EHR-based Surveillance Learning Community

June 2020 Call

Learning Community Website: www.chronicdisease.org/page/MENDSinfo

Today's Agenda

Weighting EHR-based Surveillance Estimates to Achieve Representativeness

- Introduction and background: Emily Kraus, PHII
- Obesity Surveillance Case Study: Weighting EHR-based estimates of BMI in Colorado: Liza Reifler, Kaiser Permanente Colorado

Poll Questions

- We want your thoughts on the last call about electronic phenotypes. This call was more technical than previous calls and we want to make sure our content is appropriate for our audience. How did you feel about the content and level of detail?
- Today we are talking about weighting. Please select the statement that best describes your experience with weighting.

Introduction to Weighting EHR-based Surveillance Estimates

Background

- EHR datasets are attractive because they are much larger than traditional surveillance data
  - More statistical power
  - Larger sample of minorities and special populations
- Bigger does not necessary mean representative
  - EHR non-random sample vs random sample
- People seeking healthcare do differ from those not seeking healthcare/without EHR data in important ways

Who is in the EHR??

Attributes of each healthcare organization and geography impact what type of patients are likely and unlikely to be in their EHR dataset

Surveys like that National Health Interview Survey tell us that individuals seeking healthcare are more likely to be/have:

- private insurance
- chronic medical conditions or complex medical needs
- 65+ years
- high utilizers

Multi-institutional EHR Data for Surveillance

Most EHR-based surveillance efforts combine data across multiple organizations to make the dataset larger and more representative

Organizations more likely to contribute data for surveillance

- An EHR system
- Many providers and many patients
- More resources and a robust IT infrastructure
- Experience with sharing data
- Interest in population health

Poor Representativeness & Bias

How can we think through representativeness in our EHR data?

- Who seeks medical care?
  - How does who seeks medical care vary by care setting?
  - How do local local healthcare (and insurance) policies impact healthcare utilization?
- Which organizations participate in EHR data sharing?
  - What kind of care do those organizations provide?
  - What patients do those organizations serve?
  - What insurance do those organizations accept?

Weighting (a.k.a adjustment) is a technique and group of statistical methods used to correct an imbalance between a sample and the underlying population using population benchmarks

Colorado BMI Monitoring System: Imputing Race and Weighting Data for Direct Adjustment

For: Evidence-Based, EHR-Based, Surveillance Learning Community
June 16, 2020

Liza Reifler, MPH, Biostatistician
Matthew F Daley, MD, Senior Investigator
Institute for Health Research
Kaiser Permanente Colorado

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BMI Monitoring System Background

- **Objective:**
  - Create 3-year prevalence estimates of pediatric and adult overweight/obesity at the *census tract level*
  - Describe overweight/obesity prevalence with geographic specificity and examine variation
  - Remove self-report bias in other data sources
    - Self-reported weight on surveys is often under-estimated
    - EHR: objectively measured weight and height

BMI Monitoring System Background

- **Health systems participating**
  - 3 large multisite federally qualified community health centers (Northern Colorado, suburban Denver, rural Colorado)
  - 1 large integrated urban safety net system in Denver
  - 1 regional pediatric hospital
  - 1 large managed care organization
- **A standardized data model was defined collaboratively and developed at all sites**
- **All data was sent to state health department, the data hub, for data processing, quality assurance and summarization**

EHR BMI & Demographic Data

- **Prevalence Outcomes:**
  - Pediatric Overweight — BMI percentile for sex & age 85th - <95th
  - Pediatric Obesity — BMI percentile for sex & age >= 95th
  - Adult Overweight — BMI 25 to <30 kg/m^2
  - Adult Obesity — BMI >= 30 kg/m^2

- **Required EHR data:**
  - BMI: Weight, height, sex, age in days, date of measure
  - Demographics: census tract of residence, race, ethnicity, and more

EHR Data: Measuring BMI

- **Standard definition for weight and height:**
  - Measurement units, outpatient setting
- **Timing of measurements:**
  - Pediatric: Same-day weight and height
  - Adult: Same-day or closest height to date of weight, within 3 year period
  - If multiple measurements, take most recent
- **CDC growth percentile macro for ages 2-<18 years:**
  - Flags biologically implausible measurements
  - Calculates age- and sex-specific percentiles

