Multiple Imputation for Response Biases in NLAAS Due to Survey Instruments

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Abstract

Survey responses can be influenced by the interviewee's previous experiences in the same survey or in other similar surveys. This response bias is observed in the National Latino and Asian American Study (NLAAS), where there was a strong question ordering effect on the respondents' self-reported use of psychiatric service. Because NLAAS has a built-in randomization to two different orderings (new and traditional), one of which (new) is considered to be (approximately) bias-free, we are able to use a Bayesian modeling approach to predict the unbiased responses for those who were given the questions under the other ordering (traditional). Multiple imputations are then created from the corresponding posterior predictive distribution to facilitate the correction of potential biases in common analysis using the NLAAS data. The modeling task, including the associated computation, turns out to be rather complicated due to the presence of high order interactions (e.g., among different services) in the data. In this paper, we report our current findings and problems as well as directions for further improvements.

Keywords: Questionnaire ordering effect, Multiple Imputation, NLAAS, Survey Design.

1 Questionnaire Design and Goal of Study

Survey responses can be influenced by many factors: questionnaire design, interviewees' previous experiences and so forth. Response bias due to survey instruments is observed in the National Latino and Asian American Study (NLAAS), where there was a strong question ordering effect on the respondents' self-reported psychiatric service uses. We were able to estimate the ording effect because NLAAS has two sets of questionnaire designs, traditional design and new design, which share the same questions, but have different orders in the service use part.

There are 10 categories of psychiatric services in NLAAS, each of which has a "stem question" asking the general question if the respondent ever had the service before. Together with the stem question, there are follow-up questions asking more details about that service given that the respondent had a positive response (he/she had the service); for instance, when did he/she have the service, how long was the treatment, etc. The traditional (common) design uses a "sequential" ordering. After each stem question, if the response is positive, follow-up questions are asked immediately; otherwise, the next "stem question" is asked, and the previous follow-up questions are skipped. The traditional design also arranged the whole service part questions after a series of diagnostic questions for identifying psychiatric disorders. This implies that service questions typically come 30 minutes after the interview starts, as illustrated in the left column of Figure 1. In contrast to the traditional design, the new design moved all the stem question far ahead, before all the diagnostic questions, but leaves additional follow-up questions after the diagnostic questions as illustrated in the right column of Figure 1.

One suspicion was that people who were randomly assigned to take the traditional design were more likely to underreport: they tended to report negatively, even though they had used services. There are two possible reasons for this underreporting. First, the stem questions are asked after the psychiatric diagnostic questions. Respondents tended to react more negatively when they run out of patience. Secondly, the follow-up questions are asked immediately after the stem questions. Respondent might learn from the previous service question format and underreport to avoid follow-up questions to shorten the interview. See [4] for more discussions about NLAAS design and response bias due to this ordering effect.

In order to test this ordering effect, NLAAS randomly assigned 25% of the respondents to the new design, and 75% to the traditional design. As shown in Tables 1 and 2, the overall service use rates from the new design is uniformly higher than the one form the traditional design for all the 10 services, measured as both lifetime usage and last-12-month usage. Such phenomenon is also observed within all the ethnicity groups, see [4]. However, non-service variables such as those listed in Table 3 show no significant difference between the two designs. It is therefore logical to conclude that the significant discrepancy in service use rate (with p-values < 0.01, which is robust to different model assumptions, as discussed in [4]) is due to the different orderings of questions.

The purpose of this paper is to create multiple imputations for the service user under traditional design based on the data from the new design, which is viewed as (approximately) bias free. We will use a Bayesian prediction approach to accomplish this task. The modeling task, including the associated computation, turns out to be rather complicated due to the presence of potential high order interactions (e.g., among different services) in the data. In this paper, we report our current findings and problems, and discuss possible remedies.

