Mode Effects Measurement & Correction: A Case Study

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Opinions expressed are those of the authors only

Background: Mode Effects

- Sequential modes of data collection
  - Try the cheapest mode first
  - Convert refusals if at all possible
- Different distributions of responses in different data collection modes
- Mode effects are question-specific
- Mode effects occur for different reasons
  - social desirability
  - satisficing
  - different presentation
  - different demographics due to self-selection into mode

Background: Mode Effects

- Mode effect detection
  - Compare the marginal distributions across modes
  - Build a regression model with mode as an explanatory variable
- Mode effect correction
  - Lack of validation data (bias concern)
  - Increase in the standard errors (variance concern)
  - Complex task requiring substantial time
  - Regression modeling in which survey responses are regressed on mode and demographic variables (Elliott et al. 2009; Ezzati et al. 2006)
  - Treating mode effects as a missing data problem and using multiple imputation (Christensen et al. 2006; Peytchev 2012)

Case Study: PALS

PALS
PORTRAITS OF AMERICAN LIFE STUDY
PANORAMA DE LA VIDA EN LOS ESTADOS UNIDOS

- Sponsored by Rice University's Kinder Institute for Urban Research
- National panel study
- Measure religious identification, beliefs, practices with a particular focus on capturing ethnic and racial diversity

PALS: Wave 1

- Wave 1 conducted in 2006
- National area probability sample with racial minority oversampling
- n=2,610 adult interviews
- Data collected via CAPI and ACASI
(some PAPI modules left behind)
- 58% Response Rate AAPOR(4)

PALS: Wave 2

- Wave 2 data collected through 2012
- Target: re-interview the n=2,610 Wave 1 respondents and n=389 children the HH who are now age 20+
- n=1,320 re-interviewed respondents and n=101 young adults
- Interview length about 75 min
- Budget did not permit in-person interviewing
- Primary mode: Web with CATI follow-up
- $50 incentive

PALS: Mode Effects Concerns

- Two concerns regarding potential mode effects:

1) Longitudinal comparisons: different modes used in waves 1 and 2 (Ackermann et al. 2011)
2) Wave 2 analysis: two modes (Web and CATI) confounded by sample composition (Kennedy et. al. 2012 and this presentation)

- Wave 2 randomized mode experiment:

Condition 1. Web with CATI follow-up (87% of sample)

Condition 2. CATI only (13% of sample)

PALS: Adjustment Plan

- Comparison of Web completes to CATI-only completes
  - Using regression modeling
  - Exclude mode non-compliers
- Test most questions for mode effects
- For sensitive items we may proceed using the Web mode as the benchmark because main concern in social desirability
- Make adjustments where necessary
  - Deriving adjustments from regression models in which survey responses are regressed on mode and demographic variables (Elliott et al. 2009; Ezzati et al.2006)
  - Using multiple imputation based on a response utility model

PALS: Sample Structure

Respondent Type: initial assignment -> ultimate completion mode	Completions	Unweighted %	Weighted %
CATI only	93	6.5%	7.1%
Web only	1,102	77.6%	79.4%
CATI -> Web	72	5.1%	4.1%
Web -> CATI	154	10.8%	9.4%
Overall	1,421	100%	100%

PALS: Mode Accessibility

Do you connect to the Internet from a laptop or desktop computer in your home?

Yes, home Internet	CATI only	Web only	CATI -> Web	Web -> CATI
Raw count	72	948	59	56
Unweighted %	77.4%	86.2%	81.9%	36.6%
Weighted %	89.0%	85.8%	87.9%	45.9%

Regression Adjustment

Motivation

- Consider a regression model:

$$y = x'\beta + \gamma m + \varepsilon$$

  - y is the response of interest
  - x are demographic predictors
  - m is the survey mode indicator (0 for the reference mode)
  - β is the vector of regression coefficients
  - γ is the mode effect
  - ε is the regression residual