EHR Unadjusted Estimates

- **Unadjusted estimates were reported in early monitoring periods**
  - Difficult to compare to other system's prevalence estimates
  - Stakeholders expressed concerns about the representativeness of patient population

Correcting for Selection Bias

- **Health system users data is not a random sample**
  - Selection bias is likely
  - Missing people who are uninsured, not seeking healthcare, insured by other providers
  - Data partners capture *some* of this population
- **Could higher coverage mitigate this bias?**
  - Only if higher coverage addresses *sources* of selection bias
- **Is the sample representative of population demographics?**
  - Age, race/ethnicity and gender relate to
    - Selection: Getting weight & height at medical visits
    - Outcome: BMI
  - If a group is over-represented, how might they drive obesity prevalence estimates up or down?

Direct Adjustment of Estimates

A standardized or *adjusted* overweight/obesity prevalence represents outcomes we would expect ***if*** a sample had an identical mix of demographic traits as the population

Pediatric Demographics for Study Sample and Population

AGE GROUPS	Sample (%)	Population (%)	Race/ Ethnicity	Sample (%)	Population (%)
2-5 y	25.8	28.7	Non-Hispanic white	24.1	53.4
6-11 y	36.2	38.4	Non-Hispanic black	13.6	9.4
12-17 y	38.0	32.9	Non-Hispanic Asian	3.1	3.4
			Hispanic	51.6	30.8
Sex			Other race/ethnicity	3.0	3.0
Male	51.1	50.0	Missing race/ethnicity	4.6	0
Female	48.9	50.0			

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There were differences
-**Age** (sample was older)
-**Race** (sample had more Hispanic and fewer white children, and a proportion missing race)

Adjustment Process

1. **Create complete case data or data with imputed missing demographics**
2. **Create statistical weights**
   - Use a reference population to compare demographics against sample demographics
   - For individual observations or aggregate, stratified estimates
   - Over-represented individuals have lower weights
   - Under-represented individuals have higher weights
3. **Calculate a weighted overall estimate**

Imputing Missing Race: Hot Decking

- **All observations must have complete information for adjustment**
- **7% race missing overall, 5% pediatric race missing**
- **Hot decking**
  - Imputation method done by many large data agencies: CDC, Census Bureau
    - Classify based on variable(s) with complete information
    - Randomly select another observation's value from the same class as person missing a value
  - EXAMPLE: Missing race for a 8 y.o. boy is substituted in randomly based on known race values of other 8 y.o. boys living in the same tract from the same healthcare site
  - May still lose some observations that have no one else in same class
- **Programming method**
  - We used a SAS macro (by ABT) comparable to SUDAAN hot decking

Raking Method for Weighting

- **Weighting is done through raking**
- **Compares sample to population *marginal totals* of demographics, instead of *individual cell* totals**

	Male	Female	TOTAL AGE
2-17	**A** n (%)	**B** n (%)	n (%)
18-65	**C** n (%)	**D** n (%)	n (%)
TOTAL GENDER	n (%)	n (%)	n (%)

Raking Method for Weighting

- **If we use individual cells:**
  - 10* 7* 2 = 140 possible age/race/gender combinations
  - Requires reference population estimates for *each* combination

	Male	Female	TOTAL AGE
2-17	**A** n (%)	**B** n (%)	n (%)
18-65	**C** n (%)	**D** n (%)	n (%)
TOTAL GENDER	n (%)	n (%)	n (%)

Raking Method for Weighting

- **Margin totals used in raking**
  - ACS Census tract-level margins for age, race and gender
  - Raking adjusts on each variable step-by-step, then iterates until an acceptable difference threshold is met for all margins

	Male	Female	TOTAL AGE
2-17	**A** n (%)	**B** n (%)	n (%)
18-65	**C** n (%)	**D** n (%)	n (%)
TOTAL GENDER	n (%)	n (%)	n (%)

Example of raking results on age

BEFORE

Age Groups	INPUT / Sample Total	Target/Pop Total	Sample %	Target %	Difference in %
0-4	20399	44555	6.12	6.86	**-0.742**
5-9	41529	41458	12.46	6.39	**6.075**
10-14	39300	35896	11.79	5.53	**6.263**
15-17	23875	18550	7.16	2.86	**4.307**
18-24	30516	64932	9.16	10.00	**-0.845**
25-34	41478	124226	12.45	19.14	**-6.689**
35-44	37920	98107	11.38	15.11	**-3.733**
45-54	32870	75648	9.86	11.65	**-1.789**
55-64	31651	68989	9.50	10.62	**-1.129**
65+	33728	76853	10.12	11.84	**-1.717**

