Using Callback Models to Adjust for Nonignorable Nonresponse in Face-to-Face Surveys

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Abstract

In most sample surveys, weighting procedures attempt to compensate for nonresponse bias under the assumption of "ignorable nonresponse"; i.e.,, the data that is known for both respondents and nonrespondents are sufficient to adequately adjust for nonresponse bias. Biemer and Link (2007) provided a general method for nonresponse adjustment that relaxed the ignorable nonresponse assumption. Their method, which extended the ideas of Drew and Fuller (1980) used indicators of level of effort (LOE) based on call attempts to model the probability that an individual in the sample responds to the survey (referred to as the response propensity). For many surveys, call history data are available for all sample members, including nonrespondents and since the LOE required to interview a sample member is likely to be highly correlated with response propensity, this method is ideally suited for modeling the nonignorable nonresponse.

Biemer and Link (2007) applied their approach to data for a random digit dial (RDD) telephone survey. For this study, we applied this approach to data from an in-person survey, the 2004 National Survey on Drug Use and Health (NSDUH). The NSDUH is an annual in-person, cross-sectional study conducted in all 50 states and the District of Columbia. The NSDUH is designed to measure the prevalence and correlates of drug use in the United States population age 12 and older.

1. The Callback Model

The callback model contains two types of variables: variables associated with each LOE and the grouping variables. The latter are characteristics of the sample members expected to be correlated with response propensity. The LOE variables are categorical variables each having *k* categories corresponding to *k* mutually exclusive and exhaustive call outcomes. Following Biemer and Link (2007), we defined three outcome categories: interview, refusal (final) and noncontact.[1] The first two categories were assumed to be "absorbing states;" i.e., once a case enters this state for some LOE, it can never exit the state. The noncontact category is a non-absorbing state; i.e., units not contacted at some LOE can be contacted and either interviewed or noninterviewed at a later LOE.

We defined seven LOE variables as described in the next section. Further, only cases that reached an absorbing state or were called at full effort (i.e., LOE 7) were considered in the analysis; i.e., all right censored cases (approximately 1% of all cases) were deleted from the analysis to simplify the models. These are cases that did not receive full effort before the field work terminated. Biemer and Link (2007) discuss methods for including right censored cases and show that excluding such cases does not bias the model parameters if their number is relatively small or if the censoring mechanism is independent of the LOEs conditional other variables in the model.

Many of the grouping variables we considered were ones that are also used in the traditional NSDUH nonresponse propensity models. However, unlike traditional propensity models, the callback model is not restricted to variables that are known for nonrespondents and respondents; thus, other variables available from the NSDUH interview were also used.

The callback model estimates the response propensity for domains defined by the cross-classification of the grouping variables. The response propensity estimates are based upon the callback patterns associated with all respondents in each domain. For example, domains associated with patterns that reflect easy to interview cases are assigned high response propensities while patterns reflecting high nonresponse or difficult to reach individuals are assigned low response propensities.

Like response propensity modeling and weighting class adjustments, a key assumption of the callback modeling approach is that, within a particular domain, all persons have the same response propensity at each LOE. However, with the callback modeling approach, it is possible to relax this assumption by introducing a latent indicator variable for the hardcore nonrespondent (HCNR) subpopulation. HCNRs are defined as nonrespondents having a 0 probability of ever responding to the survey under the current protocol. The HCNR indicator variable is latent since HCNRs cannot be distinguished from nonrespondents in the sample who would have responded at some point in the future had the followup process continued indefinitely. Biemer and Link (2007) showed that the inclusion of the HCNR latent variable greatly improved the fit of the callback model and provided much

[1] The third category actually includes other interim results such as making appointments or interim refusals. It could be described as any other result other than a completed interview or a final refusal. Most of the cases in this category have final result codes of "No one at Dwelling Unit" or "Respondent Unavailable." Other final result codes in this category are "Physically/Mentally Incompetent," "Language Barrier (Hispanic or Other)," "Break-Off" and "Other."

better agreement with external gold standard estimates, particularly for survey protocols specifying lower levels of effort. In our analysis, we only considered models that incorporated the HCNR latent indicator variable.

