



Incorporating Level of Effort Paradata in Nonresponse Adjustments

Paul Biemer RTI International University of North Carolina – Chapel Hill

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Outline of this talk

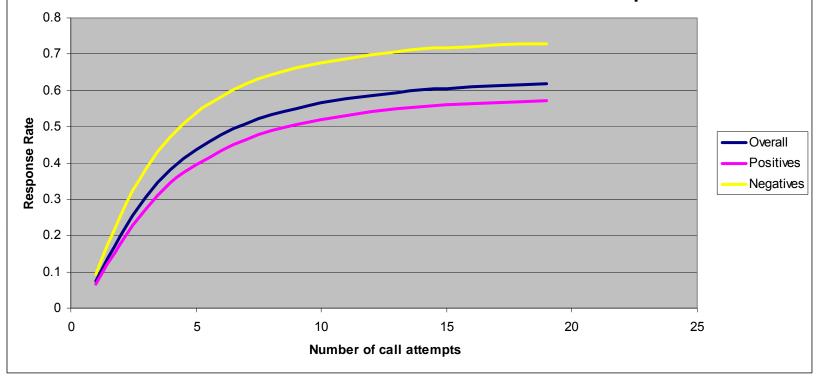
- Brief review of the literature
- Discussion of some issues in using LOE paradata
- Simple callback model for dichotomous variables
- Estimation via the EM algorithm
- Testing and adjusting for nonignorable nonresponse (NINR) bias
- Application to the National Survey on Drug Use and Health (NSDUH)
- Summary and Future Directions





What information does LOE paradata contain about response propensity?

Response Rate for Positives, Negatives and Overall as a Function of Number of Call Attempts







How can these data be used to inform the nonresponse (NR) bias mitigation process?

- Determine which variables are most subject to NR bias.
- Determine the severity of nonignorable nonresponse (NINR) bias in estimates adjusted for ignorable NR.
- Monitor NR bias during data collection for optimal reallocation of NR conversion resources.
- Adjust for NR bias in the absence of auxiliary data used as adjustment controls
- Adjust for NINR bias





What prior research has been conducted on the use of callback data for NR adjustment?

Early papers

- H.O. Hartley (1946); Politz-Simmons (1949); Simmons (1954) – Based upon retrospective reports of availability. Crude but sometimes effective.
- Remaining literature is divided between two approaches
 - Regression modeling
 - Probability modeling





Modeling Approaches

Regression Modeling

- (Alho, 1990; Anido-Valdez, 2000; Wood, White & Hotopf, 2006)
- Models response propensity at each attempt as a function of partially missing and fully observed predictors
- Inverse predicted propensities are used as weight adjustments
- Uses an modified conditional likelihood method of esitmation.
- Provides weights that adjust for NINR





Modeling Approaches (cont'd)

Probability Modeling

- (Drew-Fuller, 1980; Potthoff, Manton, Woodbury, 1993; Biemer & Link, 2007)
- Models the probability of observation in each cell of the data summary table
- Simultaneously estimates the prevalence of the cross-classifications variables along with the NR parameters
- Partially observed variables completed via the EM algorithm
- Estimates NR propensity components that can be used to build weights that adjust for NINR





What results have been achieved?

- Little has been done to address real-world complexities.
 - Biemer/Link approach was a step in this direction
- Models specifying contact probabilities only have limited applicability for interview surveys.
- No rigorous evaluation of bias reduction capability
 - Validity of the approaches demonstrated on artificial populations or from model fit statistics.
- Studies have shown that NR bias reduction can be dramatic albeit at the cost of increasing variance.





Typical Interview Survey Data Summary Table for a Binary Response Variable, y

Call Attempt	Interv $y = 1$	viewed $y = 2$	Ref/Oth NR $y = 1 \text{ or } 2$	NC (noncontact) y = 1 or 2	Censored NC $y = 1 \text{ or } 2$
1	<i>n</i> ₁₁₁	<i>n</i> ₂₁₁	<i>n</i> ₊₁₂	<i>n</i> ₊₁₃	n_{+1c}
2	<i>n</i> ₁₂₁	<i>n</i> ₂₂₁	<i>n</i> ₊₂₂	<i>n</i> ₊₂₃	<i>n</i> _{+2<i>c</i>}
		•••			
а	n_{1a1}	n_{2a1}	n_{+a2}	n_{+a3}	n_{+ac}
A (truncated)	n_{1A1}	n_{2A1}	n_{+A2}	n_{+A3}	n_{+Ac}





