Comparison of Imputation Techniques for Missing Data for Potentially Informative Missingness: An Application to Childhood Obesity using the Medical Expenditures Panel Survey

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ARC 2014

Work in Progress

Motivation for the Study

- One-third of US children and teens are either overweight or obese

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- Long-term population health impact of childhood obesity are greater prevalence of diseases (type 2 diabetes, heart disease), as well as psychological disorders (depression and low self-esteem)

(Ogden et al., 2014)

Definition of Overweight/Obesity in Children

- Body Mass Index (BMI) metric of obesity:

$$\begin{aligned} BMI &= \frac{Kilograms}{Meters^2} \\ &= 703 \cdot \frac{Pounds}{Inches^2} \end{aligned}$$

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- *Obesity*= BMI at or above 95th percentile for children of the same age and sex

2 to 20 years: Boys
Body mass index-for-age percentiles

NAME ______________________

RECORD # ______________________

Date	Age	Weight	Stature	BMI*	Comments

***To Calculate BMI:** Weight (kg) ÷ Stature (cm) ÷ Stature (cm) x 10,000
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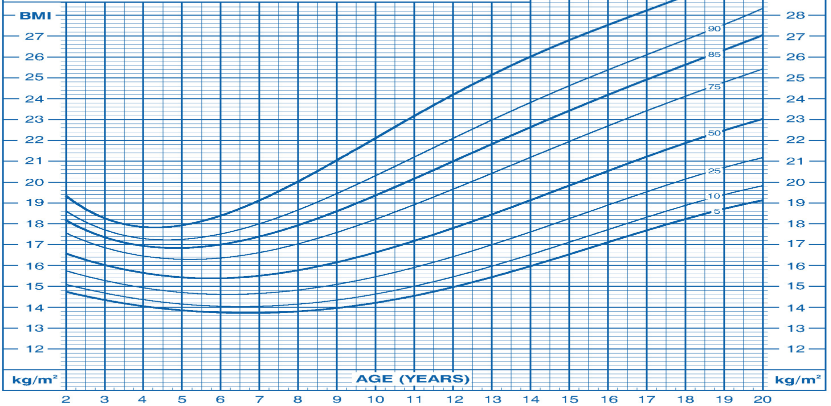

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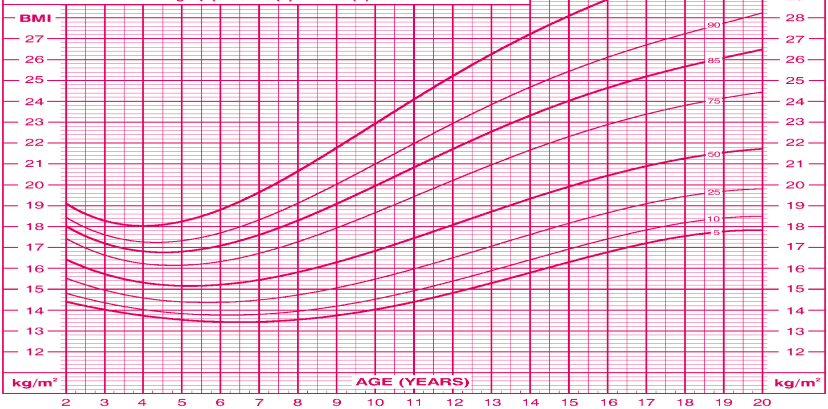

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We wish to test the missing data mechanism to best impute information.

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Or, data missing at random due to lack of knowledge of parents.

MEPS

- Overall goals of MEPS: To provide unbiased estimates of national and regional (four Census regions) expenditures with a targeted precision, and to provide unbiased estimates for targeted sub-groups, such as race or low income

(McGuire, Glazer, et al., 2013; McGuire, Newhouse, Normand, Shi, & Zuvekas, 2013; S. B. Cohen & Ezzati-Rice, 2006; Ezzati-Rice, Rohde, & Greenblatt, 2009; S. Cohen, 1996; S. B. Cohen, 2000; S. B. Cohen, Ezzati-Rice, Zodet, Machlin, & Yu, 2011; Zuvekas & Olin, 2009)

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- MEPS data used in evaluating expenditures for health reform policies and assessing the cost of drugs for Medicare recipients that resulted in adoption of Medicare Part D

