

# Predictive Modeling as an Alternative to (Re-) Weighting

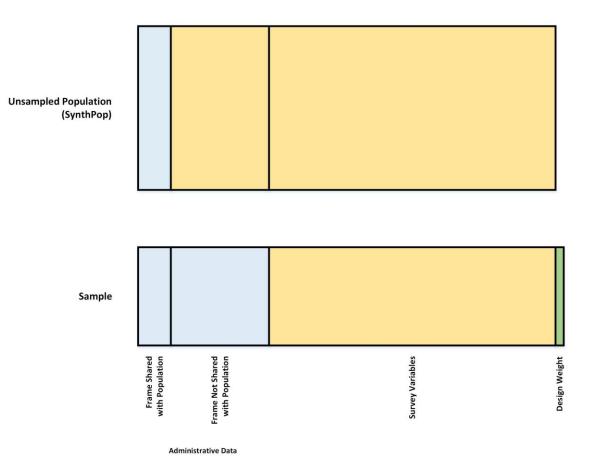
ITSEW 2019, Bergamo, June 12, 2019

Alan F. Karr RTI International

RTI International is a registered trademark and a trade name of Research Triangle Institute.

#### Surveys as Prediction Problems: Before

#### **BEGINNING OF SURVEY**



#### Introductory Example

- Pharmaceutical industry client wanted full national dataset with
  - Demographics, available from ACS = American Community Survey for a sample of people: ~15M in 5-year compilation
  - 23 variables relating to T2DM = Type II diabetes mellitus, available from NHANES = National Health and Nutrition Examination Survey for a sample of people: ~10,000 each year
- Why? Calculate Gini indices of representativity in clinical trials, once multiple inclusion and exclusion criteria are imposed
- Problem: No versions of Gini indices are available for weighted data

**Cloning:** Using *fully imputed* and mildly filtered NHANES dataset (n = 9813), create a dataset in which each record appears as many times as its weight

- Use fractional part of weight as probability to include one more copy
- Resultant dataset has 311,204,241 records

### Simple (-Minded) Strategy 2

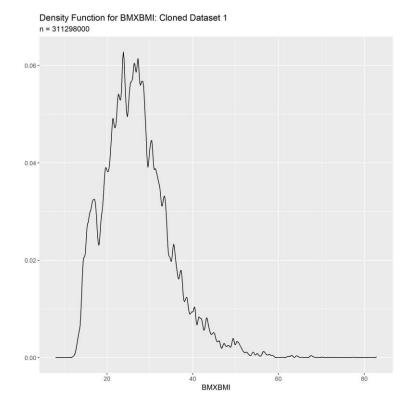
#### **Resampling (Linkage)**

 SynthPop: Create a version of the RTI Synthetic Population containing 299,444,439 records and all ACS variables. Cross-tab of age and gender:

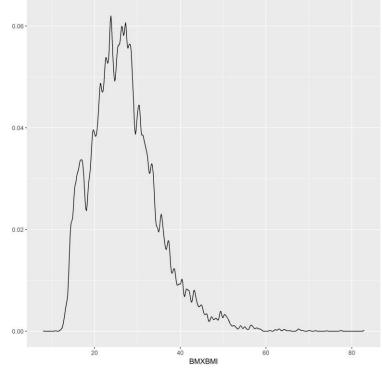
	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70+
Μ	19,848,374	20,470.012	19.381,292	19,791,339	21,388,714	21,783,825	16,053,011	15,604,110
F	20,699,392	21,390,818	18,547,929	18,242,327	19,868,352	21,181,040	14,473,830	11,784,074

 MADIS (Model-Assisted Data Integration System) Light: For each cell in this table, sample that many records from the subset of the NHANES dataset that match on age and gender, using probabilities proportional to weights