Censored case \rightarrow (prematurely) finalized as NC cases

Call Attempt	Interv $y = 1$	viewed $y = 2$	Ref/Oth NR y = 1 or 2	NC (noncontact) y = 1 or 2	Censored NC $y = 1 \text{ or } 2$
1	n_{111}	<i>n</i> ₂₁₁	n ₊₁₂	<i>n</i> ₊₁₃	n_{+1c}
2	<i>n</i> ₁₂₁	<i>n</i> ₂₂₁	<i>n</i> ₊₂₂	<i>n</i> ₊₂₃	<i>n</i> _{+2<i>c</i>}
		•••			
а	n_{1a1}	n_{2a1}	n_{+a2}	n_{+a3}	n_{+ac}
A (truncated)	n_{1A1}	n_{2A1}	n_{+A2}	n_{+A3}	n_{+Ac}





Truncated case \rightarrow completed after the maximum number of attempts specified by the model; treated as NCs

Call Attempt	Interv $y = 1$	viewed $y = 2$	Ref/Oth NR $y = 1 \text{ or } 2$	NC (noncontact) y = 1 or 2	Censored NC $y = 1 \text{ or } 2$
1	<i>n</i> ₁₁₁	<i>n</i> ₂₁₁	n ₊₁₂	<i>n</i> ₊₁₃	n_{+1c}
2	<i>n</i> ₁₂₁	<i>n</i> ₂₂₁	n ₊₂₂	<i>n</i> ₊₂₃	<i>n</i> _{+2c}
а	n_{1a1}	n_{2a1}	<i>n</i> _{+<i>a</i>2}	<i>n</i> _{+a3}	n_{+ac}
A (max att.)	n_{1A1}	n_{2A1}	n_{+A2}	n_{+A3}	n_{+Ac}





NC cases at attempt *a* are available at attempt *a*+1.

Call Attempt	Interv $y = 1$	viewed $y = 2$	Ref/Oth NR $y = 1 \text{ or } 2$	NC (noncontact) y = 1 or 2	Censored NC $y = 1 \text{ or } 2$
1	<i>n</i> ₁₁₁	<i>n</i> ₂₁₁	n ₊₁₂	<i>n</i> ₊₁₃	n_{+1c}
2 <	<i>n</i> ₁₂₁	<i>n</i> ₂₂₁	n ₊₂₂	n ₊₂₃	<i>n</i> _{+2<i>c</i>}
а	n_{1a1}	n_{2a1}	n_{+a2}	n_{+a3}	n_{+ac}
A (truncated)	n_{1A1}	n_{2A1}	n_{+A2}	n_{+A3}	n_{+Ac}





What are some issues that arise in callback modeling?

- What constitutes an attempt?
 - Definition varies by mode of data collection
 - E.g., is several calls within several hours 1 attempt or multiple attempts
 - Use the definition that is most predictive of the model parameters
- What constitutes a contact?
 - First contact with anyone in the HH?
 - First contact with sample person or guardian?
 - The contact that determines final disposition of the case (i.e., interview, refused, other)
 - Other?





- How should censoring and truncation be modeled?
 - If censoring mechanism is independent of y, it can be ignored.
 - However, standard errors of model parameters will be larger.
- How should weighting be handled in the modeling process?
 - Unweighted data e.g., Pr(*i*th unit responds | *i*th unit is sampled)
 - Weight for probabilities of selection
 - Weight for selection probs and NR using ignorable NR models
- What callback model should be used?
 - Regression model does not adapt well to these complexities
 - Probability model adapts well but has other shortcomings





Essential Idea: Model missing data mechanism and ...

Call Attempt	Interviewed $y=1$ $y=2$		Ref/Oth NR y = 1 or 2	Censored NC $y = 1$ or 2
1	n_{111}	<i>n</i> ₂₁₁	n ₊₁₂	n_{+1c}
2	<i>n</i> ₁₂₁	<i>n</i> ₂₂₁	<i>n</i> ₊₂₂	<i>n</i> _{+2<i>c</i>}
	•••	•••		
а	n_{1a1}	n_{2a1}	n_{+a2}	n_{+ac}
	•••	•••	•••	
A (truncated)	n_{1A1}	n_{2A1}	n_{+A2}	n_{+Ac}





...complete the table.