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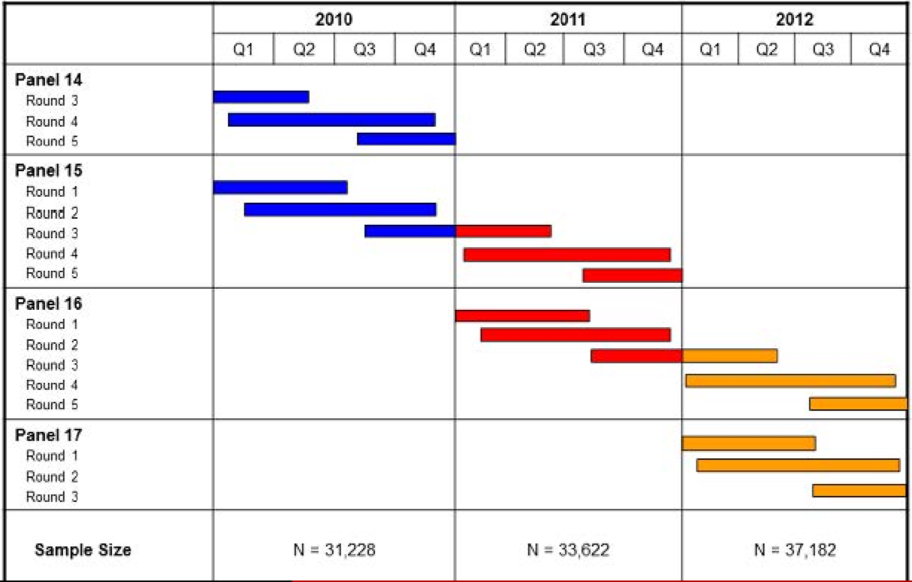
MEPS Longitudinal Design