2 Primary Modeling Specifications

2.1 Model Assumptions

Our basic model assumption is that respondents from the new design group responded accurately, while those from the

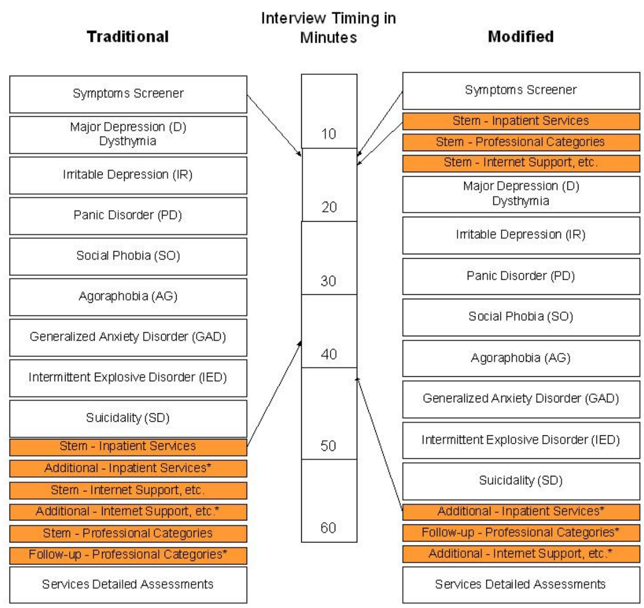

Figure 1: Interview Flow

		New	Old
1	Psychiatrist	13.7%	9.1%
2	Psychologist	12.3%	8.2%
3	Other Mental Health Professionals	5.1%	2.4%
4	General Practitioner	17.7%	12.0%
5	Other Medical Doctor	9.6%	3.7%
6	Nurse, Occupational Therapist,	4.3%	2.1%
7	Social worker	6.5%	3.5%
8	Counselor	12.5%	7.6%
9	Religous/Spiritual Advisor	12.9%	5.2%
10	Other Healer	5.4%	1.9%

Table 1: Comparing Reported Lifetime Service Use Between New Design (New) and Traditional Design (Old)

	New	Old
Psychiatrist	32.1%	30.6%
Psychologist	28.4%	20.4%
Other Mental Health Professionals	41.9%	33.7%
Other Medical Doctor	61.4%	30.4%
Nurse, Occupational Therapist,	50.0%	14.5%
Social worker	41.0%	17.8%
Counselor	23.8%	19.0%
Religous/Spiritual Advisor	42.3%	22.1%
Other Healer	49.2%	35.3%

Table 2: Comparing Reported Last Year Service Use Between New Design (New) and Traditional Design (Old): the rate is the percentage of people who report to have service last year among those who report to have service use in lifetime.

	New	Old
Major Depression	0.120	0.132
Any Affective Disorder	0.122	0.136
Any Disorder	0.143	0.137
Any Affective Disorder 12 month	0.066	0.068
Number of disorders	0.43	0.43
k10 distress	13.75	13.75
Gender	1.53	1.55
Age	41.01	41.05
Social Status	5.57	5.68
Immigration Status	0.67	0.68

Table 3: Comparing Other Background Variables

traditional design would respond in the following way: if s/he did not have services, s/he would report accurately, otherwise s/he may or may not report accurately. The ration for this assumption is that providing false positive response can only prolong the interview and hence there is no incentive for incorrect reporting. Thus, in our final imputed samples, some of the negative cases in the traditional design group would be turned into positive cases, rather the responses in the new design group remain the same, such that the service rates in the two group will be adjusted to similar level.

Specifically, for each respondent, we create one variable indicating his/her response behavior given s/he had service. We use the following notation:

- y the reported service use status, 0 for no service and 1 for having service use;
- y_s the true service use status, 0 for no service and 1 for having service. We may or may not observe y_s, depending on which group the respondent is in and his/her response.
- ξ the response behavior of those people from the traditional design group who have service use, i.e. $y_s = 1$, 0 for responding inaccurately and 1 for accurately;
- I indicates the group each individual belongs to, 0 for 25% group (new design) and 1 for 75% group (traditional design).