	Intervi	ewed	Refusals/Other NR		Refusals/Other NR Censo	
Attempt	<i>y</i> =1	<i>y</i> =2	<i>y</i> =1	<i>y</i> =2	<i>y</i> =1	<i>y</i> =2
1	n ₁₁₁	n ₂₁₁	n ₁₁₂	n ₂₁₂	n ₁₁₃	n ₂₁₃
а	n _{1a1}	n _{2a1}	n _{1a2}	n _{2a2}	n _{1a3}	n _{2a3}
A	n _{1A1}	п _{2А1}	n _{1A2}	n _{2A2}	n _{1A3}	n _{2A3}
Totals	n ₁₊₁	n ₂₊₁	n ₁₊₂	n ₂₊₂	n ₁₊₃	n ₂₊₃





This will yield a model unbiased estimate of prevalence.

	Intervi	ewed	Refusals/	Other NR	Censo	ored
Attempt	<i>y</i> =1	<i>y</i> =2	<i>y</i> =1	<i>y</i> =2	<i>y</i> =1	<i>y</i> =2
1	n ₁₁₁	n ₂₁₁	n ₁₁₂	n ₂₁₂	n ₁₁₃	n ₂₁₃
а	n _{1a1}	n _{2a1}	n _{1a2}	n _{2a2}	n _{1a3}	n _{2a3}
A	<i>n</i> _{1A1}	п _{2А1}	n _{1A2}	n _{2A2}	n _{1A3}	n _{2A3}
Totals	<i>n</i> ₁₊₁	n ₂₊₁	n ₁₊₂	n ₂₊₂	n ₁₊₃	n ₂₊₃

Estimate prevalence:
$$\hat{\pi} = \frac{n_{1+1} + n_{1+2} + n_{1+3}}{2}$$







Basic Call-back Model for Binary Response

Notation

Let

- a = call attempt;
 - = 1,...,*A*
- b = call outcome;
 - =1 for interview,
 - =2 for refusal/other nr
 - =3 for noncontact





Basic Call-back Model for Binary Response

 π = true prevalence

$$\alpha_{y,a} = \Pr(\text{contact at attempt } a | y)$$

$$\beta_{y,a} = \Pr(b = 1) = \Pr(\text{interview} | y, \text{ contact at attempt } a)$$

$$1 - \beta_{y,a} = \Pr(b = 2) = \Pr(\text{refusal/oth NR} | y, \text{ contact at attempt } a)$$

$$\delta = \Pr(\text{censored at attempt } a)$$





Simple Call-back Model for Binary Response

Assume:

$$\alpha_{y,a} = \alpha_y$$
 for all a
 $\beta_{y,a} = \beta_y$ for a

For a binary response variable, *y*, this results in six parameters: π , α_1 , α_2 , β_1 , β_2 , and δ





Cell Frequencies and Probabilities

	Interviewed		Refusals/ Other NR	Censored NCs
	<i>y</i> =1	<i>y</i> =2	<i>y</i> is unknown	<i>y</i> is unknown
Cell freq $a = 1, \dots, A$	n_{1a1}	n_{2a1}	n_{+a2}	n_{+a3}
Prob $a = 1, \dots, A$	π_{1a1}	π_{2a1}	$\pi_{+a2} = \pi_{1a2} + \pi_{2a2}$	$\pi_{+a3} = \pi_{1a3} + \pi_{2a3}$





Probabilities for Basic Model

Interview:
$$y=1$$
 $\pi_{1a1} = (1-\delta)^{a-1} [\pi (1-\alpha_1)^{a-1} \alpha_1 \beta_1]$

Interview: y=2
$$\pi_{2a1} = (1-\delta)^{a-1}[(1-\pi)(1-\alpha_2)^{a-1}\alpha_2\beta_2]$$

Refused
$$\pi_{+a2} = (1 - \delta)^{a-1} [\pi (1 - \alpha_1)^{a-1} \alpha_1 (1 - \beta_1) + (1 - \pi)(1 - \alpha_2)^{a-1} \alpha_2 (1 - \beta_2)]$$