2. Applying the Callback Model to the NSDUH

The NSDUH interview process consists of a household screener used to enumerate household members and identify eligible respondents followed by 0, 1 or 2 interviews with members of the household selected for an interview. In 2004, 169,514 households were screened and interviews were conducted with 67,760 respondents. The weighted screener response rate was 90.9 percent and the weighted interview response rate was 77.0 percent.

2.1 Level of Effort

For measuring the level of effort, we considered several indicators based on the number of individual call attempts to complete interviews as well as numbers of call days to complete interviews. For the analyses in this study, we used an indicator of effort based on "call slots". The level of effort was defined as follows:

LOE i = i call slot attempts for i = 1 to 4,
LOE 5 = 5 or 6 call slot attempts,
LOE 6 = 6, 7, 8 or 9 call slot attempts, and
LOE 7 = 10 or more call slot attempts.

Here, the term "call slot" refers to both interview and screener attempts. In order to create call slots, the day is divided into three time periods; Mornings (before 12pm), Afternoons (12 to 5pm), and Evenings (after 5pm).

All call attempts within the same time period during the same day are aggregated into a single call slot. For example, two call attempts in the morning and one in the afternoon on the same day to the same dwelling unit are treated as two call slot attempts. The "call slot attempt" approach was chosen as a compromise between looking at individual call attempts, which may overstate the level of effort, and call days, which yielded too little variability in a level of effort measure. ***Table 1*** shows the distribution of the number of call slot attempts required to interview respondents in 2004.

2.2 Grouping Variables

To identify the grouping variables that are most correlated with nonresponse, we used Chi-squared Automatic Interaction Detector (CHAID) software. As noted previously, the dependent measure in fitting the callback models in our analysis was trichotomous – viz., interviewed, noninterviewed and noncontact by LOE k – and pertains only to the interview process. Thus, the sample for this analysis was confined to only those cases that were successfully screened at the NSDUH screening stage. The study was confined to just interview nonresponse because the screener nonresponse rate was low and negligible.

Separate analyses were performed among the respondent cases for call attempts (or LOEs) 1, 2 and 3. The dependent variable was whether or not the interview had been completed by that particular call attempt. Biemer and Link (2007) found little benefit from considering more than three call attempts for identifying grouping variables for the callback model. As we expected, the top six or so variables identified for call attempt k=1 overlapped considerably with those identified in for higher values of k.

Approximately 20 variables thought to be correlated with both nonresponse and the outcome variables of interest were examined in the CHAID analysis In addition, we estimated a logistic regression model predicting whether or not the interview was completed within the first three call slots (among completed interviews). Respondents in the Northeast and South regions were more likely to complete the interview in the first three call slots than those in the West region. Respondents in Metropolitan Statistical Areas (MSAs) were less likely to be early completes than those in non-MSAs. Those between the ages of 18 to 49 were less likely to be early completes than respondents 50 and older. Respondents who reported receiving assistance from one or more government programs (Supplemental Security Income, Food Stamps, cash assistance and non-cash assistance) were more likely to be early completes.

Two factors that had negative effects on early completion were the presence of access barriers and having been interviewed by an interviewer with any prior NSDUH experience before 2004. Respondents in households with two persons selected for the interview were more likely to be early completes than respondents in households with only one person selected. Finally, respondents working full-time were less likely to be early completes than those not working or not in the labor force.

The top 10 grouping variables identified in this analysis comprised the set of grouping variables used in fitting the callback models. These were age, race/ethnicity, sex, health, presence of access barriers, income, government program participation, density, region and number of sample persons selected. While more than 10 variables could have been chosen, this number was sufficient to adequately model response propensity.

2.3 Model Fitting and Producing Alternative Weights

We used the •EM software (Vermunt, 1997) to fit the latent callback models, using all seven LOE variables. To identify the grouping variables to be retained, the selection process proceeded as follows:

1. Starting with the 10 best grouping variables from the CHAID analysis, we fit all 10 single grouping variable models in order to determine which variables were best for explaining the variation in the table formed by cross classifying all 17 variables.