#### Sample Results: No Meaningful Difference



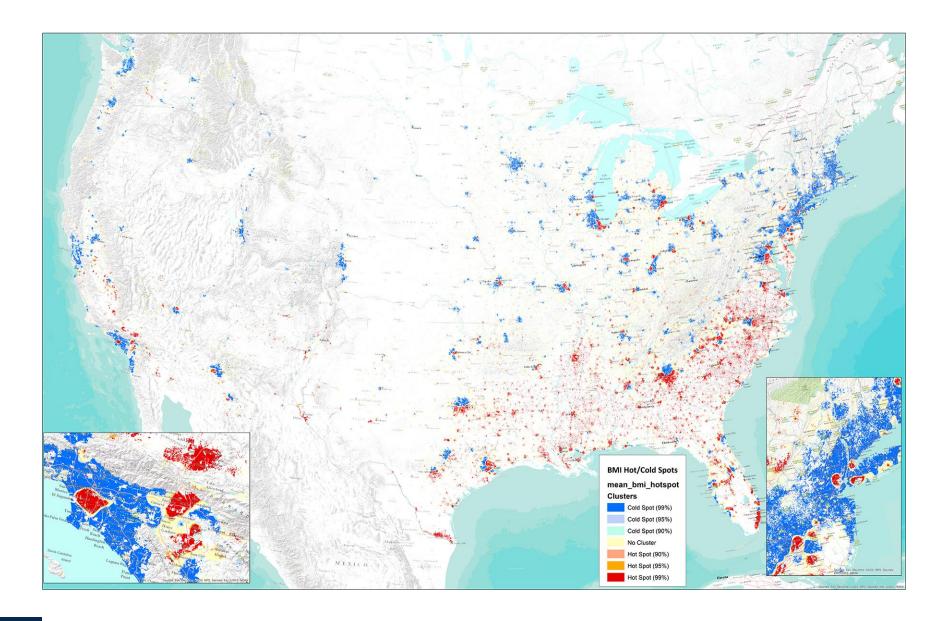
Density Function for BMXBMI: Dataset 1



#### What's the Real Issue with these Strategies?

- Not enough variability! Every combination of the 23 NHANES variables in the synthesized national dataset appears intact in the NHANES dataset.
- Question to Ponder: Uncertainty quantification. Sources include:
  - Sampling and other forms of TSE in ACS
  - Sampling and other forms of TSE in NHANES, as well as added uncertainty from imputation
  - Cloning or resampling that creates national dataset
- This year's candidate for a new form of TSE: data augmentation error

### A Step in the Right Direction: 2015 Obesity Data Challenge



#### Behind the Curtain

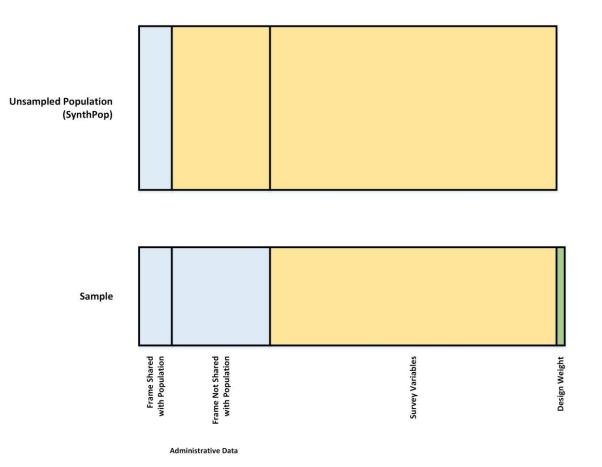
- SynthPop of ~ 200M adults containing 4 categorical predictors: age, gender, race/ethnicity, educational attainment, matched to released totals at block group level + block group geography
- **NHANES** dataset containing the 4 predictors and BMI

[Data harmonization]

- Log-normal models for BMI: 95 distributions, one for each combination of the 4 predictors (one combination collapsed into another because of insufficient sample)
- Simulation: for each SynthPop record, simulate a value of BMI from the associated log-normal distribution
  - Produces values of BMI that do not appear in the NHANES data!

#### Surveys as Prediction Problems: Before

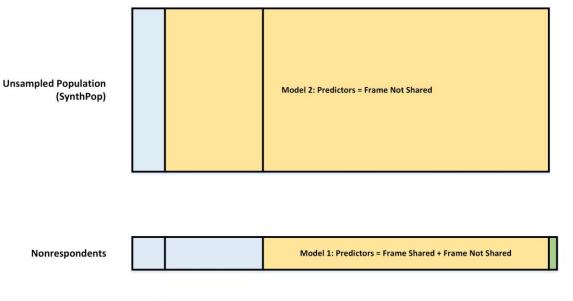
#### **BEGINNING OF SURVEY**

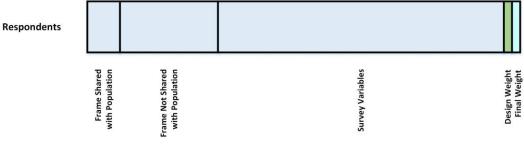


10

#### Surveys as Prediction Problems: After

#### END OF SURVEY





Administrative Data

### An Example (avoids reweighting)

- 2013 Medical Expenditure Panel Survey, Household Component (n = 26,863)
- Simulate nonresponse using FamilyIncome and TotalExpenditure
  - 22,209 respondents, 4654 nonrespondents
- Shared frame: Age, Gender, Race/Ethnicity, Region [in US]
  - [Recoding]
- Unshared frame: EducationalAttainment, HealthInsurance, MaritalStatus, FamilyIncome
  - [Recoding]
- Partition modeling (subsequently, in other contexts, nonparametric density estimation) with weights used to reconstruct survey variables for nonrespondents
  - Presence of any of 5 diseases (arthritis, asthma, CHD, diabetes, high cholesterol)
  - BMI
  - TotalExpenditure (interesting because of atom at 0)