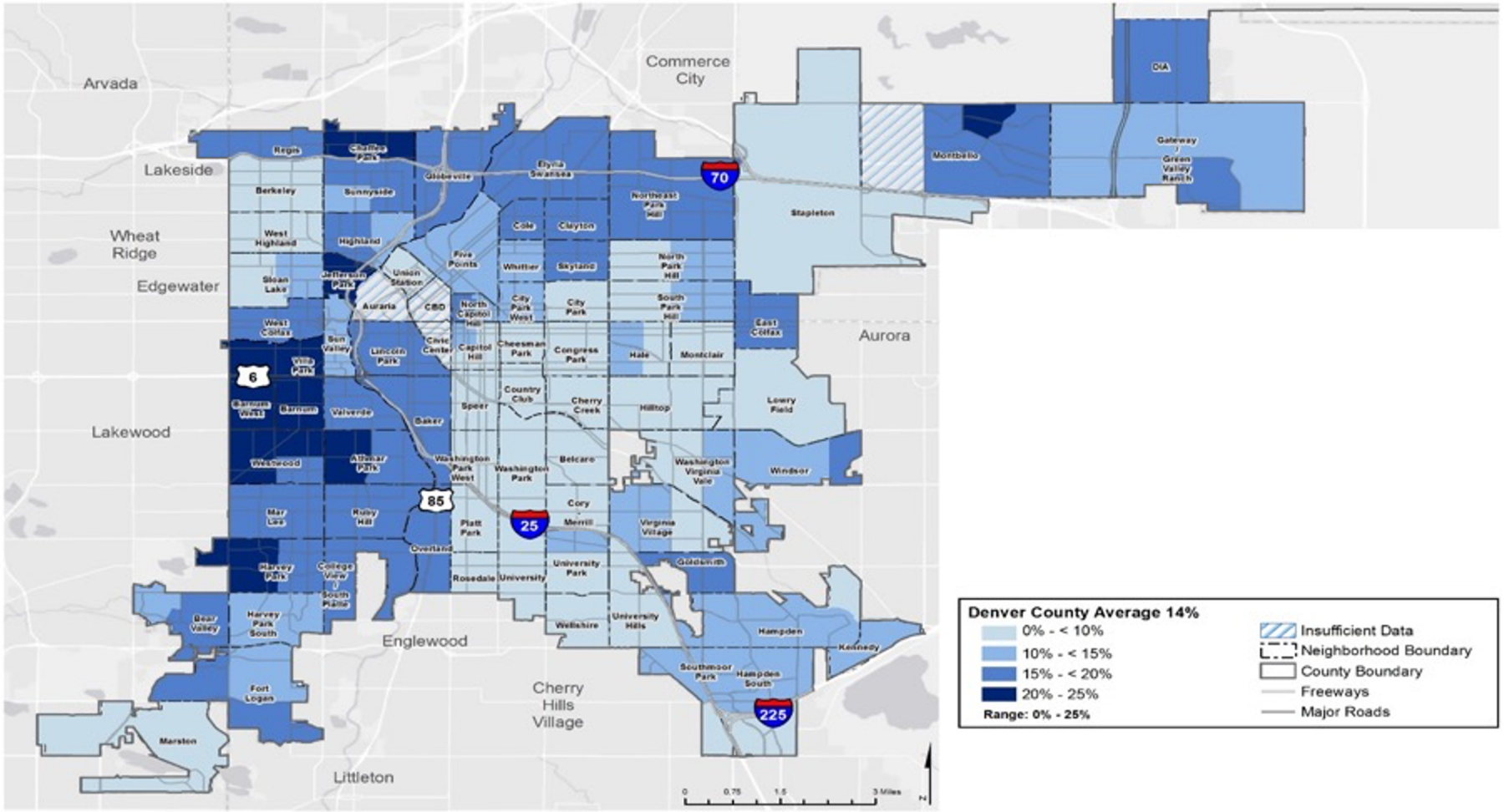
AFTER

Age Groups	INPUT / Sample Total	Target/Pop Total	Sample %	Target %	Difference in %
0-4	44554.97	44555	6.86	6.86	**-0.000**
5-9	41457.96	41458	6.39	6.39	**-0.000**
10-14	35895.96	35896	5.53	5.53	**-0.000**
15-17	18549.98	18550	2.86	2.86	**-0.000**
18-24	64931.97	64932	10.00	10.00	**-0.000**
25-34	124226.08	124226	19.14	19.14	**0.000**
35-44	98107.02	98107	15.11	15.11	**0.000**
45-54	75648.00	75648	11.65	11.65	**0.000**
55-64	68989.02	68989	10.63	10.63	**0.000**
65+	76853.05	76853	11.84	11.84	**0.000**

