

Robustness to Parametric Assumptions in Missing Data Models

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Suppose we have a random sample from a population of interest. For each sampled unit we observe the covariate X , which we assume is discrete with support $\{x_1, \dots, x_K\}$. For some units, we also observe the variable Y . Let $D = 1$ if we observe Y , and $D = 0$ otherwise. We are interested in the population mean of Y , $\theta = \mathbb{E}[Y] = \sum_{k=1}^K p_k \mu_k$, where $\mu_k = \mathbb{E}[Y|X = x_k]$ and $p_k = \Pr(X = x_k)$.

We assume that Y is missing at random (MAR): $Y \perp D|X$. Suppose also that the propensity score $e_k = \Pr(D = 1|X = x_k)$ is bounded away from zero (a support condition). Then, in large samples, there will be at least some units with Y observed for each possible value of X , so that $\mathbb{E}[Y|X = x_k, D = 1]$ is identified. Since $\mu_k = \mathbb{E}[Y|X = x_k, D = 1]$ under MAR, we have

$$\theta = \sum_{k=1}^K p_k \mathbb{E}[Y|X = x_k, D = 1].$$

Let M_k equal the number of sampled units with $X = x_k$ (i.e., in cell k), and let $\hat{p}_k = [\sum_{j=1}^K M_j]^{-1} M_k$. The poststratification estimator for θ is

$$\hat{\theta}_{PS} = \sum_{k=1}^K \hat{p}_k \bar{Y}_k,$$

where \bar{Y}_k is the average of Y across those units with $D = 1$ and $X = x_k$ (i.e., the complete-case k cell mean or the sample analog of $\mathbb{E}[Y|X = x_k, D = 1]$).

When M_k is large for all $k = 1, \dots, K$ the poststratification estimator $\hat{\theta}_{PS}$ works well in practice and attains the semiparametric variance bound for θ derived by Jinyong Hahn (1998). Unfortunately, in many applications it is common for K to be large and M_k to be small (at

least for some values of k). In such settings the problem of empty cells, where Y is unavailable for all sampled units with $X = x_k$, may be severe (Paul R. Rosenbaum 1987).

In settings with small cells, there may be substantial gains from imposing restrictions on the means μ_k , but there is also a danger of misspecification. We explore ways to increase the robustness of parametric imputation estimators. First, we develop a simple empirical Bayes estimator, which combines parametric and unadjusted estimates of μ_k in a data-driven way. Second, we consider ways to use knowledge of the propensity score to help guard against misspecification of μ_k , using a double robust estimator and an empirical Bayes approach. This does not contradict the efficiency bound analysis of Hahn (1998), which is relevant for settings where M_k is large for all k .

I. Sampling Framework and Estimators

Following Joshua Angrist and Hahn (2004) we consider a stratified random sampling scheme. Let N be the total sample size with M_k chosen such that $M_k/N = p_k$ for all k (i.e., we assume that p_k , which characterizes the marginal distribution of X , is known). Within each cell, the probability of observing the outcome Y is e_k , so that the number of observed outcomes is $n_k \sim \text{Binomial}(e_k, M_k)$.

Conditional on n_2, \dots, n_K , the observed outcomes Y_{k1}, \dots, Y_{kn_k} are i.i.d. (and independent across cells) with mean μ_k and variance σ_k^2 .

The poststratification estimator for θ , modified to take into account that the p_k are known, is

$$\hat{\theta}_{PS} = \sum_{k=1}^K p_k \bar{Y}_k,$$

where $\bar{Y}_k = n_k^{-1} \sum_{i=1}^{n_k} Y_{ki}$. The nonparametric imputation estimator of Hahn (1998), and the estimated propensity score weighting estimator of Hirano, Guido W. Imbens, and Geert Ridder (2003) (modified appropriately for the missing data problem considered here), are both equal

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to $\hat{\theta}_{PS}$ in the discrete covariate case. This estimator may perform poorly if some cells have a small number of complete observations. If some cells are empty (i.e., $n_k = 0$), then the estimator must be modified, for example, by dropping empty cells or combining cells in some way.