In the new design group, where respondents are assumed to report accurately, the true service use is observed: that is $y = y_s$. In the traditional design group, where underreporting may occur, we can write $y = y_s \cdot \xi$. Assuming that,

$$y_s \sim \text{Bernoulli}(p), \quad \xi | y_s = 1 \sim \text{Bernoulli}(r),$$

the likelihood function based on a single y is

$$p^y(1-p)^{1-y}(1-I) + (pr)^y(1-pr)^{1-y}I. \qquad (1)$$

Of interest here is the true service indicator, y_s. Under our model assumptions, y_s is missing only when $I = 1$ and $y = 0$. Therefore, we will create imputations from the posterior predictive distribution $y_s | y = 0, I = 1$.

2.2 Intuition for Maximum Likelihood Estimate

Assume we have n samples, n_0 of them with $I = 0$ and n_1 with $I = 1$. Define $m_0 = \sum_i y_i(1 - I_i)$ and $m_1 = \sum_i y_i I_i$, which are the numbers of positive responses in group $j = 0, 1$ respectively. The likelihood function is then given by

$$L(p, r) \propto p^{m_0}(1-p)^{n_0-m_0}(pr)^{m_1}(1-pr)^{n_1-m_1}$$

The maximum likelihood estimate takes following forms:

- When $\frac{m_0}{n_0} > \frac{m_1}{n_1}$, $\hat{p} = \frac{m_0}{n_0}$ and $\hat{r} = \frac{m_1 n_0}{n_1 m_0}$;
- When $\frac{m_0}{n_0} \le \frac{m_1}{n_1}$, $\hat{p} = \frac{m_0+m_1}{n_0+n_1}$ and $\hat{r} = 1$.

Intuitively, when group 0 has higher observed service rate, group 1 provides little information because it suffers from underreporting. However, if group 1 has higher observed rate, the MLE approach will estimate that the correct response rate, r, in group 1 to be 100%, therefore the two groups will be pooled together in estimating p. The latter situation occurs for some small subsamples, but typically we are in the former situation for the NLAAS data.

2.3 Multivariate Probit Regression with Clustering

Besides the service use variables, NLAAS also recorded many other variables, such as age, gender as well as some mental disorder variables. These variables are well known to be useful in predicting service use. In addition, NLAAS recorded the time each respondent took before he/she reached service question, which is useful for predicting the reporting behavior. To incorporate them in imputation suitably, we adopted a multivariate probit regression model.

Specifically, in NLAAS, we have 10 categories of life-time service use variables. To model them together, let $y_s^1, \ldots, y_s^{10}$ indicate the 10 service uses and $\xi^1, \ldots, \xi^{10}$ indicate the responding behavior for the response of each service. Then the multivariate probit regression assumes

$$y_s^i = \begin{cases} 1 & z_s^i > 0 \\ 0 & z_s^i \le 0 \end{cases}, \quad (2)$$

$$\xi^i = \begin{cases} 1 & z_l^i > 0 \\ 0 & z_l^i \le 0 \end{cases}, \quad (3)$$

$$\begin{pmatrix} z_s^1 \\ \vdots \\ z_s^{10} \\ z_l^1 \\ \vdots \\ z_l^{10} \end{pmatrix} \sim N((X\beta)^T + W_k, \Sigma), \quad (4)$$

if the respondent is in sampling block (cluster) k, where $\Sigma = \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & (1-\rho)I_{10} + \rho\mathbf{11'} \end{pmatrix}$, Σ_{11} is a 10 by 10 matrix, α is a positive scalar, $W_k = \left(W_k^1, \ldots, W_k^{20}\right)^\top$, and $W_k^j \sim N\left(0, (\alpha^j)^2\right)$, $j = 1, \ldots, 20$. Note that because in the relationship $y = y_s\xi$, ξ can be defined arbitrarily when $y_s = 0$, for technical convenience, here we extend the definition of $\xi | y_s = 1$ to $\xi | y_s = 0$, that is, we assume ξ is independent of y_s.

Also note that the response behavior latent variable, z_l^i, are correlated with each other with a common correlation, ρ, but are independent of the service use, z_s^j. The common correlation assumption on z_l^j helps to reduce the number of parameters and hence model (and computation) complexity, but it is an assumption that can be relaxed. The use of W_k and α^j helps to model the cluster effect due to survey design, by allowing respondents in the sample block k to share the same W_k.

