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# Non-Probability Sampling Assumptions and Methods

J. Michael Brick
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# The Non-Probability Sampling Explosion

- Global $$$ for online research 19% to 35% from 2006-12
- 43% of all surveys conducted online in 2012
- Online surveys used by all types of organizations
  - Commercial
  - Academic
  - Government

# Non-Probability Sampling (NPS) Literature

- Two AAPOR panels
- Monograms
- Ever increasing number of journal articles from many disciplines
- International scope

# What Is THE Issue

- Representation
- Probability sampling is strong on representation
  - Fixed sampling frame and probabilities of selection basis for inference that is relatively robust despite problems
- Non-probability sampling weaker on representation
  - Models and assumptions that are hard to justify or test

# NPS Online Design Approaches

- Matching
  - Identify units from a probability sample or census that have characteristics highly related to the key survey outcome variables and locate NPS respondents matching those characteristics
- Quotas
  - Essentially the same as matching but typically based on demographic variables
- Blending
  - Combining samples; sometimes NPS with probability sample and sometimes multiple NPS

# Typical NPS Weighting Approaches

- Weight observed sample with initial weights of unity
  - Unweighted
  - Poststratification or raking
  - Inverse Probability Weighting (IPW)

# Poststratification or Raking

- **Consider Outcome model**
  $E_O y_k = \mu + \alpha_g = \mu_g$ for all $k \in s_g$ , $g$=1,…,$G$

- **Poststratification (unweighted poststratification cell mean adjusted to population total for the cell) is unbiased under this model**
- **Poststratification is criticized as not accounting for selection bias**

# Inverse Probability Weighting

- Consider Missingness Model

$$E_M(R_k \mid \mathbf{Z}) = \pi_{\mathbf{Z}_k}$$

where $\pi_{\mathbf{Z}_k}$ is propensity of unit *k*

- Inverse of propensity score adjustment (observation weighted using reference sample, see Lee (2006)) is unbiased under this model

- IPW criticized as being unstable when propensities are extreme

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# A Compositional Model

- First IPW then poststratification to give $\{w_k\}$
- Lee and Valliant (2009) describe this weighting method
- Related to calibration and doubly robust augmented IPW (AIPW), but called compositional because only counts of population controls allowed (GREG not in this class)

# Properties

1) $w_k > 0 \ \forall \ k \in s$
2) $\sum_{k \in s} w_k \boldsymbol{\delta}_k = \mathbf{N}$ where ***N*** is a vector of pop totals
3) Estimates of totals are linear or smooth function of estimated totals
4) Unbiased and consistent if either outcome or missingness model holds

# Marginal Structural Model

- Structural model specified by mean and variance models.
- Assume a population structure with clustering generates the data and observations within cluster may be correlated (for variance computation).
- Resample clusters to estimate variance of estimates

- Under the models $\hat{y}_{com}$ is unbiased and consistent and, with large samples, 95% CI is