Adjusted Pediatric Obesity Rates 2014-2016

Overall County-Level Obesity Rate:
14%

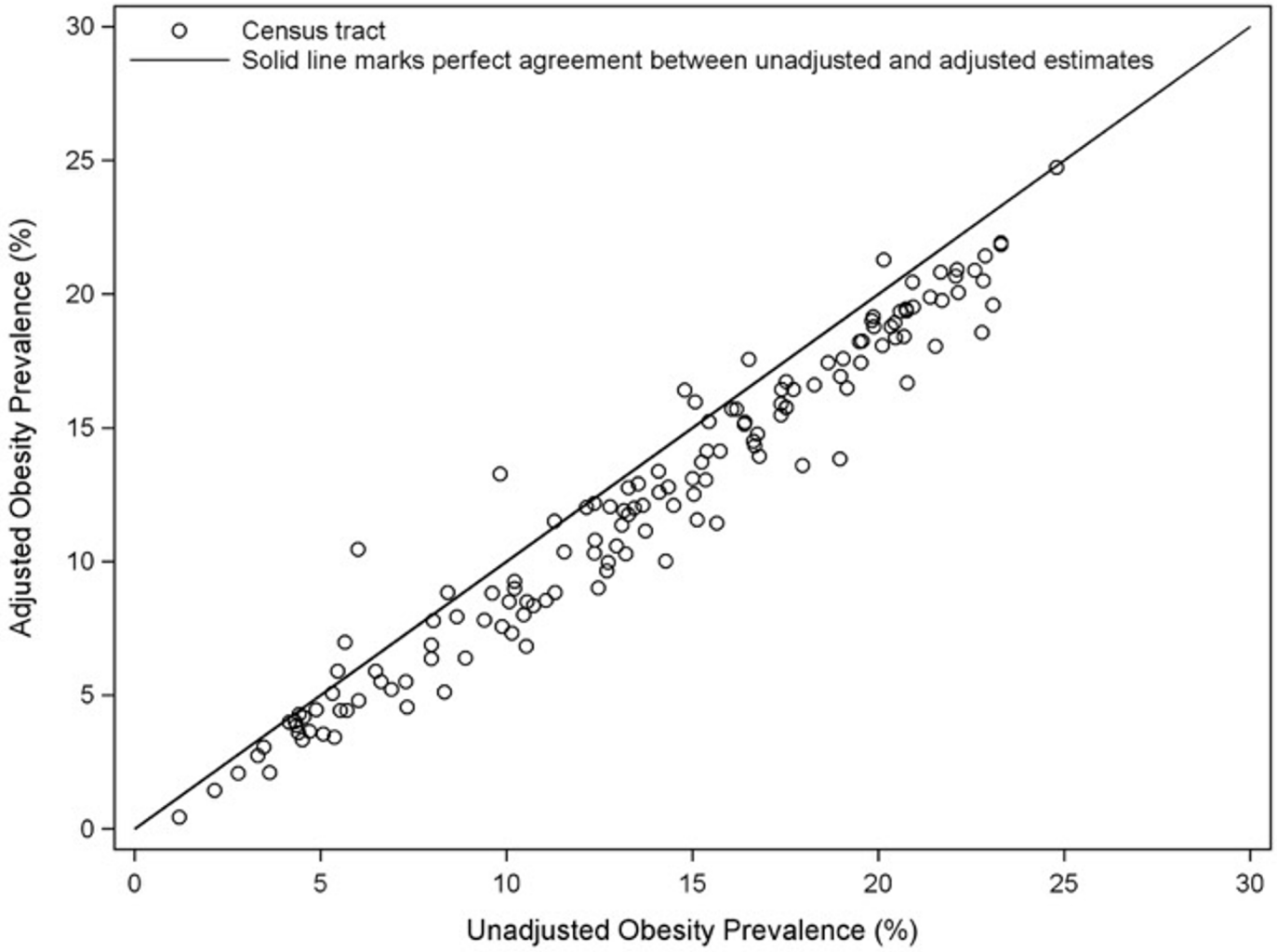
Coverage:
66%
of ~136 000
2-17 year olds