An alternative is to posit a restricted model for the cell means:

$$(1) \quad \mu_k = x'_k \beta,$$

where β is a low-dimensional parameter. (We could also easily handle specifications of the form $\mu_k = t(x_k)' \beta$ for a known function t .) Then,

$$\mathbb{E}[\bar{Y}_k | n_1, \dots, n_K] = x'_k \beta,$$

$$\text{V}(\bar{Y}_k | n_1, \dots, n_K) = \sigma_k^2 / n_k,$$

and, conditional on (n_1, \dots, n_K) , the $(\bar{Y}_1, \dots, \bar{Y}_K)$ will be mutually independent. We could estimate β by a weighted least squares (WLS) regression of the \bar{Y}_k on x_k , with weights proportional to n_k . (This is equivalent to an ordinary least squares (OLS) regression of all the observed Y_{ki} on X_{ki}) Then, the parametric imputation estimator is

$$\hat{\theta}_{PI} = \sum_{k=1}^K p_k(x'_k \hat{\beta}).$$

The parametric estimator would typically do better when the assumption on the means (1) holds, and could be used even if some cells are empty. However, if (1) does not hold, then $\hat{\theta}_{PI}$ may be severely biased. Our goal is to develop estimators that improve upon the poststratification estimator when cell sizes are small, but are not as sensitive to misspecification as the parametric imputation estimator.

Following Carl N. Morris (1983) and Gary Chamberlain (2009), we consider an empirical Bayes approach. (See also David S. Lee and David Card (2008) for a closely related approach.) In the following statements, we implicitly condition on n_1, \dots, n_K . Suppose that

$$\bar{Y}_k | \mu_k \stackrel{\text{ind}}{\sim} \mathcal{N}(\mu_k, v_k), \quad k = 1, \dots, K,$$

where $v_k = \sigma_k^2 / n_k$, and

$$\mu_k \stackrel{\text{ind}}{\sim} \mathcal{N}(x'_k \beta, \tau^2), \quad k = 1, \dots, K.$$

This reduces to (1) when $\tau^2 = 0$. Under this setup the marginal distribution of the cell averages $\bar{Y}_1, \dots, \bar{Y}_K$ is

$$(2) \quad \bar{Y}_k \stackrel{\text{ind}}{\sim} \mathcal{N}(x'_k \beta, v_k + \tau^2).$$

Let $\gamma_k = v_k / (v_k + \tau^2)$. The posterior for μ_k , treating β , v_k , and τ^2 as known, is

$$\mu_k \stackrel{\text{ind}}{\sim} \mathcal{N}(\mu_k^*, v_k(1 - \gamma_k)),$$

where

$$\mu_k^* = (1 - \gamma_k) \bar{Y}_k + \gamma_k(x'_k \beta).$$

This suggests the (infeasible) estimator

$$\hat{\theta}_{EB0} = \sum_{k=1}^K p_k[(1 - \gamma_k) \bar{Y}_k + \gamma_k(x'_k \beta)].$$

To construct a feasible version, let $\hat{\beta}$ be the least squares estimator as in the imputation estimator. Let $\hat{\tau}^2$ be the pseudo maximum likelihood estimator of τ in (2), taking as given the regression estimates¹ $\hat{\beta}$ and the following estimates of the v_k :

$$\hat{v}_k = \frac{\hat{\sigma}_k^2}{n_k},$$

where the $\hat{\sigma}_k^2$ are the within-cell sample variances of the y_{ki} . We then form

$$\hat{\gamma}_k = \frac{\hat{v}_k}{\hat{v}_k + \hat{\tau}_k^2},$$

and

$$\hat{\theta}_{EB1} = \sum_{k=1}^K p_k[(1 - \hat{\gamma}_k) \bar{Y}_k + \hat{\gamma}_k(x'_k \hat{\beta})].$$