$$\hat{y}_{com} \pm 2\sqrt{v(\hat{y}_{com})}$$

# Case Study

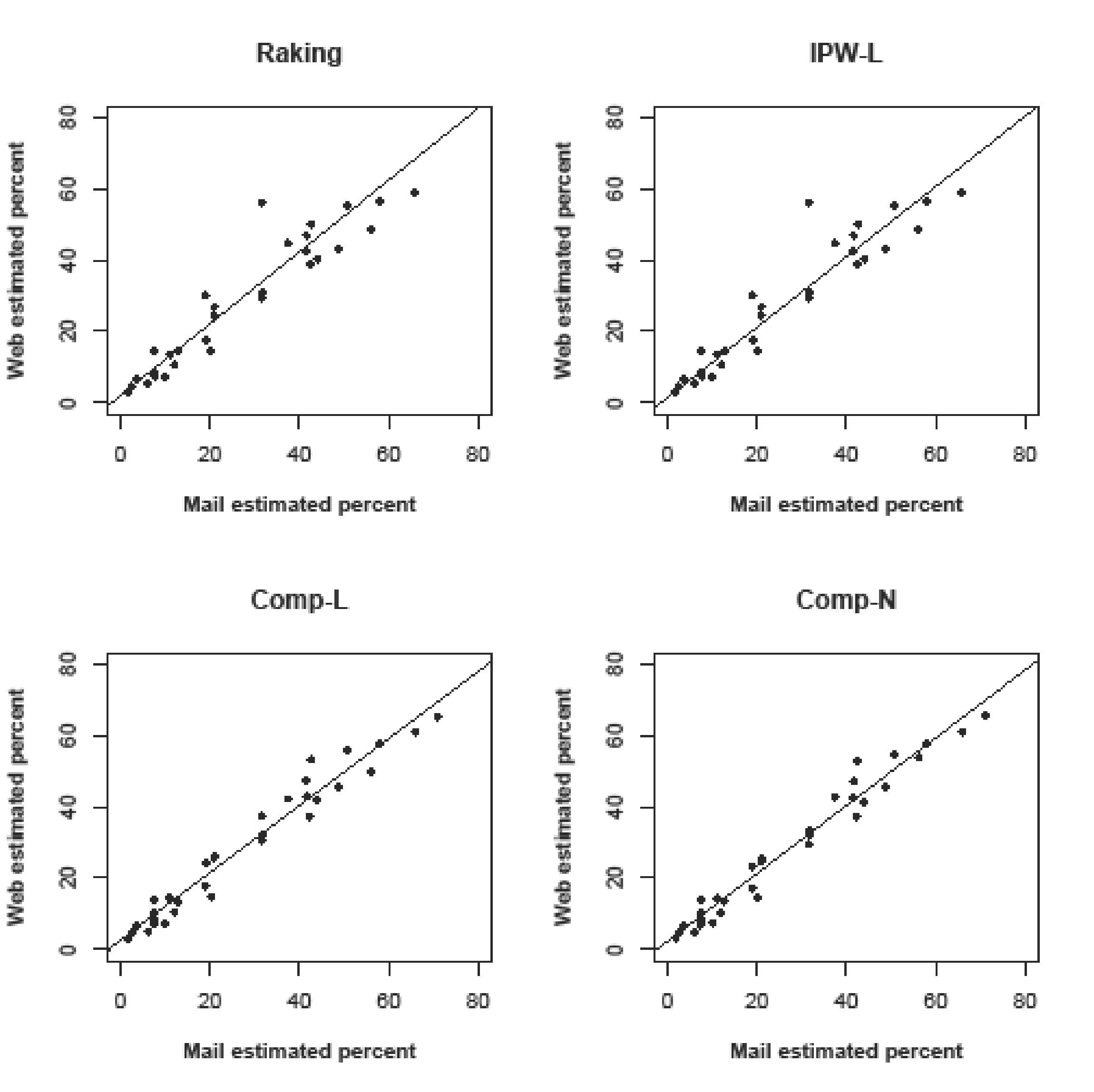
- Collaboration between Pew Research Center, SurveyMonkey, and Westat.
- SurveyMonkey Audience Panel (9/14)
  - 5,301 adult respondents
- ABS (mail) survey (9-10/14) RR=29%
  - 2,668 respondents
  - Serves as reference sample

# Weighting Methods

| | IPW | Raking |
|---|---|---|
| Raking | None | 7 dimensions |
| IPW-L | Logistic - 4 groups | None |
| Comp-L | Logistic - 4 groups | 7 dimensions |
| Comp-N | Exact - 16 groups | 7 dimensions |