NC – Censored
$$\pi_{+a3} = (1 - \delta)^{a-1} \delta [\pi (1 - \alpha_1)^a + (1 - \pi)(1 - \alpha_2)^a]$$





EM Algorithm to Estimate Parameters

E-step at *t*th iteration

Refusals
$$\hat{n}_{1a2}^{[t]} = n_{+a2} \frac{\hat{\pi}_{1a2}^{[t]}}{\hat{\pi}_{1a2}^{[t]} + \hat{\pi}_{2a2}^{[t]}}, \quad \hat{n}_{2a2}^{[t]} = n_{+a2} \frac{\hat{\pi}_{2a2}^{[t]}}{\hat{\pi}_{1a2}^{[t]} + \hat{\pi}_{2a2}^{[t]}}$$

NC-censored
$$\hat{n}_{1a3}^{[t]} = n_{+a3} \frac{\hat{\pi}_{1a3}^{[t]}}{\hat{\pi}_{1a3}^{[t]} + \hat{\pi}_{2a3}^{[t]}}, \quad \hat{n}_{1a3}^{[t]} = n_{+a3} \frac{\hat{\pi}_{2a3}^{[t]}}{\hat{\pi}_{1a3}^{[t]} + \hat{\pi}_{2a3}^{[t]}}$$





EM Algorithm to Estimate Parameters

M-step at (t+1)th iteration

$$\begin{aligned} \hat{\alpha}_{1}^{[t+1]} &= \frac{\sum_{a} (n_{1a1} + \hat{n}_{1a2}^{[t]})}{\sum_{a} a(n_{1a1} + \hat{n}_{1a2}^{[t]} + \hat{n}_{1a3}^{[t]})}; \quad \hat{\alpha}_{2}^{[t+1]} = \frac{\sum_{a} (n_{2a1} + \hat{n}_{2a2}^{[t]})}{\sum_{a} a(n_{2a1} + \hat{n}_{2a2}^{[t]} + \hat{n}_{2a3}^{[t]})} \\ \hat{\beta}_{1}^{[t+1]} &= \frac{\sum_{a} n_{1a1}}{\sum_{a} (n_{1a1} + \hat{n}_{1a2}^{[t]})}; \quad \hat{\beta}_{2}^{[t+1]} = \frac{\sum_{a} n_{2a1}}{\sum_{a} (n_{2a1} + \hat{n}_{2a2}^{[t]})} \end{aligned}$$

$$\hat{\delta} = \frac{\sum_{a} n_{+a3}}{n}$$





Estimate of Prevalence

$$\pi^{[t+1]} = \frac{\sum_{a} (n_{1a1} + \hat{n}_{1a2}^{[t]} + \hat{n}_{1a3}^{[t]})}{\sum_{y} \sum_{a} (n_{ya1} + \hat{n}_{ya2}^{[t]} + \hat{n}_{ya3}^{[t]})}$$





Tests of Ignorability

$$H_0: \alpha_1 = \alpha_2 \text{ and } \beta_1 = \beta_2$$
$$H_1: \alpha_1 \neq \alpha_2 \text{ and } \beta_1 = \beta_2 \text{ or } H_1': \alpha_1 \neq \alpha_2 \text{ or } \beta_1 \neq \beta_2$$
Test statistics

$$G^{2}(M_{0}) - G^{2}(M_{1}) \sim \chi_{1}^{2}$$
 $G^{2}(M_{0}) - G^{2}(M_{1}') \sim \chi_{2}^{2}$

$$G^2(M) = 2\sum_c n_c \ln \frac{n_c}{\hat{n}_{c,M}}$$





Tests of Ignorability

$$H_0: \alpha_1 = \alpha_2 \text{ and } \beta_1 = \beta_2$$

$$H_1: \alpha_1 \neq \alpha_2 \text{ and } \beta_1 = \beta_2 \text{ or } H_1': \alpha_1 \neq \alpha_2 \text{ or } \beta_1 \neq \beta_2$$