2.4 Prior Specifications

From the model setup (2) – (4), we need to specify a prior distribution for $(\beta, \Sigma_{11}, \rho, \alpha)$, for which we set them to be mutually independent. Therefore we only need to choose marginal distribution for β, Σ_{11}, ρ, and α respectively. First, we assume

$$p(\rho) \sim \ Beta(1, 1).$$

This prior forces all the responding latent variables to be positively correlated, which reflects our prior belief that someone who tends to underreport on one service use also tends to underreport to the others. One candidate of the prior distribution of Σ_{11} (10×10) is inverse Wishart (Inv-wish) distribution. Its precision matrix is chosen to be identity matrix and the degree of freedom (d.f.) is chosen to be $10 + 3 = 13$, which is the smallest d.f. such that the distribution has a finite mean. Since the probit model can only identify Σ_{11} up to a positive constant, we choose the prior of Σ_{11} to be the correlation matrix derived from the inverse Wishart matrix. We denote this distribution by,

$$p(\Sigma_{11}) \sim \text{Inv-Wish-Cor}(I, 13).$$

It turns out that the posterior distribution of ρ and Σ_{11} are not very sensitive to the choice of prior distribution. In contrast, the prior distribution of $\beta = (\beta_1, ..., \beta_{20})$ need to be more carefully chosen, where β_i's are m by 1 vectors (m is the number of columns of covariate matrix X). In particular, a flat prior distribution on β will result in an improper posterior distribution. Take a simple case discussed in Section 2.1 for example, where there is only one service use and no background variable. The posterior distribution with flat prior is

$$p(\beta_1, \beta_2 | y) \propto \Phi_{\beta_1}^{m_0} \cdot (1 - \Phi_{\beta_1})^{n_0 - m_0} \cdot (\Phi_{\beta_1}\Phi_{\beta_2})^{m_1} \cdot (1 - \Phi_{\beta_1}\Phi_{\beta_2})^{n_1 - m_1}, \quad (5)$$

where β_1 is the mean of service use latent variable, β_2 is the mean of response behavior latent variable, $\Phi_t = P(Z < t)$, $Z \sim N(0, 1)$, and m_i and n_i, i = 0,1, are defined in Section 2.2. Note that as $\beta_2 \to \infty$, the right hand side of (5) converges to $\Phi_{\beta_1}^{m_0} \cdot (1 - \Phi_{\beta_1})^{n_0 - m_0} \cdot (\Phi_{\beta_1})^{m_1} \cdot (1 - \Phi_{\beta_1})^{n_1 - m_1} > 0$. Thus, the posterior distribution is not proper. In fact, a more natural prior distribution should be "flat" in the rate which ranges from 0 to 1, instead of the β's. So a natural prior distribution of (β_1, β_2) is $N(0, I_2)$, because Φ_{β_i}, $i = 1, 2$, are independent uniform distributions.where I_2 is 2 by 2 identity matrix. However, under more complicated situations, such natural prior distribution does not always exist. In particular, when the covariate matrix has more than one column - X is an n by m matrix, $n > m$, it is impossible to find a distribution of β_1 such that $X\beta_1 \sim N(0, I_n)$.

Before we proceed, we assume that all the continuous covariates in X have been standardized to have sample mean 0 and sample variance 1. Furthermore, each categorical variable corresponds to multiple "dummy variable" columns in X, which takes values in {0,1}. For such columns we multiply them by a scalar such that each of them has sample variance 1. These standardization procedures are for convenience and will not change the nature of the model. For each β_i we choose an independent multivariate normal prior distribution with variance $\tilde{\Sigma} = \frac{n}{\bar{m}}(X^\top X)^{-1}$, where $\bar{m}$ is the number of covariates plus one, which is usually less than the number of columns of X because of the presence of categorical variables. We then set the prior distribution of β to be

$$p(\beta_i) \sim \begin{cases} N(\mu_s, \tilde{\Sigma}), & i \leq 10 \\ N(0, \tilde{\Sigma}), & i > 10 \end{cases}$$

where $\mu_s^\top = (-0.8, 0, \ldots, 0)$ is m by 1 vector and only the first element is not 0. β_i is for service use when $i \leq 10$, and for response behavior when $i > 10$ (recall that β_i's are column vectors of matrix β). For each service use, we choose the prior service use rate distribution to have the majority of mass in the range which matches the psychologists' prior knowledge. For the response behavior, we choose it such that the resulting prior on the response probability is approximately uniform, reflecting our week prior knowledge.