- Variance computed using jackknife based on MSA of respondent

# Comparing Web and Mail Substantive Estimates



# Diagnostics

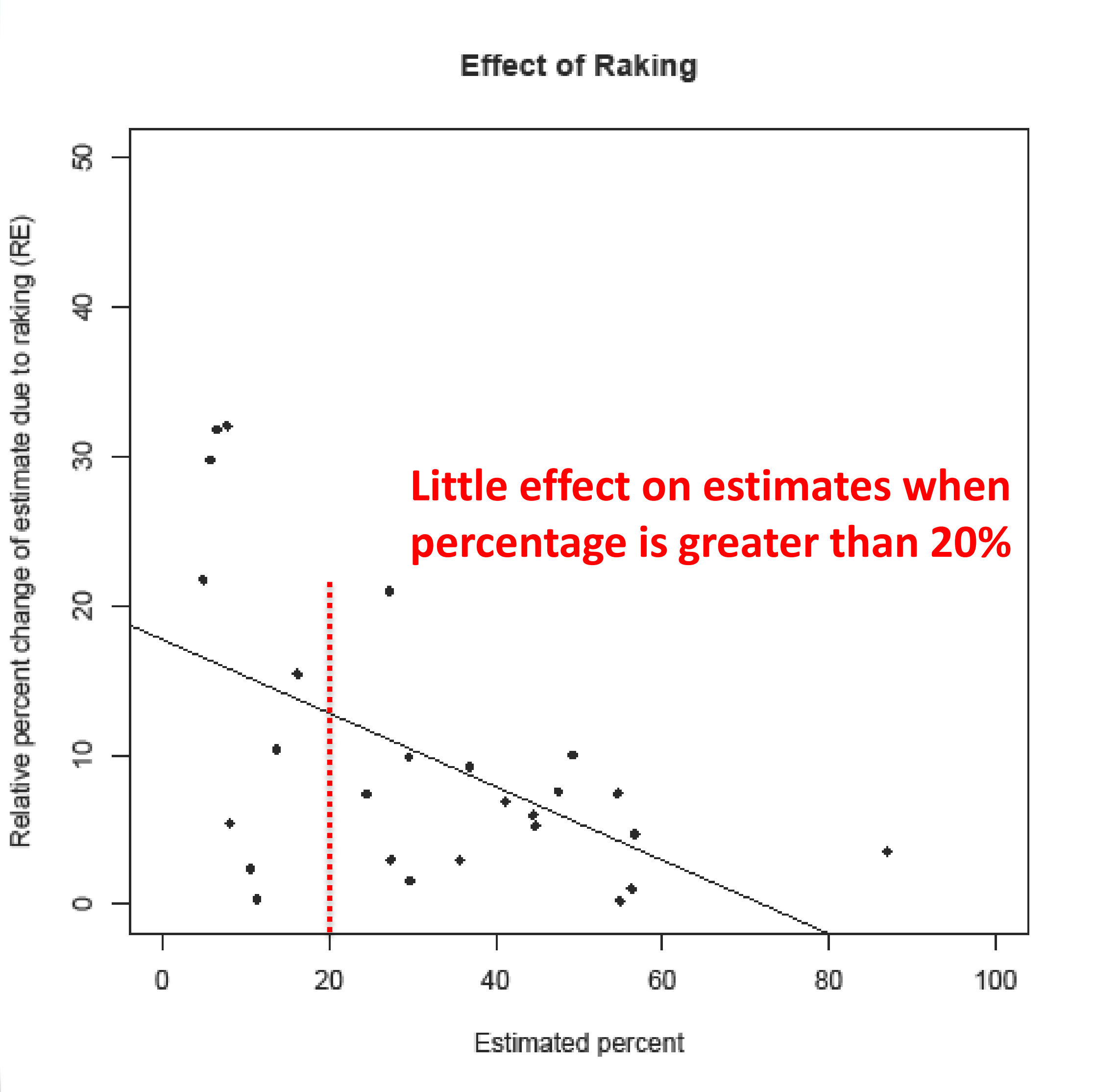
- Examine effects and assumptions
  - Begin with bias reduction due to raking
  - Assess propensity model fit and IPW adjustments
  - Assess outcome model for a particular estimate

# Effect of Poststratification or Raking on Bias

- The Relative Raking Effect (RE) is a measure of how much an estimate changes (relative to the IPW estimate) due to raking.
- Computed for substantive items in Web survey is a modification of the poststratified measure

$$RE(y) = 100\left( \frac{\sum_g N_g \hat{N}_{ipw,g}^{-1} \tilde{y}_g - \sum_g \tilde{y}_g}{\sum_g \tilde{y}_g} \right)$$