- Regression adjustment:
  - Form predicted value $\hat{y}$ purging the term $\hat{\gamma}m$ from the equation:

$$\hat{y} = x'\hat{\beta} \text{ or } \hat{y} = x'\hat{\beta} + \hat{\varepsilon}$$

- Can be generalized to other regression models (e.g., logistic)

Multiple Imputation Adjustment

Microeconomic Utility Ideas

- Economists think about binary or ordinal response variables as imperfect observations of an underlying "utility" of the response
- Logistic regression model:
  - Utility part: $y^* = x'\beta + \gamma m + \varepsilon$, residual ε has a logistic distribution
  - Observed choice: $y = \begin{cases} 1, & y^* > 0 \\ 0, & y^* \le 0 \end{cases}$
- If we observe response y=1, we can only conclude that $\varepsilon > -x'\hat{\beta} - \hat{\gamma}m$
- We can simulate the residual from this conditional distribution
- To avoid too much randomness, repeat the simulation M times
- Purge the utility of the mode effect $\hat{\gamma}m$ and simulate the response y for the utilities thus defined

PALS: Mode Effect Findings

- 349 variables screened for mode effects, from “What color is your hair today” to “Did you vote in 2008 elections”
- 19 variables have demonstrated significant mode effects in a two-way table
  – Rao-Scott (1981) corrected p-values for the test itself
  – Benjamini-Hochberg (1995) false discovery rate multiple testing adjustment
- 5 variables demonstrated significant effects in regression models

PALS: Mode Effect Findings

- “In the past 12 months, have you helped directly by giving some of your time… to close family?”
- “In the past 12 months, have you helped directly by giving some of your time… to neighbors?”
- “What color is your hair today?”
- “In the past 5 years, have … you had a major financial crisis?”
- “Not including people living in your home, about how many people, if any, would you say you feel close to?”

PALS: Mode Effect Adjustments

"In the past 12 months, have you helped directly by giving some of your time… to close family?"

Proportion "Yes"	Raw data	Regression adjustment	Utility MI adjustment
CATI only	92.6% (2.7%)	75.5% (2.4%)	73.0% (9.1%)
Web only	76.2% (1.9%)	76.3% (1.9%)	76.2% (1.9%)
CATI -> Web	73.2% (7.1%)	77.2% (1.7%)	73.2% (7.1%)
Web -> CATI	75.3% (4.4%)	77.2% (2.3%)	60.2% (6.4%)
Overall	77.1% (1.6%)	76.4% (1.8%)	74.4% (1.8%)