The prior distribution of α^j is set to be flat prior on $\mathbb{R}$, that is,

$$p(\alpha^j) \propto 1, \; j = 1, \ldots, 20.$$

Note that the sign of α^j is not identifiable. But this does not affect our imputation because only $(\alpha^j)^2$ enters the model. It is for technical convenience that we let α live on the whole real line instead of $\mathbb{R}^+$.

2.5 Last 12 Month Service Use Model

Besides the lifetime service use, NLAAS also collects data on the last-12-month service, for which similar underreporting is also observed as shown in Table 2. When setting up the last-12-month service model, we need to consider the following natural logical constraint: someone who did not have lifetime service should not have service in the last 12 month either. This logic is respected in the observed data, so it should be also respected in the imputed data. For each service, we have a bivariate r.v. (y_s, y_l) taking value from $\{(1,1), (1,0), (0,0)\}$, where y_l is the true last-12-month service use. The couple can be modeled as $(y_s, y_l) = (y_s, y_s\tilde{y}_s)$, where y_s and $\tilde{y}_s$ are independent Bernoulli random variables, $\tilde{y}_s$ is the indicator that if the respondent has last-12-month service use given that s/he has lifetime service use. Thus we model the lifetime service use and last-12-month service use jointly under the constraint stated above. Note that the posterior distribution of the lifetime service use indicator, y_s, does not depend on the reported last-12-month service use. An intuitive explanation is that y_s is not directly observed if and only if the respondent is in the traditional design group and reported negatively. In such cases, the corresponding recorded last-12-month service use is always negative. Thus the reported last-12-month service use does not provide any information about the true lifetime service use if the lifetime service use was not reported accurately. This allows us to impute the lifetime service use without considering the reported last-12-month service use. Therefore we can first model and impute the lifetime service use, and then model and impute the last-12-month service uses conditional on the lifetime service use.

In the traditional design group, if the observed service use is $(1,1)$, the true last-12-month service use is positive; if the observed service use is $(0,0)$, then $\tilde{y}_s$ completely missing, since the respondent was never asked about the last year service use. If the observed service use is $(1,0)$, for which the respondent was asked about her/his last-12-month service use, s/he could either underreport or not have service use in the last 12 months. In the last case, we introduce a new respondence behavior indicator for the last-12-month service use, $\tilde{\xi}$, such that it is independent of $(y_s, \xi, \tilde{y}_s)$ and the reported last-12-month service use equals to $y_s\xi\tilde{y}_s\tilde{\xi}$. That is, $\tilde{\xi}$ is a direct analog to ξ in the lifetime service use model.

3 Computation Via MCMC

We use the following MCMC algorithm to sample from the posterior distribution, resulting from combining the likelihood and prior specification in Section 2.

- Sample from $P(z|\beta, \Sigma_{11}, \rho, \alpha, W)$, a truncated multivariate normal. Draw each couple (z_s^i, z_l^i) one by one given the rest, each conditional distribution is a bivariate truncated independent normal distribution. Here $W = \{W_1, ..., W_K\}$ are the random effect terms.
- Sample from $P(\beta|z, \Sigma_{11}, \rho, \alpha, W)$, multivariate normal distribution. The mean and variance can be computed by following linear regression routine combined with the prior distribution we specified in Section 2.4.
- $P(\Sigma_{11}|\beta, z, \alpha, W)$, draw matrix Γ from $Inv-Wish(S, d)$, where $S = (z - X\beta)^\top(z - X\beta)$ and $d = n + 3$. Treat Γ as a variance-covariance matrix, and Σ_{11} is the corresponding correlation matrix.
- Updating ρ by directly Metroplis-Hasting step is very in efficient. Therefore we propose the following solution. Let $\Sigma_1 = \rho\mathbf{11}'$ and $\Sigma_2 = (1-\rho)I$, and define η as