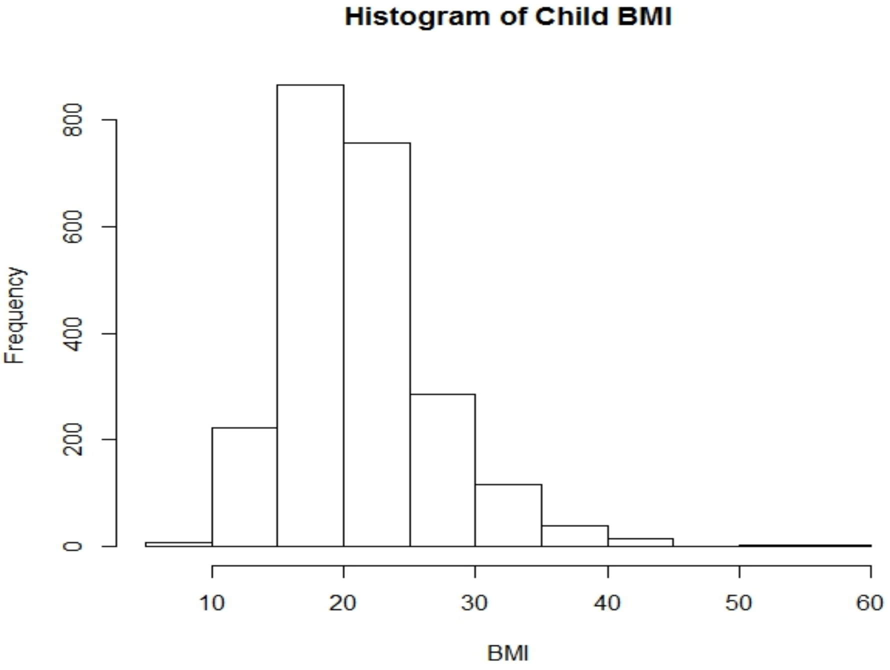


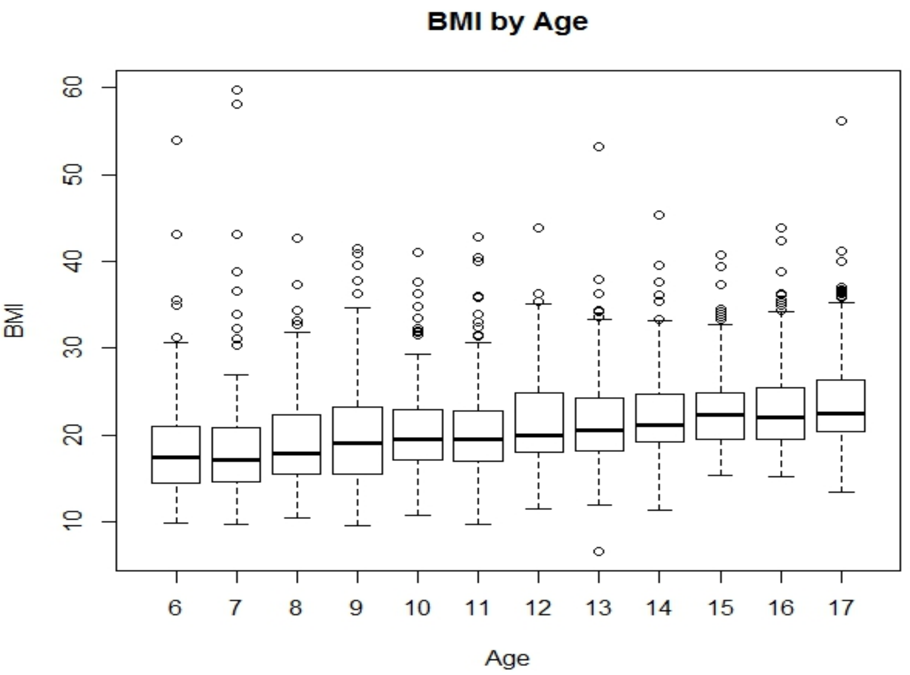
MEPS Data for This Study

- Examine Panel 15 of MEPS in 2011
- Subset children ages 6 to 17 inclusive
- Sample:
  - Total # Observations: 2,855 with almost 20% missing BMI
  - # *Missing* BMI: 539 (537 *true* missing + recoded 2 observations as missing with BMI of 103.3 and 106.2)

Child BMI Descriptives

n	mean	sd	median	min	max	skew	kurtosis	se
2316	21.32	5.77	20.40	6.60	59.80	1.27	3.61	0.12


Histogram of Child BMI
Frequency
0
200
400
600
800
10
20
30
40
50
60
BMI


BMI by Age
BMI
60
50
40
30
20
10
6
7
8
9
10
11
12
13
14
15
16
17
Age

Example: Child Age Descriptives

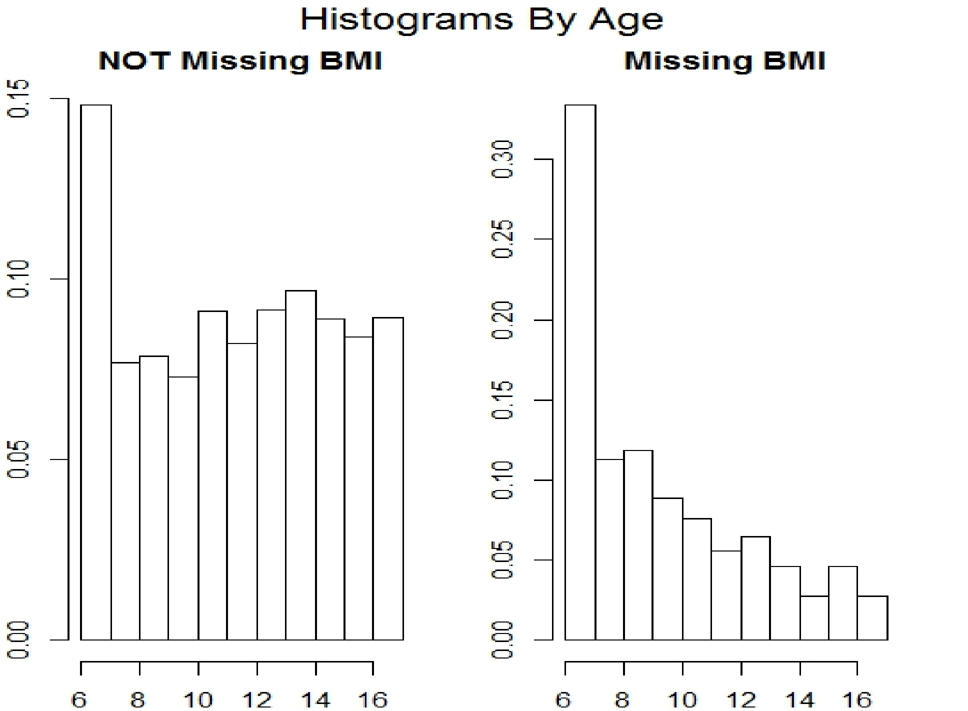
Table: Age Descriptives for Observations with BMI Missing

n	mean	sd	median	min	max	skew	kurtosis	se
539	9.68	3.15	9.00	6.00	17.00	0.71	-0.55	0.14

Table: Age Descriptives for Observations with BMI Not Missing

n	mean	sd	median	min	max	skew	kurtosis	se
2316	11.74	3.41	12.00	6.00	17.00	-0.10	-1.17	0.07

Two-sample t-test of difference between 2 means: p-value < 2.2e-16


Histograms By Age
NOT Missing BMI
Missing BMI
0.00
0.05
0.10
0.15
0.20
0.25
0.30
6
8
10
12
14
16

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(Rubin, 1976; Enders, 2010)

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One Approach

- Log(BMI) is approximately normal
- Could just include observed data and carry on
- But we are throwing away 20% of sample

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  3. For each method, generate 1,000 sets of imputed data
  4. Compare imputed distribution of missing value to true distribution

Results: Using Log(BMI)

Approach	Mean	Std. Dev.	MSPE
Stochastic Regression	3.021	0.258	0.0668
Semi-Parametric Regression	3.022	0.259	0.0672
Hot Deck	3.018	0.260	0.0687
Truth	3.051	0.273	

Future Work

- Explore MNAR approaches
- Choose informative missing pattern for data from MEPS and test models

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