Test statistics
preferred

$$G^2(M_0) - G^2(M_1) \sim \chi_1^2 \qquad G^2(M_0') - G^2(M_1) \sim \chi_2^2$$

$$G^2(M) = 2\sum_c n_c \ln \frac{n_c}{\hat{n}_{c,M}}$$





Indicators of Nonignorable Bias Based on M₁

Designed to measure the magnitude of the NR bias prior to, during and after traditional NR weighting

$$\Delta G^{2} = G^{2}(M_{0}) - G^{2}(M_{1})$$

$$R = \frac{G^{2}(M_{0}) - G^{2}(M_{1})}{G^{2}(M_{0})}$$

$$D = \frac{G^{2}(M_{0}) / df_{0} - G^{2}(M_{1}) / df_{1}}{G^{2}(M_{0}) / df_{0}}$$





Indicators of Nonignorable Bias Based on M₁

Designed to measure the magnitude of the NR bias prior to, during and after traditional NR weighting

$$\Delta G^{2} = G^{2}(M_{0}) - G^{2}(M_{1}) \text{ preferred}$$

$$R = \frac{G^{2}(M_{0}) - G^{2}(M_{1})}{G^{2}(M_{0})}$$

$$D = \frac{G^{2}(M_{0}) / df_{1} - G^{2}(M_{1}) / df_{0}}{G^{2}(M_{0}) / df_{0}}$$





Application – National Survey on Drug Use and Health

- NSDUH is quarterly survey to estimate the prevalence of drug, alcohol and tobacco use in U.S.
- 170,000 households are screened and 67,500 interviews are conducted per year
- Response rates are approx. 90% (screener) and 78% (interview)
- Only screener respondents are used in our analysis (i.e., adjustments pertain only to interview survey nonresponse)





Current NSDUH NR Adjustment

- Uses the GEM (generalized exponential model), a logistic regression response propensity adjustment
- Incorporates 13 grouping variables and their interactions including a number of state specific components
- This model will be referred to as the GEM model
- We also considered the GEM+ model obtained by simply adding the LOE variable to the GEM model.







- Call attempt attempt to contact recorded by l'er; similar to call slots (morning, afternoon, evening of same day)
- Contact attempt first call attempt resulting in face to face contact with the sample member
- Contact outcomes interview, refused, other NR and NC (censored)





Some Research Questions Addressed in this Research

- Will the test for ignorability be rejected for key estimates?
- Is the probability callback model a valid approach remove the NINR bias?
- Which model works best?
- How do the probability model results compare with simply adding the LOE variable (i.e., number of call attempts) to the GEM model?





Some Callback Models Considered

Model

Mod0 - $\alpha_1 = \alpha_2 = \alpha$ and $\beta_1 = \beta_2 = \beta$ Mod1 – α_1, α_2 and $\beta_1 = \beta_2 = \beta$ Mod2 – $\alpha_{11}, \alpha_{12}, \alpha_{21}, \alpha_{22}$ and $\beta_1 = \beta_2 = \beta$ Mod3 - $\alpha_1 = \alpha_2 = \alpha$ and β_1, β_2 Mod4 – α_1, α_2 and β_1, β_2

Homogeneous contact and interview probabilities (GEM)

Homogeneous contact probs Heterogeneous interview probs Same as Mod1 except contact probs change after attempt 1

Homogeneous contact probs Heterogeneous interview probs Heterogeneous contact and interview probs





Our Approach

- Fit the standard GEM model to obtain estimated response propensities for each unit
 - To create NINR bias for some variable x*, x* was omitted from the GEM model.
 - e.g., $logit(p_i) = \mathbf{X}'_{-x^*} \boldsymbol{\beta}$ makes x^* an ignored variable in the estimation of response propensity, p_i
 - Choices for x^* included age, race and sex
- Divide the sample into 20 strata based upon the propensity, p_i
- Compare the estimates of the missing variable, x*, across the NINR adjustment models