$$\eta = \mu + \sqrt{\rho}\begin{pmatrix} Z \\ \ldots \\ Z \end{pmatrix}, \;\; z_l|\eta \sim N(\eta, \Sigma_2),$$

  where Z is univariate standard normal distribution. Note that under this setting, z_l is multivariate normal with mean $\mu = X\beta + W_k$, and variance $\Sigma = \Sigma_1 + \Sigma_2$. We observed that moving η and ρ together is much more efficient than updating ρ alone. We proposed the following procedure: first, draw $\eta|(z_l, \rho, \beta)$, which is normal distribution, where z_l is the latent variable for responding behavior. Second, update (η,ρ) by Metropolis-Hasting algorithm.

- Sample $P(\alpha|\beta, \Sigma, \rho, z, W_k)$, multivariate normal distribution.
- Sample $P(W_k|\beta, \Sigma, \rho, z, \alpha)$, multivariate normal distribution. The sampling of α and W_k are explored thoroughly in [5].

4 Results

To create multiple imputations, we draw 5 samples from the posterior distribution, obtained from the algorithm as specified in the previous section. To make inference using multiple imputations, one needs to follow the combining rules as given in [11], as well as in [3]. As a way to check the validity of the multiple imputations we created, we compare the averaged imputed rates (over the five imputations) for the traditional design group with those observed rates under the new design. This comparison is presented for the Latino cohort in Tables 4 and 5.

For each ethnicity group, three columns are provided. The first column is the observed service rate of the new design group; the second column has the imputed average service rate of the traditional design group; and the third group is the observed service rate of the traditional design group. Ideally, the rates in the second column should be similar to those in the first column. We observed from the tables that for individual service use, the imputed rates based on the multivariate probit model did a reasonably good job. But for the last two variables, that is, "Any Formal Mental Health Service", which means a respondent has any of the first eight services listed in Table 1, or "Any Mental Health Service", that is, a respondent had any of the ten services listed in Table 1, the imputed rates are consistently higher (by about 2-5%) than the observed rates under the new design. In the next section, we will discuss possible reasons for this over imputation and ways to deal with this problem.

5 Future work

We suspect that the reason for the over imputation in the two "Any" variables is that the multivariate probit model fails to capture high order interactions among the service variables. We suspect there are high-way positive interactions among the three classes of services, that is, among "Specialist", "Generalist" and "Human Services". One common phenomenon is that a potential patient sees a generalist, who recommend him/her to see a specialist, and this patient is likely to need human services as well if s/he does have a disorder. A multivariate Gaussian distribution is completely determined by its mean, variance and pairwise correlations, and therefore it is not suitable to capture such three-way interaction. We need to find some multivariate distribution which has more freedom in fitting the dependent structure and should also be easy to make statistical inference, especially Bayesian inference.

Besides the high-way interaction problem with the multivariate probit regression, there are other issues need to be addressed in our future work. Most of the standard analysis of NLAAS is using survey based estimators. Our imputation model is not survey based, although we have random effect terms to take into account of the cluster effect. This leads to the uncongeniality problem which is due to the inconsistency between the imputation model and standard analysis procedure as well as the difference in the assumptions between the imputers and the analysts, as discussed in [10]. More specifically, many survey designs use cluster sampling but currently the multiple-imputation combining rules are derived using individual units, not clusters. Lastly, the MCMC algorithm we currently use needs to be improved.