Although we motivated the estimator by a Gaussian hierarchical model, the estimator has a number of appealing properties that do not depend on normality. When cell sizes M_k are large, so that n_k is also large when the support condition holds, the $\hat{\gamma}_k$ will be close to zero, and the estimator will be similar to the

¹ We could estimate β and τ jointly by pseudo maximum likelihood, but for our extensions below, this form is somewhat more convenient. Another alternative is to carry out full Bayesian hierarchical inference.

poststratification estimator $\hat{\theta}_{PS}$. On the other hand, if the parametric model is close to being correct, and $\hat{\tau}^2$ is close to zero, the estimator will be similar to the parametric imputation estimator.

However, for intermediate values of $\hat{\gamma}_k$, the estimator is not a simple weighted average of $\hat{\theta}_{PS}$ and $\hat{\theta}_{PI}$. Instead, within each cell we take a weighted average of \bar{Y}_k and $x'_k \hat{\beta}_k$, with the weights depending on the value of $\hat{\tau}^2$ and on the \hat{v}_k . Thus, the estimator is similar to a kernel-type smoothing estimator with an adaptive bandwidth: when n_k is large, $\hat{\theta}_{EB1}$ typically places more weight on the nonparametric estimate \bar{Y}_k relative to the parametric estimate $x'_k \hat{\beta}_k$.

The estimator needs to be modified in order to deal with empty or nearly empty cells. If $n_k = 0$, then \bar{Y}_k is not defined. In that case, we set $\hat{\gamma}_k = 1$, so that the estimator uses the parametric model to impute the cell mean. If $n_k = 1$, then the variance estimate $\hat{\sigma}_k^2 = 0$. For such cells we, instead, use the average estimated variance among the cells with $n_k \geq 2$ in order to obtain the shrinkage term $\hat{\gamma}_k$. The parameter τ^2 is estimated using only the cells with $n_k \geq 2$.

II. Double Robustness

James Robins and coauthors have proposed an alternative approach to robustifying estimators based on parametric mean restrictions. In the double robust (DR) approach, the empirical researcher posits a model for the means, and a model for the propensity score (in our notation, the e_k). A DR estimator is one that is consistent for the parameters of interest, provided at least one of the two parametric restrictions is satisfied. Various DR estimators have been proposed, including James M. Robins, Andrea Rotnitzky, and Lue Ping Zhao (1994); Hirano and Imbens (2001), Heejung Bang and Robins (2005), Jeffrey M. Wooldridge (2007), Weihua Cao, Anastasios A. Tsiatis, and Marie Davidian (2009), and Graham, Christine Campos de Xavier Pinto, and Daniel Egel (2010).

Suppose we have two possible parametric restrictions:

ASSUMPTION DR1: $\mu_k = x'_k \beta$ for all k .

ASSUMPTION DR2: $e_k = G(x_k)$ for all k , where G is a known function.

Bang and Robins (2005) show that a DR estimator can be constructed by augmenting a regression with the inverse of the (parametric) propensity score. In our setup, this can be implemented through the following weighted linear projection problem: choose α_1^*, α_2^* to solve

$$(3) \min_{\alpha_1, \alpha_2} \sum_{k=1}^K p_k e_k \mathbb{E} [(\bar{Y}_k - x'_k \alpha_1 - G^{-1}(x_k) \alpha_2)^2].$$

The results in Bang and Robins (2005) imply the following result, which we prove for completeness:

PROPOSITION 1: *If DR1, DR2, or both hold, then*

$$\theta = \sum_{k=1}^K p_k [x'_k \alpha_1^* + G^{-1}(x_k) \alpha_2^*].$$

PROOF:

The minimization problem (3) is equivalent to the problem

$$(4) \min_{\alpha_1, \alpha_2} \sum_{k=1}^K p_k e_k (\mu_k - x'_k \alpha_1 - G^{-1}(x_k) \alpha_2)^2.$$