#### Sample of Results: Any of 5 Diseases

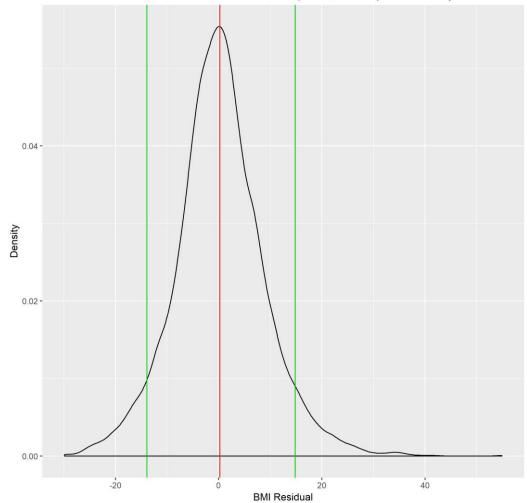
Truth

<b>Respondent?</b>	Any Of Five	None	Sum
Ν	2976	1678	4654
Y	9261	12948	22209
Sum	12237	14626	26863

Predictions

Respondent?	Any Of Five	None	Sum
Ν	2692	1962	4654
Y	9261	12948	22209
Sum	12237	14626	26863

#### Example of Results: BMI

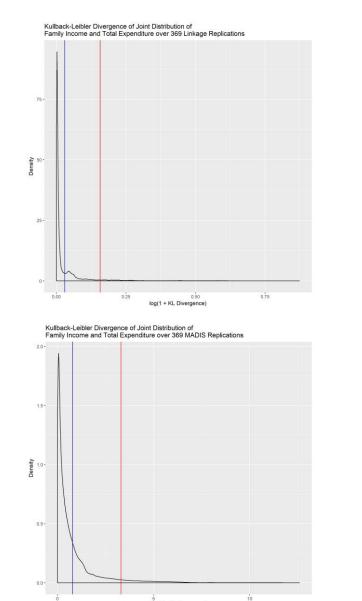


BMI Residuals for MEPS with Simulated Nonresponse, Nonrespondents Only

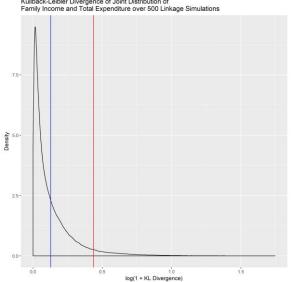
### Where Things Stand

- Re-weighting amounts to cloning respondent records
- Resampling/linkage can be useful, but still cannot create records not present in the respondent data
- Modeling has the potential to
  - Create much richer datasets
  - Increase usability (initial example)
- It is possible to account for modeling-induced uncertainty
  - Observed to date: modeling variability is often comparable to sampling variability

### Pondering UQ

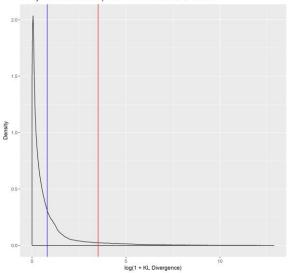


log(1 + KL Divergence)



Kullback-Leibler Divergence of Joint Distribution of Family Income and Total Expenditure over 500 Linkage Simulations

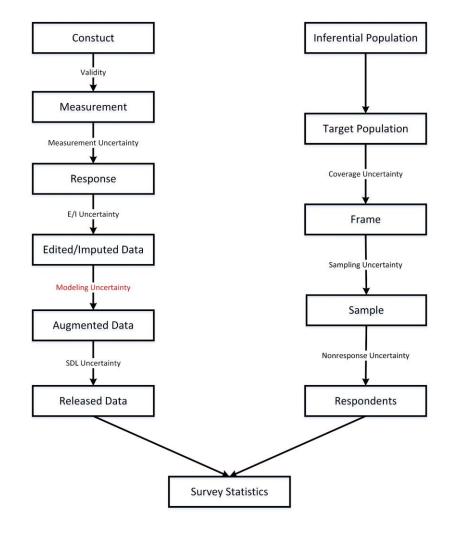
Kullback-Leibler Divergence of Joint Distribution of Family Income and Total Expenditure over 500 MADIS Simulations



#### **Unresolved Challenges**

- Modeling lacks transparency and reproducibility
  - "Trust us, we're smart"
  - Adding multiple variables requires conditional independence assumptions that are hard to verify
- Too much of the modeling process is manual, therefore not scalable
  - Identification of variables that match
    - May be resolvable via AI and high-quality metadata
  - Harmonization
  - Order of addition of variables
- Model validation
  - Simulation of additional nonresponse is a good potential strategy
- Uncertainty quantification

### Parting Shot



**Total Survey Uncertainty** 

## delivering the promise of science

for global good



Alan F. Karr, Director, CoDA karr@rti.org +001 919 316 3423