# Relative Raking Effect for Substantive Items



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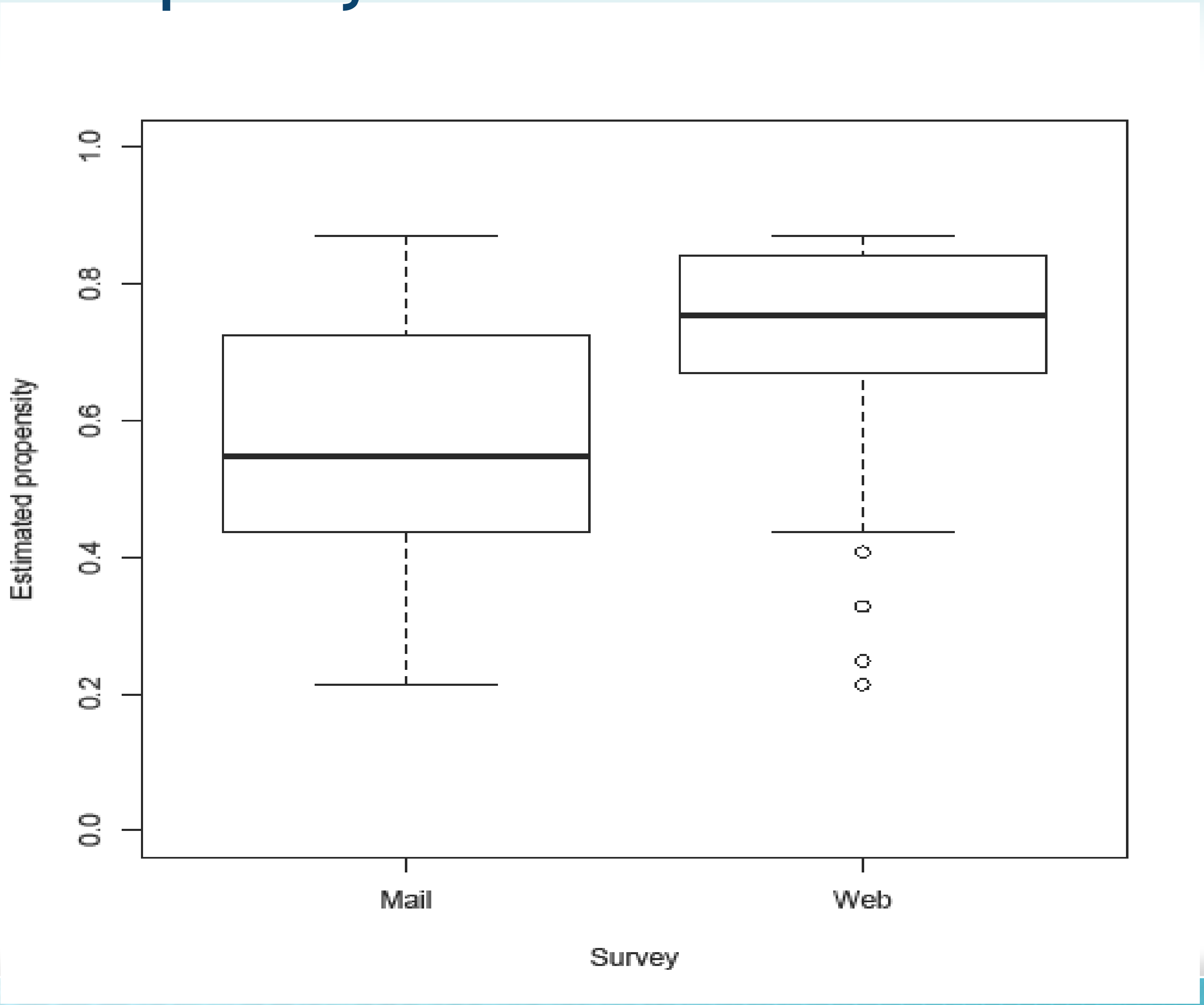
# Common Support Analysis

- IPW is intended to reduce selection bias
- Commonly used tool of causal analysis is examination of the propensity distributions of the control (in our case Mail PS survey) and treated sample (Web NPS survey)
  - Shown for the IPW-L propensities