Tests of Ignorability





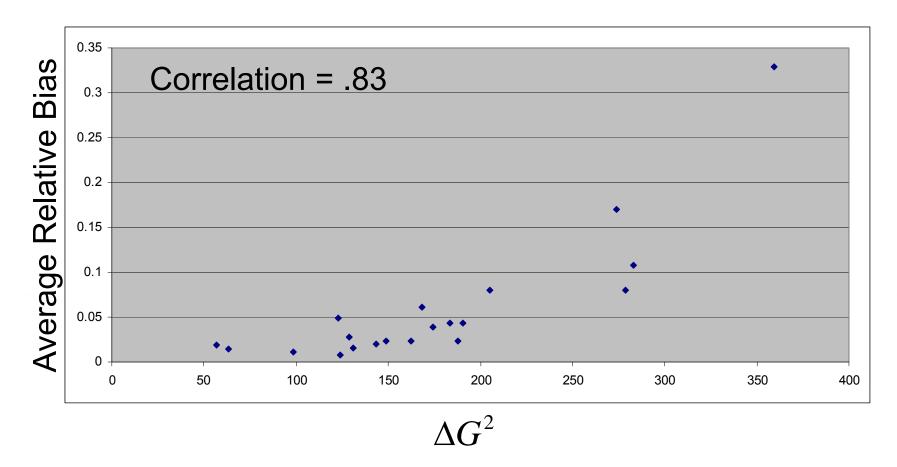
Tests of H₀ vs. H₁

Ignored Variable, x*	ΔG^2	df	χ^2_{df}	$\alpha_{y} = \alpha$
Age	174	4	9.5	Rejected
Race	172	4	9.5	Rejected
Sex	62	1	3.8	Rejected
Alcohol Use	60	1	3.8	Rejected
Marijuana Use	135	1	3.8	Rejected
Cocaine Use	165	1	3.8	Rejected





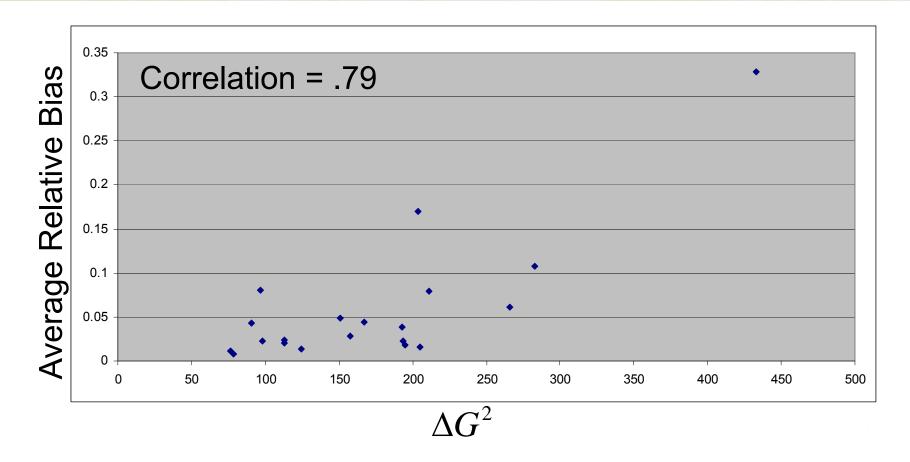
Average Relative Bias as a Function of ΔG^2 for 20 Propensity Strata: AGE







Average Relative Bias as a Function of ΔG^2 for 20 Propensity Strata: RACE









Comparison of Estimates





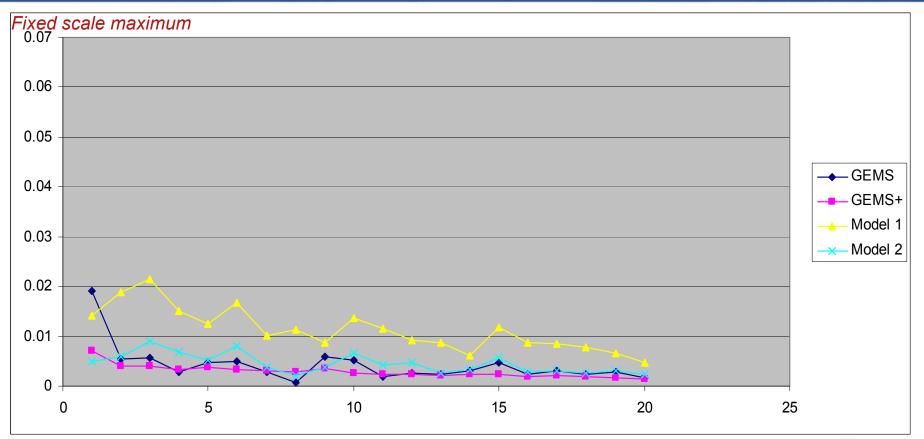
Problems with Heterogeneous β 's Models

- Heterogeneous outcome probability models (e.g., Mod3 and Mod4) performed quite poorly
- Based upon a simulation study, behavior of these models appears consistent with callback data recording errors
 - Suppose some proportion of callbacks are not recorded
 - It can be shown that estimates of the callback model parameters are biased.
 - Biases were generally low for the homogeneous β 's models
 - Biases were quite large for the heterogeneous β 's models particularly for small values of π
- These models will not be considered further in the results.