2. Using the top five grouping variables from this analysis, we consider all possible models of five, four, three and two grouping variables.
3. Among all the models considered in (b), choose the model that (i) fits the data as determined by a chi-squared goodness of fit test or has a dissimilarity index of 5% or less and (ii) minimizes the model BIC.

Implementing this approach, the best model contained four grouping variables: race/ethnicity as reported by the screener respondent (Race), government program participation (Prog), Age and number of persons selected within the household (Selected). Two of the variables – Race and Prog – were only known for respondents while the other two variables – Age and Selected – were known for all nonrespondents as well as respondents. Even with this small set of optional variables, the number of possible restrictions on the model made model selection a daunting task. For this study, we only considered models for which the interactions between the grouping variables and the LOE variables were restricted to be equal across all LOE. In other words, we assumed that the response probability at LOE k given a nonresponse at LOE k-1 was equal to the response probability at LOE 1 for $k = 2,\ldots,7$.

Three versions of this model were fit in the analysis as summarized in ***Table 2***. Model 1 was the most parsimonious model with only 168 parameters. The other two models were more complex. Models 2 and 3 had nearly the same number of parameters but employed different restrictions on the interactions terms as noted in ***Table 2***. For each of these models, nonresponse adjustment weights were generated and estimates were produced and compared with the unadjusted estimates as well as with an approach representing the current NSDUH method.

The NSDUH nonresponse model incorporates 13 grouping variables and their interactions including a number of state specific components (Chen, et al., 2003). A latent callback model that incorporated all the complexity of the NSDUH nonresponse model as well as the LOE and latent indicator variables would be even more complex.

The key differences between the NSDUH (or traditional) approach for nonresponse propensity modeling and the callback model is that the latter incorporates the LOE variables, variables only observable among respondents and a latent HCNR indicator variable. If these features were omitted from the callback model, the result would essentially be a logistic regression model much like that used for the NSDUH approach. Therefore, one means for comparing the effectiveness of the two approaches is to develop a parallel model which is equivalent to the latent callback model but excludes the modeling features that are unique to the latent callback modeling approach. Although this model would be much less complex than the current NSDUH model, it represents the NSDUH (or traditional) approach and provides some indication of how much the unique features of the callback model can further reduce nonresponse bias. For comparisons with the models in ***Table 2***, the equivalent NSDUH model is essentially a fully saturated logistic regression model with two dependent variables: age and selected. We refer to this model as the simulation model since it is only intended to simulate the comparison between the traditional model and the callback modeling approaches.

3. Results

Table 3 compares five sets of estimates and their standard errors for five variables from the screener survey: region, access, density, race/ethnicity and age. These variables are of interest primarily because they are available for both respondents and nonrespondents and therefore their “true” distributions can be estimated using weights prior to interview level nonresponse adjustment. Thus, the gold standard estimates for these variables are in column 1 of ***Table 3***. The columns labeled Model 1, Model 2 and Model 3 correspond to the three callback models and the column labeled NSDUH-SIM corresponds to the simulated NSDUH estimate described above.

Table 4 compares the absolute biases for the estimates in ***Table 3***. Following the last category of each variable in the table is the Dissimilarity Index defined as 0.5 times the sum of the absolute biases over the categories of the variable. This measure summarizes the absolute biases in each estimation approach and may be interpreted as the proportion of the population that is misclassified by the estimation approach assuming the full sample estimate is the true distribution.