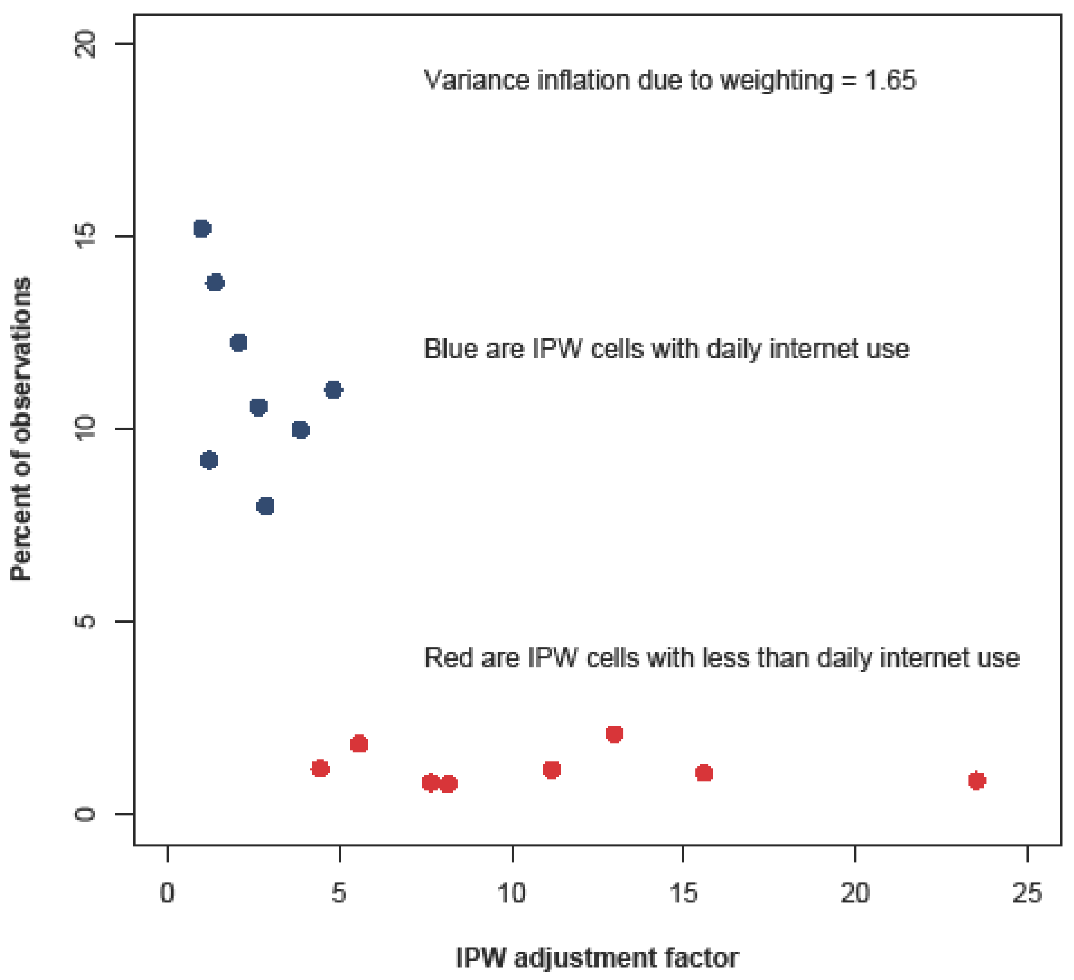
# IPW-L Propensity Distribution



# IPW Adjustment Factors

- The graph shows weak evidence for the common support assumption and raises concerns about the effectiveness and stability of the IPW adjustments
- Considerable range of weights and instability when using the logistic regression approach (IPW-L)