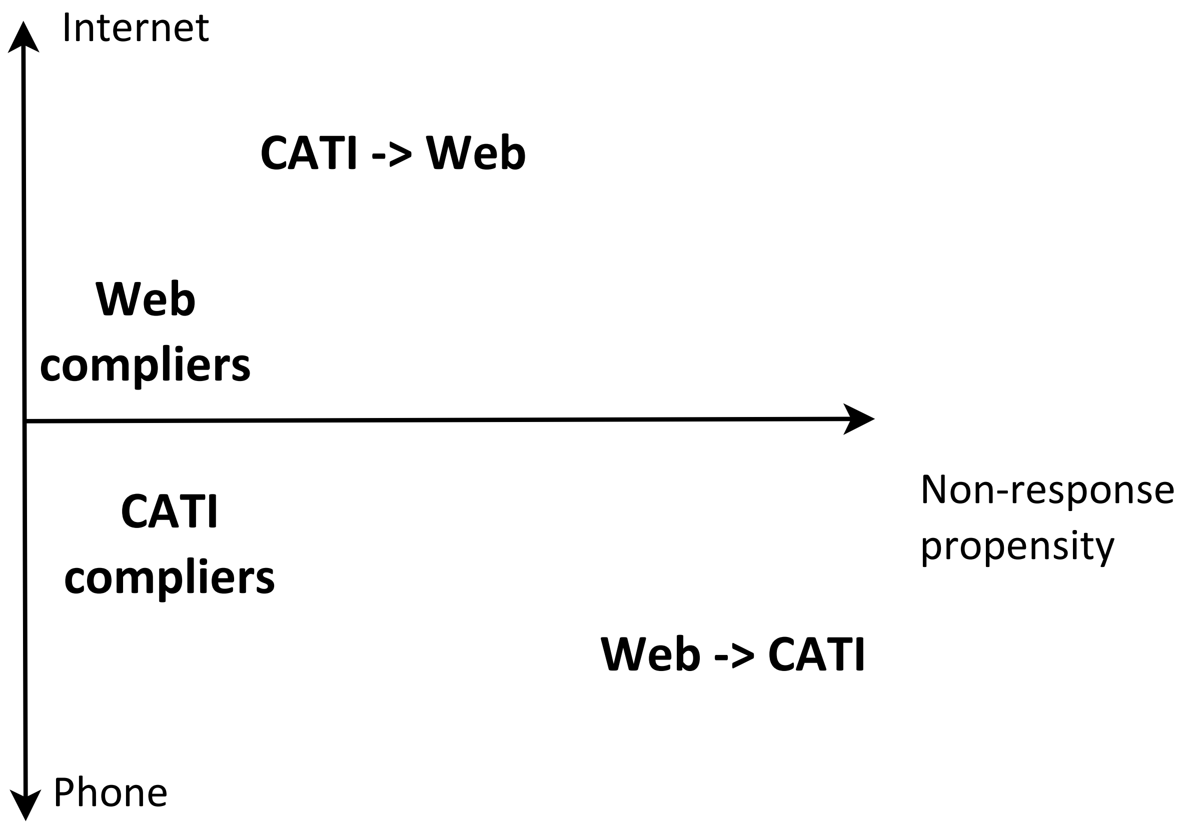
PALS: Mode Effect Adjustments

"In the past 5 years, have …
you had a major financial crisis?"

Proportion "Yes"	Raw data	Regression adjustment	Utility MI adjustment
CATI only	14.2% (4.6%)	32.1% (2.8%)	30.6% (9.6%)
Web only	34.9% (2.7%)	35.5% (2.6%)	34.9% (2.7%)
CATI -> Web	45.3% (9.2%)	40.1% (3.1%)	45.3% (9.2%)
Web -> CATI	21.3% (5.2%)	29.6% (2.7%)	35.4% (7.4%)
Overall	32.9% (2.3%)	34.9% (2.5%)	35.2% (2.5%)

Limitations

- Common support issue?



Conclusions/Next Steps

- Comprehensive test for mode differences after survey completion
- Account for multiple comparisons
- If necessary develop corrections if there is compelling evidence that it will decrease total survey error (not just bias)
- If corrections are used, incorporate them into the standard errors
- For future work, assess trade-off between switching modes to reduce nonresponse bias, potentially increasing measurement error, and devoting resources to correcting mode effects
- Preliminary conclusion: mode effects correction is probably not advisable in most multi-mode studies, but it could be for some and more work is needed to understand when it should be done and best practices for implementation

