

**A ROBUST CALIBRATION-ASSISTED METHOD
FOR LINEAR MIXED EFFECTS MODEL UNDER
CLUSTER-SPECIFIC NONIGNORABLE MISSINGNESS**

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Supplementary Material

In this supplementary material, we prove the lemma 1, equations (3.7) and (3.8), and Theorem 1.

S1 Proof of Lemma 1

The key idea is to use the calibrated condition (3.3) and cluster-specific nonignorable assumptions (2.2). We first state the lemma again.

Lemma 1.

$$E \left\{ \sum_{j=1}^{n_i} x_{ij} (y_{ij} - x_{ij} \beta) \right\} = E \left\{ \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}} (x_{ij} - \tilde{x}_i) (y_{ij} - x_{ij} \beta) \right\}, \quad (\text{S1.1})$$

where $\tilde{x}_i = n_i^{-1} \sum_{j=1}^{n_i} \{\delta_{ij}/\hat{\pi}_{ij}(\gamma) - 1\} x_{ij}$, and

$$E \left[\left\{ \sum_{j=1}^{n_i} (y_{ij} - x_{ij}\beta) \right\}^2 \right] = E \left[\left\{ \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (y_{ij} - x_{ij}\beta) \right\}^2 - C_i(\eta) \right], \quad (\text{S1.2})$$

where $C_i(\eta) = \sum_{j=1}^{n_i} \{\delta_{ij}/\hat{\pi}_{ij}^2(\gamma) - 1\} \sigma^2$.

Proof. For (S1.1), it is enough to show

$$E \left[\sum_{j=1}^{n_i} \left\{ \left(\frac{\delta_{ij}}{\hat{\pi}_{ij}} - 1 \right) x_{ij} - \frac{\delta_{ij}}{\hat{\pi}_{ij}} \tilde{x}_i \right\} (y_{ij} - x_{ij}\beta) \right] = 0$$

$$\begin{aligned} & E \left[\sum_{j=1}^{n_i} \left\{ \left(\frac{\delta_{ij}}{\hat{\pi}_{ij}} - 1 \right) x_{ij} - \frac{\delta_{ij}}{\hat{\pi}_{ij}} \tilde{x}_i \right\} (y_{ij} - x_{ij}\beta) \right] \\ &= E \left[\sum_{j=1}^{n_i} \left\{ \left(\frac{\delta_{ij}}{\hat{\pi}_{ij}} - 1 \right) x_{ij} - \frac{\delta_{ij}}{\hat{\pi}_{ij}} \tilde{x}_i \right\} (a_i + e_{ij}) \right] \\ &= E \left[\sum_{j=1}^{n_i} \left\{ \left(\frac{\delta_{ij}}{\hat{\pi}_{ij}} - 1 \right) x_{ij} - \frac{\delta_{ij}}{\hat{\pi}_{ij}} \tilde{x}_i \right\} a_i \right] \\ &= E \left\{ \sum_{j=1}^{n_i} \left(\frac{\delta_{ij}}{\hat{\pi}_{ij}} - 1 \right) x_{ij} a_i \right\} - E(n_i \tilde{x}_i a_i) = 0, \end{aligned}$$

where the last equality holds by definition of \tilde{x}_i and the second equality

holds because CSNI implies

$$E(e_{ij} \mid x_{ij}, a_i, \delta_{ij}) = E(e_{ij} \mid x_{ij}, a_i) = 0. \quad (\text{S1.3})$$

For the equation (S1.2),

$$\begin{aligned}
 E \left[\left\{ \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (y_{ij} - x_{ij}\beta) \right\}^2 - C_i \right] &= E \left[\left\{ \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (a_i + e_{ij}) \right\}^2 - C_i \right] \\
 &= E \left[\left\{ n_i a_i + \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} e_{ij} \right\}^2 - \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)^2} - 1 \right\} \sigma^2 \right] \\
 &= E \left[(n_i a_i)^2 + \left\{ \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} e_{ij} \right\}^2 - \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)^2} - 1 \right\} \sigma^2 \right] \\
 &= E \left[(n_i a_i)^2 + n_i \sigma^2 + \sum_{j=1}^{n_i} \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)^2} (e_{ij}^2 - \sigma^2) \right] = n_i^2 D + n_i \sigma^2,
 \end{aligned}$$

and

$$\begin{aligned}
 E \left[\left\{ \sum_{j=1}^{n_i} (y_{ij} - x_{ij}\beta) \right\}^2 \right] &= E \left[\left\{ \sum_{j=1}^{n_i} (a_i + e_{ij}) \right\}^2 \right] = E \left\{ (n_i a_i + \sum_{j=1}^{n_i} e_{ij})^2 \right\}, \\
 &= E \left\{ (n_i a_i)^2 + \left(\sum_{j=1}^{n_i} e_{ij} \right)^2 \right\} = n_i^2 D + n_i \sigma^2.
 \end{aligned}$$