First, suppose DR1 holds. Then, clearly (4) is solved by setting $\alpha_1^* = \beta$ and $\alpha_2^* = 0$. Then,

$$\begin{aligned} \sum_{k=1}^K p_k [x'_k \alpha_1^* + G^{-1}(x_k) \alpha_2^*] &= \sum_{k=1}^K p_k [x'_k \beta] \\ &= \sum_{k=1}^K p_k \mu_k = \theta. \end{aligned}$$

Next, suppose DR2 holds. The first-order conditions for (4) imply

$$\sum_{k=1}^K p_k \frac{e_k}{G(x_k)} (\mu_k - x'_k \alpha_1^* - G^{-1}(x_k) \alpha_2^*) = 0.$$

Hence, if $e_k = G(x_k)$ for all k ,

$$\sum_{k=1}^K p_k \mu_k = \sum_{k=1}^K p_k [x'_k \alpha_1^* + G^{-1}(x_k) \alpha_2^*].$$

To construct a feasible version of this estimator, let

$$\hat{e}_k = \frac{n_k}{M_k}.$$

Then, $p_k \hat{e}_k \propto n_k$, so we could solve

$$\min_{\alpha_1, \alpha_2} \sum_{k=1}^K n_k (\bar{Y}_k - x'_k \alpha_1 - G^{-1}(x_k) \alpha_2)^2.$$

This is WLS of \bar{Y}_k on $(x'_k, G^{-1}(x_k))'$, with weights proportional to n_k , and is equivalent to OLS of the observed Y_{ki} on $(X'_{ki}, G^{-1}(X_{ki}))'$. Let $\hat{\alpha}_1$ and $\hat{\alpha}_2$ denote these estimates. The Bang and Robins DR estimator is

$$\hat{\theta}_{DR} = \sum_{k=1}^K p_k [x'_k \hat{\alpha}_1 + G^{-1}(x_k) \hat{\alpha}_2].$$

An empirical Bayes extension can be based on the marginal model

$$\bar{Y}_k \stackrel{\text{ind}}{\sim} N(x'_k \alpha_1 + G^{-1}(x_k) \alpha_2, v_k + \tau^2).$$

We can form the empirical Bayes estimate exactly as before, after augmenting the regressor vector with the term $G^{-1}(x_k)$. Note, however, that under Assumption DR2, we will *not* necessarily have $\tau^2 = 0$. This suggests that it may be useful to consider alternative estimators for τ^2 , which shrink the estimate to zero when the data indicate that the propensity score restriction is close to being satisfied. We defer such extensions to future work.

III. Monte Carlo Study

We carry out a simple simulation study to compare the various estimators. Suppose the covariate cells are

$$\{x_1, \dots, x_K\} = \{-J, \dots, 0, \dots, J\},$$

so that $K = 2J + 1$, and $M_k = M$ for all k , so that $p_k = 1/K$. We specify $\mu_k = x_k \beta$, which implies that $\theta = 0$. The propensity score is

$$e_k = \begin{cases} 0.75 & \text{if } x_k < 0 \\ (0.5K - 0.75J)/(K - J) & \text{if } x_k \geq 0. \end{cases}$$

This gives an overall probability of $1/2$ of observing the outcome. The outcomes Y_{ki} are independently drawn from a normal distribution with mean μ_k and variance σ^2 (the variance

is constant across cells). Under this model, the variance bound for estimating θ is

$$VB = \sum_{k=1}^K p_k \frac{\sigma^2}{e_k}.$$

(See Theorem 5 of Xiaohong Chen, Han Hong, and Alessandro Tarozzi 2004, and Section 5.2 of Imbens and Wooldridge 2009.)

We consider six designs, with J chosen such that $K = 5, 15, 25, 75, 125$, and 375 ; $N = 3,000$ across all designs such that the common cell sizes are $M = 600, 200, 120, 40, 24$, and 8 . We choose σ^2 based on K and M to set $VB = 30$. This implies that an efficient estimator should have a standard deviation of 0.1 in large samples. We also choose β so that the variance of μ_k is equal to 30 in each design. For each design we perform 1,000 Monte Carlo replications.