2014-2016 Denver County Pediatric Obesity Estimates

Estimation Method	Percent Obese (95%CI)
UNADJUSTED	16.9 (16.7, 17.2)
ADJUSTED Raking Race hot decked	13.9 (13.6, 14.1)

2014-2016 Denver County Census Tract Pediatric Unadjusted and Adjusted Obesity Prevalence



Discussion: Results

- **Adjusted pediatric estimates were lower than unadjusted**
  - Ages and race/ethnicities that tend to have higher obesity rates within our system were over-represented compared to the population

Discussion: Reference Population

- **Limits/ trade-offs on available reference population demographic estimates**
  - ACS census tract level demographics for the full population
    - Geographic representativeness
    - Provides local level understanding of the distribution of overweight/obesity without adjusting away demographic differences inherent across communities

  - Census county level demographics, stratified by pediatrics and adults
    - Sub population representativeness
    - Higher Hispanic ethnicity distribution for those <18 years old
    - Provides an estimate of burden of pediatric obesity over all Denver county, but would be less representative within each census tract/community

Discussion: Feasibility

- **Direct adjustment resources**
  - Time intensive (raking 144 tracts)
  - Feasible for individual level data or stratified, aggregate estimates
- **Duplication of individuals across systems is possible**
  - Subsequent work has tried to correct for this
- **Other outcomes studied with similar data models**

Discussion Questions

- What was the most challenging part of creating adjusted estimates?
- How did you explain the adjustment in lay language to stakeholders? Do you feel like they got it?
- What do you make of the variation in difference between crude and adjusted estimates?
- Have others on the phone used a different approach to weighting EHR-based estimates?

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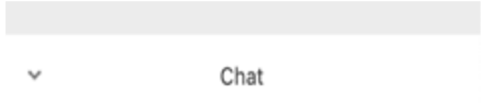

Housekeeping

- Next meeting: July 21 at 3pm EST
- Educational Topics include: Modeling

PLEASE COMPLETE THE POST WEBINAR SURVEY!

Extra Slides

Overall Sample Race/Ethnicity

Race/ Ethnicity	Sample* (%)	Population (%)
Hispanic	30.0	30.7
White	54.0	59.9
Black	8.0	9.1
Asian/Pacific Islander	3.8	
American Indian	0.4	
Multi-ethnicity	1.2	0.2
Other	2.2	
*Proportions include imputed missing race		

Race/ethnicity is more balanced over the whole sample, adults and children, is more even before raking

Discussion on Application in an Aggregate Data Model

- **Hot decking**
  - Needs to be done on individual level/at site
  - SAS macro available for SAS-capable sites
  - Should this be done on a) all site data or b) eligible project sample?
- **Raking**
  - Can only weight/adjust for traits measured in population
  - Can be done after hub has summarized all aggregate data
  - Recommend performing in SAS instead, R, or any software where programming is already developed

Process/Steps

SITE

1. Prepare dataset with most recent eligible BMI
2. Hot deck to fill in missing race
   - Must be done at site, individual level data
3. Summarize data into aggregate strata and outcome measures
   - Takes planning
     - Strata categories need to match demographic categories are available from Census
   - EACH SITE SENDS THIS TO HUB

1. HUB aggregates site data and recalculates stratified estimates

HUB/Lead

1. Obtain census/ACS demographics for year/geography(ies)
2. Prepare census data for raking
   - Must collapse any census margins that we don't observe in sample data
3. Rake
   - DO IN SAS
8. Calculate weighted outcome estimates

Example of Aggregate Data Set

Geo ID	Age Group	Race/ Eth	Gender	Input Weight	Obese Percent	RAKED Weight	Geo Total Pop
08031	0-4	BLACK	F	949	8.1138	1910.52	649214
08031	5-9	BLACK	F	1738	12.3130	1755.99	649214
08031	10-14	BLACK	F	1655	20.9063	1572.57	649214
08031	15-17	BLACK	F	1203	24.2727	960.19	649214
08031	18-24	BLACK	F	2124	24.8588	4478.25	649214
…							