For the most part, the absolute biases are small, averaging less than 0.5 percentage points. The Dissimilarity Indexes are generally one percent or less except for one variable, race/ethnicity. This variable exhibits a relative large bias for the three callback model estimates. Note that this race variable, which is available for the entire sample, is not the same variable that was used in fitting Models 1 – 3, which was available only for respondents. The difference is that, for noninterviews, race/ethnicity in the table is a proxy report of the selected person’s race given by the screening respondent. We suspect the reason for the large discrepancies between the “true” distribution and the model estimates is due to the proxy reports. This will be discussed in more detail below. Note also that for age, the nonresponse adjustments seem to work perfectly. This is expected since all models force the age distribution to equal the screener control totals.[2]

[2] About 2.8 percent of respondents self-report a race/ethnicity on the interview that is different from the race/ethnicity from the screener report. In contrast the discrepancy for the five category age variable is only 1.1 percent.

Table 5 presents estimates of selected drug use variables (marijuana, any other illicit drug, alcohol, cigarettes and cocaine) for the same five estimation approaches. There are no gold standards for these comparisons and thus no way to evaluate the nonresponse bias reduction ability of each method. The purpose of including this table is simply to illustrate the range of estimates produced by the different approaches. One striking result is that there is little variation across methods and all estimates agree to within one percentage point. In fact, one result not shown in the table is that the estimates from Model 3 also differed only slightly from the NSDUH final estimates: the largest absolute difference observed was only 0.5 percentage points for lifetime marijuana use. The largest relative difference was for past month cocaine use (0.84 percent versus 0.82 percent). Of all the variables considered in this analysis, the drug use variables seem to be the least affected by the nonresponse weighting adjustment approach.

In ***Table 6***, we summarize the dissimilarity indexes for all the screener variables and a few selected interactions. In addition to the five methods shown in the previous tables, we also included the current NSDUH nonresponse adjusted estimate to show its nonresponse bias reduction capability. As expected, the current NSDUH approach exhibits the smallest dissimilarity with the true distribution. Of the three callback modeling approaches, Model 3 seems to be best overall followed closely by Model 1. Model 3 also appears somewhat better than the NSDUH-SIM weighted approach except for the race/ethnicity variable. However, the improvements are relatively small.

We believe the large dissimilarities between the callback models relative to the NSDUH-SIM model for race/ethnicity are due to the use of proxy reports on race/ethnicity from the screener. Note from Table 6 that the dissimilarity index is very small for the unadjusted estimator which implies that the imputation model is very close to a missing completely at random model with respect to this variable. The callback models attempt to account for nonignorable nonresponse in the estimates and, thus, may be expected to differ. Since we assume that proxy reports on race/ethnicity are less accurate than self-reports, we have put less importance on the results for the race/ethnicity variable in our analysis.

4. Discussion

Traditional response propensity models employed in nonresponse weighting adjustments are logistic regression models where the dichotomous dependent variable is the data collection outcome (for e.g., response vs. nonresponse) and the independent variables are characteristics which can predict nonresponse. The latent callback model can be viewed as an extension of the traditional model to incorporate additional data that heretofore were not incorporated into the response propensity prediction process, viz., the number of call attempts to obtain a response, variables known only for respondents and a latent indicator variable for the HCNRs. Viewed in this manner, it seems reasonable to expect that any logistic response propensity model can be improved by adding the features of the latent callback model just as any regression model can be improved by the addition of other variables which are correlated with the outcome variable.

To check this premise, we constructed several latent callback models consisting of four variables and compared them to an equivalent model that was constructed using the traditional logistic regression approach; i.e., the model used was essentially the same the latent callback model with the special callback model features omitted. Across a range of variables that were available from the NSDUH screener, the callback model showed improvement over the traditional model as hypothesized. Although the magnitude of the improvements was not dramatic, our results clearly showed that gains in accuracy are possible using the special features of the callback model in response propensity weighting.

One explanation as to why larger improvements were not obtained using the callback modeling approach is that the callback models were fairly simple. There are several ways in which the models could be improved. First, the models could incorporate a greater number of grouping variables. These would include those that are used in the current NSDUH model as well as variables from the interview that are available for respondents only. Second, all the models we considered restricted the response propensities to be equal across LOEs. This restriction could be relaxed to allow response propensities to vary by LOE. Finally, the NSDUH model incorporates state and quarter specific variables which could also be incorporated into the callback models.