Average Bias for Four Models: RACE

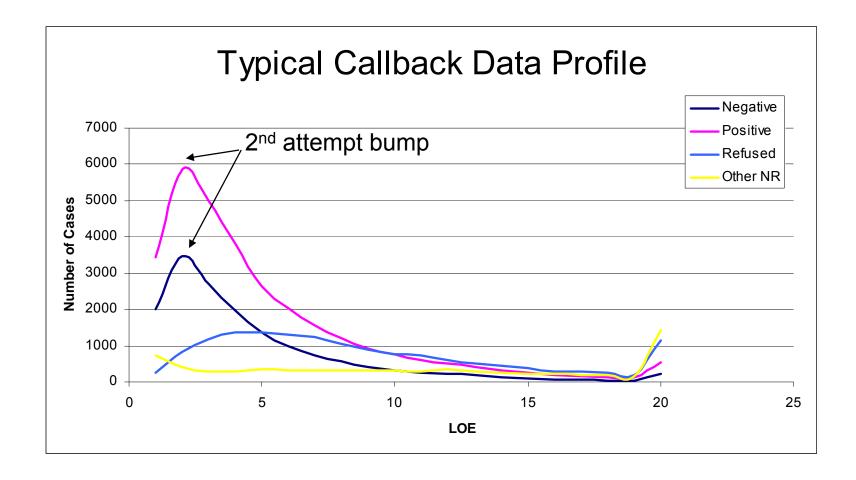


Propensity Stratum





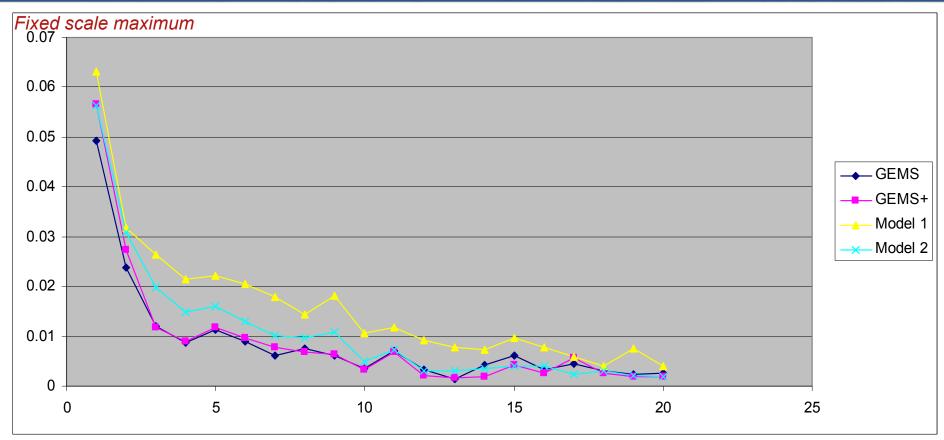
Mod2 Provides for Change in Contact Probabilities after Initial Attempt