We apply the estimators developed above under two parametric specifications (where required). In the first, μ_k is correctly assumed to be linear in x_k . In the second, μ_k is erroneously assumed to be constant over x_k . To conserve space we report only the latter sets of results in detail.

These results are reported in Table 1. Each row of the Table corresponds to an estimator, with columns denoting the different designs. The entries show mean bias for each estimator/design, as well as its standard deviation across Monte Carlo replications (in parentheses).

The sampling distribution of the poststratification estimator $\hat{\theta}_{PS}$ is well approximated by conventional asymptotic approximations for designs where the number cells K is small, and cell size M is reasonably large. However, when $K = 375$ (so that $M = 8$), the presence of empty cells induces substantial bias and inflates variance.

Not surprisingly, the parametric imputation, double robust, and empirical Bayes estimators all perform well when they incorporate a correctly specified conditional mean model (results not shown). When the conditional mean model is incorrect, as in Table 1, their properties diverge. The parametric imputation estimator is biased when it is based on an incorrectly specified conditional mean model. The double robust estimator exhibits low bias. Although in our experiments this estimator is also based on an incorrect conditional mean model, it does utilize

TABLE 1—MONTE CARLO RESULTS FOR INCORRECTLY SPECIFIED CONDITIONAL MEAN MODEL

K	5	15	25	75	125	375
$\hat{\theta}_{PS}$	-0.0043 (0.0996)	0.0037 (0.1023)	-0.0014 (0.0994)	0.0016 (0.1030)	0.0032 (0.1018)	-0.2471 (0.1243)
$\hat{\theta}_{PI}$	-1.9401 (0.1359)	-2.2162 (0.1317)	-2.2840 (0.1336)	-2.2360 (0.1294)	-2.3528 (0.1283)	-2.3641 (0.1292)
$\hat{\theta}_{DR}$	-0.0054 (0.1212)	0.0059 (0.1188)	-0.0041 (0.1196)	0.0017 (0.1196)	0.0045 (0.1170)	0.0018 (0.1187)
$\hat{\theta}_{EB1}$	-0.0096 (0.0997)	-0.0145 (0.1025)	-0.0325 (0.0997)	-0.0886 (0.1031)	-0.1394 (0.1226)	-0.6982 (0.3131)
$\hat{\theta}_{EB2}$	-0.0043 (0.0997)	0.0038 (0.1023)	-0.0011 (0.0996)	0.0017 (0.1028)	0.0037 (0.1016)	0.0007 (0.1101)

the true propensity score. Its sampling distribution, however, is relatively more dispersed than that of the poststratification estimator. The empirical Bayes estimator moderately outperforms the parametric imputation estimator across all designs. However, for K large/ M small it also exhibits substantial bias. Incorporating the true propensity score into the marginal model eliminates this bias. Importantly, the sampling distribution of this estimator is less dispersed than that of the double robust estimator, with a standard deviation 15 to 20 percent smaller.

IV. Conclusion

In many applications the number of discrete covariate cells is large relative to the sample size. In such situations many cells may contain few, or even no, observations of the outcome of interest Y . Using a parametric model to impute cell means is one approach to solving this empty cell problem. We have outlined an alternative approach to estimating cell means and associated population average parameters. In cells with many observed outcomes, our approach is nonparametric; in cells with few such observations it is essentially parametric; while in intermediate cases we combine a nonparametric and parametric estimate of the cell mean. Incorporating the propensity score into our parametric imputation model appears to help guard against misspecification.

In further work it would be useful to explore other ways of choosing the γ_k and to formally characterize the large sample properties of our estimator. Of particular interest are asymptotic sequences, which allow K to grow with N , as first suggested by Angrist and Hahn (2004).

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