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Table 1. Distribution of LOE (Call Slots) Needed to Complete Interview, 2004 NSDUH

LOE NEEDED TO COMPLETE	CALL SLOTS	FREQUENCY	PERCENT	CUMULATIVE PERCENT
1	1	7,733	11.41	11.41
2	2	6,506	9.60	21.01
3	3	13,769	20.32	41.33
4	4	10,921	16.12	57.45
5	5-6	13,301	19.63	77.08
6	7-9	8,975	13.25	90.33
7	10+	6,555	9.67	100.00

Table 2. Summary of the Three Latent Callback Models Used in the Analysis

Model	# of Parameters	Grouping Variable Interactions are…	Interactions of X with Grouping Variables	Interactions of LOE with Grouping Variables
1	168	Unrestricted	All possible 3 way	All possible 3 way
2	324	Restricted to 3 way interactions	All possible 4 way	All possible 5 way
3	322	Unrestricted	All possible 3 way	All possible 5 way

Common Attributes

4 grouping variables – Race, Program Participation, Age, 1 or 2 Persons selected
7 LOE variables.
Latent variable *X* denoting HCNR
Equal response propensities across all LOEs

Table 3. Comparison of Callback Model, NSDUH-SIM and "True" Estimates

	"Truth"		Model 1		Model 2		Model 3		NSDUH-SIM	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Region										
Northeast	19.04	0.29	18.44	0.34	18.39	0.35	18.51	0.35	18.54	0.34
North Central	22.48	0.29	22.01	0.32	21.82	0.31	22.26	0.32	22.74	0.32
South	35.64	0.41	36.67	0.47	36.58	0.46	36.47	0.47	36.55	0.46
West	22.83	0.37	22.88	0.41	23.21	0.41	22.76	0.41	22.17	0.39
Access										
Controlled Access	14.79	0.41	14.81	0.45	14.78	0.45	14.49	0.44	14.18	0.42
No Controlled Access	85.21	0.41	85.19	0.45	85.22	0.45	85.51	0.44	85.82	0.42
Density										
MSA, >= 1 million	45.72	0.49	45.38	0.53	46.01	0.53	45.43	0.53	44.63	0.53
MSA, < 1million	32.64	0.46	32.66	0.50	32.51	0.48	32.64	0.49	32.93	0.49
Non-MSA	21.64	0.33	21.97	0.38	21.47	0.36	21.93	0.37	22.44	0.37
Race/Ethnicity[1]										
White, Non-Hispanic	69.42	0.38	66.25	0.44	65.73	0.45	68.34	0.44	69.67	0.41
Black, Non-Hispanic	11.56	0.29	12.52	0.33	11.32	0.29	10.54	0.27	12.09	0.31
Other, Non-Hispanic	6.12	0.20	5.52	0.20	5.01	0.18	4.70	0.17	5.28	0.19
Hispanic	12.91	0.26	15.71	0.36	17.94	0.40	16.43	0.37	12.95	0.28
Age										
12-17	10.57	0.12	10.57	0.13	10.57	0.13	10.57	0.13	10.57	0.13
18-34	27.81	0.31	27.81	0.33	27.81	0.33	27.81	0.33	27.81	0.33
35+	61.62	0.33	61.62	0.37	61.62	0.36	61.62	0.36	61.62	0.36

Table 4. Comparison of Absolute Bias and Dissimiarity Indices for Callback Models and Traditional Estimates

