.02%	1.12%	0%	32.99%	0.04%	1.67%	0%	12.01%	0.07%	1.14%
		NPS	100%	9.59%	-2.55%	2.57%	100%	27.41%	-5.54%	5.56%	100%	10.50%	-1.44%	1.54%
Base	Design-Based	PS	0%	12.13%	-0.01%	1.08%	0%	32.99%	0.04%	1.52%	0%	12.01%	0.06%	1.14%
		NPS	100%	11.31%	-0.84%	0.95%	100%	31.48%	-1.47%	1.54%	100%	10.50%	-1.45%	1.58%
		Composite - TB	9.8%	12.09%	-0.05%	1.04%	9.0%	32.91%	-0.04%	1.47%	6.5%	11.96%	0.01%	1.12%
		Composite - BS	50.1%	11.88%	-0.26%	0.90%	47.0%	32.61%	-0.34%	1.32%	40.2%	11.66%	-0.29%	1.08%
	Model-Based	PS	0.0%	12.13%	-0.02%	1.08%	0%	32.99%	0.04%	1.52%	0%	12.01%	0.06%	1.14%
		NPS	100.0%	11.36%	-0.78%	0.90%	100%	31.51%	-1.44%	1.51%	100%	10.49%	-1.45%	1.58%
		Composite - BS	50.8%	11.89%	-0.25%	0.89%	47.6%	32.61%	-0.34%	1.31%	40.0%	11.66%	-0.29%	1.08%
		Composite - Ind	73.2%	11.60%	-0.54%	0.78%	71.7%	32.08%	-0.87%	1.19%	67.3%	11.13%	-0.82%	1.12%
Deep	Design-Based	PS	0.0%	12.13%	-0.01%	1.08%	0%	32.99%	0.04%	1.53%	0%	12.01%	0.06%	1.14%
		NPS	100.0%	12.02%	-0.12%	0.53%	100%	32.71%	-0.24%	0.56%	100%	10.33%	-1.62%	1.76%
		Composite - TB	12.6%	12.13%	-0.02%	1.01%	11.8%	32.97%	0.02%	1.42%	6.5%	11.95%	0.00%	1.12%
		Composite - BS	54.3%	12.08%	-0.06%	0.80%	54.4%	32.92%	-0.03%	1.11%	36.8%	11.65%	-0.30%	1.10%
	Model-Based	PS	0.0%	12.13%	-0.01%	1.08%	0%	32.99%	0.04%	1.52%	0%	12.01%	0.06%	1.14%
		NPS	100.0%	12.10%	-0.04%	0.53%	100%	32.79%	-0.16%	0.54%	100%	10.32%	-1.62%	1.76%
		Composite - BS	54.1%	12.10%	-0.04%	0.81%	54.7%	32.93%	-0.02%	1.10%	36.7%	11.65%	-0.30%	1.10%
		Composite - Ind	75.6%	12.04%	-0.10%	0.55%	77.1%	32.83%	-0.12%	0.66%	67.9%	10.97%	-0.97%	1.23%
						-27.89%				**-34.29%**				**-3.35%**

MATHEMATICA Policy Research

A Brief Look at Matching Methods

The Basics

- **Guo and Fraser (2010)**
  - **Randomized trial not possible**
  - **Combine treated and external non-treated cases in observational studies for causal inference that closely parallels our problem.**
- **The central theme of these methods is build a model to predict treated status among a mix of treated and non-treated cases**
- **Match treatment to potential control cases under various methods (i.e., propensity score matching, Greedy matching, optimal matching).**

Non-Randomized Trial

Treated and Non-Treated from Different Sources

Potential Application