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	Puerto Rican			Cuban			Mexican			Other Latinos		
	New	Imp	Old	New	Imp	Old	New	Imp	Old	New	Imp	Old
Specialist	33.5	33.4	24.9	26.7	22.5	19.0	14.9	15.9	10.3	18.7	20.1	13.4
Psychiatrist	28.8	24.0	15.9	19.7	16.4	13.4	11.0	10.8	6.6	9.4	11.9	8.0
Psychologist	20.6	20.8	14.1	16.2	13.3	10.8	10.4	9.2	5.8	13.5	15.0	8.7
Other Mental Health Prof,	10.7	10.7	5.4	4.7	5.0	2.6	5.0	5.1	2.7	4.5	4.9	3.1
Generalist	32.5	32.0	26.2	21.4	26.3	19.9	18.3	18.8	12.7	16.8	18.3	10.5
General Practitioner	28.5	29.8	24.8	18.5	22.2	16.8	16.6	17.0	10.6	12.7	15.1	8.5
Other Medical Doctor,	15.5	13.9	7.4	10.3	12.9	5.1	7.0	7.2	1.9	10.2	10.3	4.3
Nurse, Occupational Therapist, and Other Health Professional	13.4	9.4	3.4	4.0	5.1	3.3	3.0	2.8	1.7	3.3	3.3	1.4
Human Service	38.5	32.3	22.9	17.4	14.7	8.7	20.1	17.7	10.4	24.9	22.7	13.5
Social worker	17.9	15.1	10.4	5.1	3.7	2.8	7.4	5.3	2.6	5.5	7.1	3.9
Counselor	29.6	21.9	13.0	11.0	7.6	3.9	11.2	11.0	7.2	13.7	16.2	9.7
Religous/Spiritual Advisor	16.3	19.2	10.2	11.8	11.1	5.5	14.0	11.3	5.3	16.5	12.3	5.2
Alternative Service	13.0	8.1	1.5	6.6	5.5	2.9	4.0	4.4	1.1	4.0	6.2	2.4
Any Formal Mental Health Service	46.3	48.1	41.0	33.9	36.5	30.7	25.0	29.2	21.3	29.5	35.7	25.2
Any Mental Health Service	50.0	51.2	42.6	37.6	39.2	31.4	30.0	32.5	22.3	35.3	38.4	26.5

†All numbers are in 10^{-2} scale. †New: observed service rates in the new design group. †Imp: imputed service rates in the old design group. †Old: observed service rates in the old design group.

Table 4: Latino lifetime service use

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	Puerto Rican			Cuban			Mexican			Other Latinos		
	New	Imp	Old	New	Imp	Old	New	Imp	Old	New	Imp	Old
Specialist	10.7	12.9	8.0	5.7	6.8	5.5	5.2	5.3	3.0	6.9	7.3	3.3
Psychiatrist	10.0	8.7	5.0	5.1	5.7	5.0	3.3	3.9	1.9	2.7	4.3	1.8
Psychologist	3.9	5.6	2.5	2.7	2.5	1.5	2.8	2.6	1.5	3.6	4.5	2.0
Other Mental Health Prof	3.4	3.8	1.7	1.0	2.1	0.5	2.2	2.3	1.3	2.4	2.1	1.3
Generalist	21.3	18.5	6.7	14.2	17.3	5.9	9.2	10.5	3.7	10.8	8.9	3.6
Other Medical Doctor	21.3	18.0	6.5	13.3	17.2	5.6	9.2	10.2	3.6	10.8	8.5	3.5
Nurse, Occupational Therapist, Other Health Professional	4.8	2.9	0.3	2.3	1.7	0.4	0.8	1.1	0.3	1.8	1.5	0.1
Human Service	16.5	13.1	4.6	7.0	5.3	1.0	8.5	7.5	2.9	14.0	9.1	3.2
Social worker	6.2	4.7	1.7	3.4	1.4	0.4	2.6	1.9	0.8	2.7	2.6	0.2
Counselor	6.8	5.9	3.1	4.8	2.0	0.4	2.5	3.4	1.5	3.8	4.6	2.0
Religous/Spiritual Advisor	8.6	7.6	1.6	3.5	3.4	0.8	5.8	5.0	1.5	8.8	4.9	2.0
Alternative Service	7.9	3.3	0.4	2.5	2.3	0.8	1.9	1.8	0.5	3.7	3.1	1.4
Any Formal Mental Health Service	25.9	25.8	14.4	18.0	19.5	8.6	12.7	13.9	6.7	15.4	14.8	6.6
Any Mental Health Service	30.8	30.3	15.4	18.6	21.2	9.2	16.6	16.4	7.3	22.3	17.3	7.2

†All numbers are in 10^{-2} scale. †New: observed service rates in the new design group. †Imp: imputed service rates in the old design group. †Old: observed service rates in the old design group.

Table 5: Latino last year service use