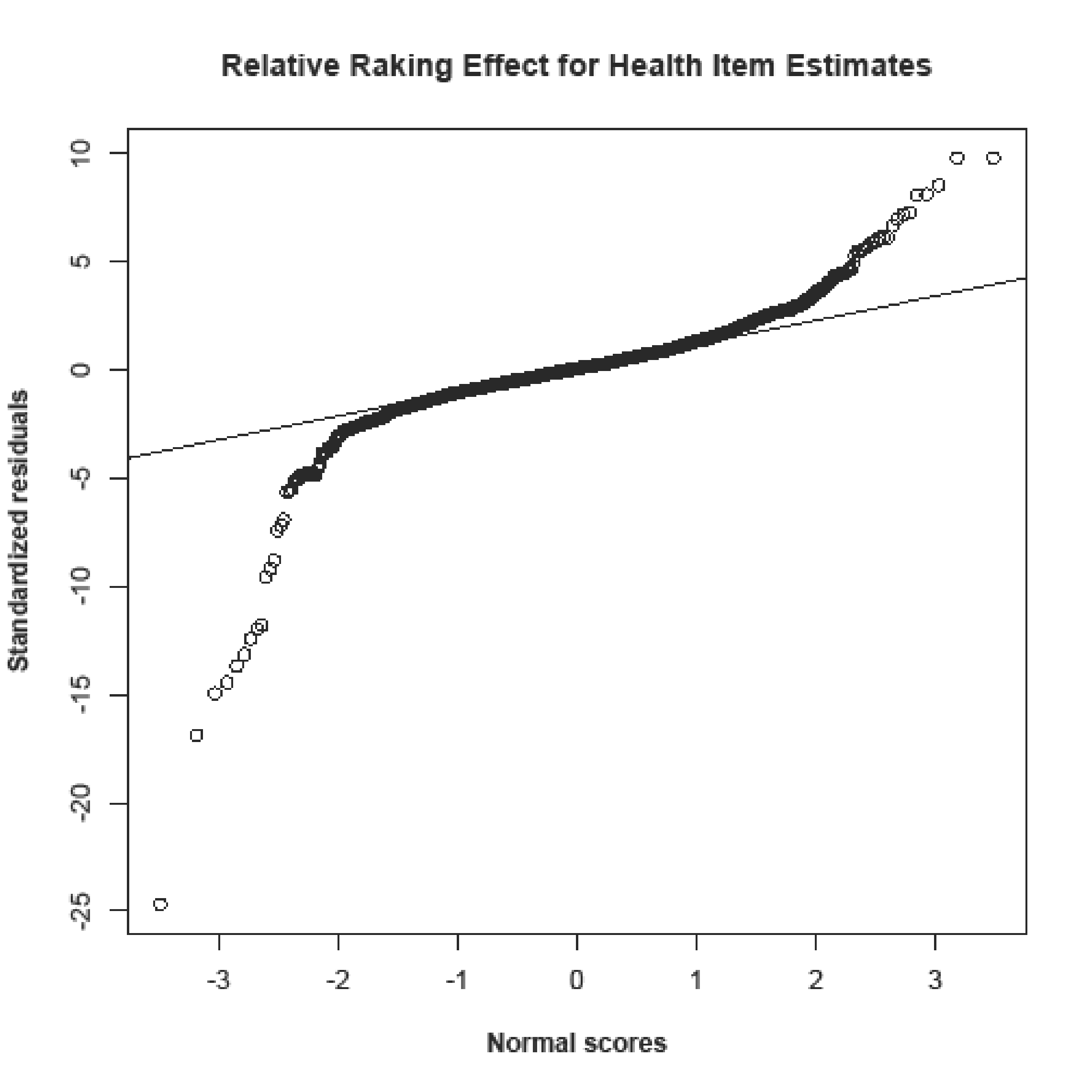
# IPW-N Relative Adjustment Factors



# Closer Look at Outcome Model

- Under model we would assume standardized differences from the "predicted" mean would be approximately N(0,1)
- Examine this for "how you rate your health" by computing residuals from raking dimension means across other raking dimensions

# QQ Plot of Residuals for Comp-N estimates



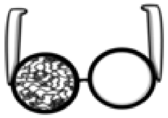
# Variance Estimation

- Estimated design effect (deff) is not simply the clustering and weight adjustment effect
- Median deff for Comp-L is 14.9 (mean 48.3)
  - Without replicating, median is 5.8/mean 6.2
  - Hugely unstable logistic model of propensity
- Median deff for Comp-N is 5.5 (mean 6.5)
  - No difference with replicating IPW-N
  - This means the effective sample size is closer to 1,000 than 5,000

# Discussion

- The formal structure helps in evaluating NPS
- Assumptions for unbiased estimation not well supported
- We need more evaluation tools
  - Especially tools for understanding when estimates from NPS may be more reliable are needed

# What About PS?



- Tools and more theory needed for PS since 10% response rates and low coverage rates are too far from assumptions of design-based theory

- Compositional model may be applicable
  – Current set of tools for evaluating effectiveness of weighting are very limited

# Thanks !!!

mikebrick@westat.com