Average Bias for Four Models: AGE

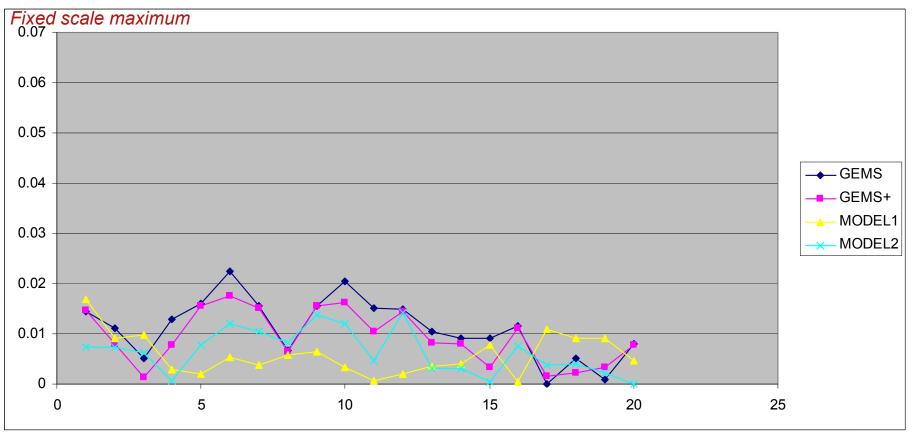


Propensity Stratum





Average Bias for Four Models: SEX

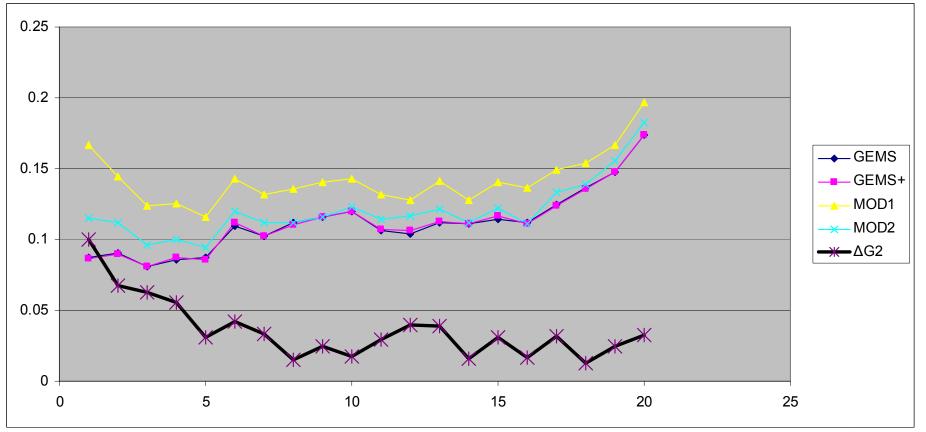


Propensity Stratum





Estimates of Past Year Marijuana Use and ΔG^2 (Rescaled) by Propensity Group



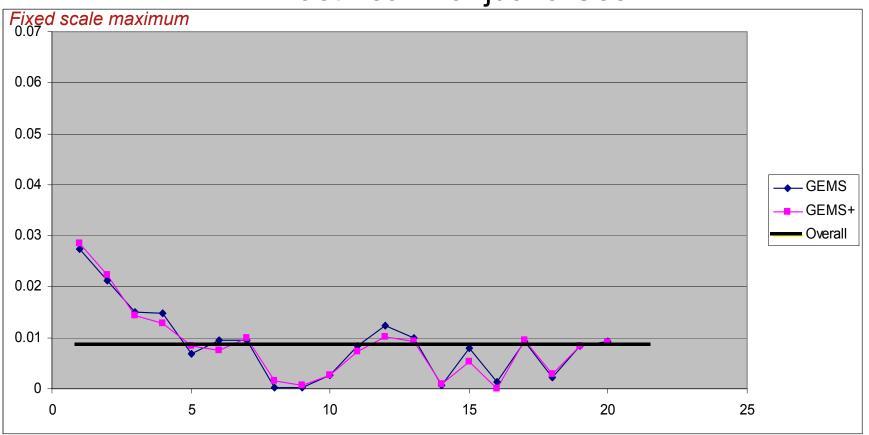
Propensity Stratum





Bias in GEM and GEM+ Adjustments Using Mod2 as the Gold Standard

Past Year Marijuana Use









Summary and Future Directions







- χ^2 NINR indexes performed well in these tests
- Can be applied post-survey weighting as a check on residual NINR bias
- Models with heterogeneous contact probabilities performed well
- Models with heterogeneous interview probabilities did not perform well
- Suspect the problem is errors in the callback data
- Surprisingly, the GEM+ model was also effective at eliminating NINR bias.
 - It outperformed the probability callback models for some estimates





Future Directions

Model Improvements

- Alternative definitions for call attempt, contact attempt and contact outcome
- Expand application of the models to other variables
- Consider modifications to field procedures for recording of call attempts

Other Applications

- Optimization of fieldwork (e.g., responsive design)
- Representivity measures for international surveys