	Model 1	Model 2	Model 3	NSDUH-SIM
Region				
Northeast	0.60	0.65	0.53	0.50
North Central	0.47	0.66	0.22	0.26
South	1.03	0.93	0.83	0.91
West	0.05	0.38	0.07	0.67
Dissimilarity	1.07	1.31	0.83	1.17
Access				
Controlled Access	0.02	0.01	0.30	0.61
No Controlled Access	0.02	0.01	0.30	0.61
Dissimilarity	0.56	0.66	0.71	1.19
Density				
MSA, > 1 million	0.34	0.29	0.30	1.09
MSA < 1million	0.02	0.12	0.01	0.29
Non-MSA	0.33	0.17	0.29	0.80
Dissimilarity	0.34	0.29	0.30	1.09
Race/Ethnicity				
White, Non-Hispanic	3.17	3.69	1.08	0.25
Black, Non-Hispanic	0.96	0.24	1.02	0.54
Other, Non-Hispanic	0.60	1.10	1.42	0.83
Hispanic	2.81	5.03	3.52	0.05
Dissimilarity	3.77	5.03	3.52	0.83
Age				
12-17	0.00	0.00	0.00	0.00
18-34	0.00	0.00	0.00	0.00
35+	0.00	0.00	0.00	0.00
Dissimilarity	0.00	0.00	0.00	0.00

Table 5. Comparison of Esitmates of Unadjusted, Callback Model Adjusted and Traditional Estimates of Substance Use

	Unadjusted		Model 1		Model 2		Model 3		NSDUH-SIM	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Marijuana										
Lifetime	0.4079	0.0036	0.4027	0.0038	0.4018	0.0037	0.4073	0.0038	0.4092	0.0037
Past year	0.1108	0.0019	0.1067	0.0019	0.1057	0.0018	0.1060	0.0019	0.1072	0.0019
Past month	0.0633	0.0014	0.0613	0.0015	0.0605	0.0014	0.0606	0.0014	0.0613	0.0014
Any Illicit Drug except Marijuana										
Lifetime	0.2975	0.0032	0.2934	0.0034	0.2938	0.0033	0.2979	0.0034	0.2969	0.0033
Past year	0.0856	0.0016	0.0826	0.0017	0.0822	0.0016	0.0822	0.0017	0.0827	0.0016
Past month	0.0359	0.0010	0.0346	0.0010	0.0345	0.0011	0.0346	0.0011	0.0347	0.0010
Alcohol										
Lifetime	0.8194	0.0026	0.8193	0.0029	0.8211	0.0028	0.8252	0.0027	0.8262	0.0026
Past year	0.6503	0.0033	0.6452	0.0037	0.6504	0.0036	0.6555	0.0035	0.6533	0.0035
Past month	0.4994	0.0037	0.4935	0.0039	0.4999	0.0040	0.5058	0.0039	0.5032	0.0038
Cigarettes										
Lifetime	0.6697	0.0030	0.6688	0.0033	0.6681	0.0032	0.6742	0.0032	0.6770	0.0031
Past year	0.2971	0.0032	0.2951	0.0032	0.2940	0.0034	0.2942	0.0034	0.2957	0.0033
Past month	0.2539	0.0031	0.2536	0.0032	0.2513	0.0033	0.2519	0.0033	0.2537	0.0031
Cocaine										
Lifetime	0.1421	0.0025	0.1428	0.0026	0.1424	0.0027	0.1449	0.0027	0.1442	0.0026
Past year	0.0242	0.0008	0.0236	0.0009	0.0234	0.0008	0.0233	0.0008	0.0235	0.0008
Past month	0.0085	0.0005	0.0084	0.0005	0.0083	0.0005	0.0082	0.0005	0.0083	0.0005

Table 6. Dissimilarity Indices for Screener Variables and their Cross-classifications

TABLE	UNADJUSTED	MODEL 1	MODEL 2	MODEL 3	NSDUH-SIM	NSDUH
Density	1.07	0.34	0.29	0.30	1.09	0.15
Region	1.45	1.07	1.31	0.82	1.17	0.23
Age	2.98	0.00	0.00	0.00	0.00	0.07
Selected	0.55	0.00	0.00	0.00	0.00	0.33
Access	0.56	0.20	0.01	0.30	0.61	0.92
Race	0.96	3.86	5.32	3.72	0.70	0.16
Density×Region×Age	3.21	1.56	2.02	1.66	1.76	0.61
Density×Region×Selected	1.65	1.48	1.61	1.86	1.69	0.65
Density×Region×Access	1.72	1.63	1.69	1.44	1.79	0.94