Thank You

www.palsresearch.org

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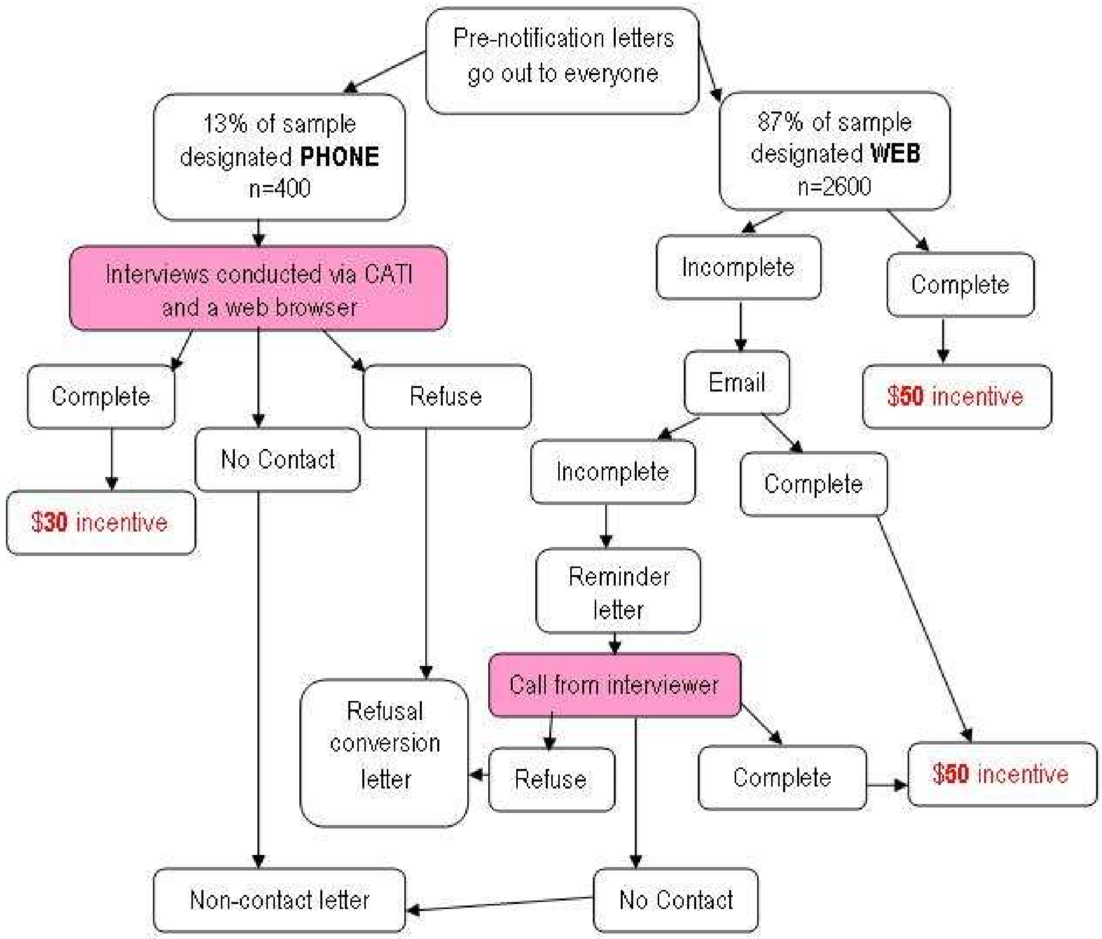
Wave 2 – Data Collection



Wave 2 – Respondent Contacts

- Locating Letter
- Pre-notification Letter
- E-mail Invitation (web only)
- Noncontact Letter
- Refusal Conversion Letters (Tailored)
- Phone calls (10 call design)

Why not out-of-the-box MI?

- ${}^{\{k\}}y_i$ = response of unit i in mode k
  - $k = 1$: CATI
  - $k = 0$: Web (reference)
- Imputation (e.g., MICE): simulate ${}^{\{0\}}y_i | x_i, \theta$
  - Simulates noisy data when $\gamma = 0$ in population
- IUMI (this work): simulate ${}^{\{0\}}y_i | x_i, {}^{\{1\}}y_i, \theta$
  - Leaves data intact when $\gamma = 0$ in population

Why not Bayesian?

- Complex design – need to model all stages of selection – don't have the information ☹
- Still need a good response model, otherwise boils down to a Bayesian logistic regression
- Empirical Bayesian approach here: simulate from ${}^{\{0\}}y_i|x_i, \hat{\theta}$ rather than full predictive distribution ${}^{\{0\}}y_i|x_i$

Uncertainty about $\hat{\gamma}$?

- Subtract $\tilde{\gamma} \sim N\left(\hat{\gamma}, \{\mathrm{s.e.}[\hat{\gamma}]\}^2\right)$ rather than just $\hat{\gamma}$ when doing the mode effect correction
- The standard errors increased slightly in the third decimal point