Thus, we have (S1.2). \square

Additionally, for the equation (3.7),

$$\begin{aligned}
 &E \left[\bar{x}_i \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (y_{ij} - x_{ij}\beta) \right] \\
 &= E \left[\bar{x}_i \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i + e_{ij}) \right] \\
 &= E \left[\bar{x}_i \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} a_i \right] = 0,
 \end{aligned}$$

where the second equality follows from (S1.3). Similarly, for the equation

(3.8) in the paper, it is enough to show that

$$E \left[\sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (y_{ij} - x_{ij}\beta)^2 \right] = 0. \quad (\text{S1.4})$$

Note that

$$\begin{aligned} & E \left[\sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (y_{ij} - x_{ij}\beta)^2 \right] \\ &= E \left[\sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i + e_{ij})^2 \right] \\ &= \sum_{j=1}^{n_i} E \left[E \left\{ \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i + e_{ij})^2 \mid x_{ij}, a_i, \delta_{ij} \right\} \right] \\ &= \sum_{j=1}^{n_i} E \left[E \left\{ \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i^2 + 2a_i e_{ij} + e_{ij}^2) \mid x_{ij}, a_i, \delta_{ij} \right\} \right] \\ &= \sum_{j=1}^{n_i} E \left[E \left\{ \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i^2 + e_{ij}^2) \mid x_{ij}, a_i, \delta_{ij} \right\} \right] \\ &= E \left[\sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} - 1 \right\} (a_i^2 + \sigma^2) \right] = 0, \end{aligned}$$

where the fourth equality follows from (S1.3) and the last equality follows

from (3.3). Therefore, (S1.4) is established.

S2 Proof of Theorem 1

We first check the conditions for the asymptotic normality of $U_1(\eta) = \sum_{i=1}^K U_{1i}(\eta)$ for $p = 1$. Since

$$\begin{aligned} U_{1i}(\eta) &= \sum_{j=1}^{n_i} \left\{ \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (x_{ij} - \tilde{x}_i)(y_{ij} - x_{ij}\beta) - \bar{x}_i \tau_i \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (y_{ij} - x_{ij}\beta) \right\} \\ &= \sum_{j=1}^{n_i} c_{ij}(\gamma) (a_i + e_{ij}), \end{aligned}$$

where

$$c_{ij}(\gamma) = \frac{\delta_{ij}}{\hat{\pi}_{ij}(\gamma)} (x_{ij} - \tilde{x}_i - \bar{x}_i \tau_i).$$

Define $B_K^2 = \sum_{i=1}^K V\{U_{1i}(\eta)\}$. Since $\sum_{j=1}^{n_i} \delta_{ij} > 0$, $\hat{\pi}_{ij}(\gamma)$ is bounded away from zero. Under conditions of bounded moments, we have

$$\sum_{i=1}^K n_i^2 \cdot C_1 \leq B_K^2 \leq \sum_{i=1}^K n_i^2 \cdot C_2$$

for some constants $C_2 > C_1 > 0$.

Now, to achieve the asymptotic normality of $B_K^{-1}U_1(\eta)$, we can use Liapounov condition:

$$\lim_{K \rightarrow \infty} \frac{\sum_{i=1}^K E\{|U_{1i}(\eta)|^{2+\delta}\}}{B_K^{2+\delta}} = 0. \quad (\text{S2.5})$$

Now, there exists $C_3 = O(1)$ such that

$$E\{|U_{1i}(\eta)|^{2+\delta}\} \leq \sum_{i=1}^K n_i^{2+\delta} \cdot C_3,$$

and we have

$$\frac{\sum_{i=1}^K E\{|U_{1i}(\eta)|^{2+\delta}\}}{B_K^{2+\delta}} \leq \frac{\sum_{i=1}^K n_i^{2+\delta}}{\left(\sum_{i=1}^K n_i^2\right)^{(2+\delta)/2}} \cdot C_4,$$

for some $C_4 = O(1)$. Thus, (3.13) implies (S2.5) and the asymptotic normality of $U_1(\eta)$ can be established. Asymptotic normality of $U_1(\eta)$ when $p > 1$ and that of $\Psi(\eta) = \{U_1(\eta), U_2(\eta), U_3(\eta), \psi(\gamma)\}$ can be established similarly, using Cramer-Wold device.

To establish the asymptotic normality of the solution $\hat{\eta}_K$ to $\Psi_K(\eta) = 0$, where $\Psi_K(\eta) = \Psi(\eta)$, we apply the first-order Taylor expansion to get

$$0 = B_{2K}^{-1}\Psi_K(\eta^*) + \mathbf{\Gamma}(\tilde{\eta}_K)(\hat{\eta}_K - \eta^*), \quad (\text{S2.6})$$

where $B_{2K}^2 = \sum_{i=1}^K V\{\Psi_i(\eta)\}$, $\mathbf{\Gamma}(\cdot) = \partial(B_{2K}^{-1}\Psi_K)(\cdot)/\partial\eta^T$, and $\tilde{\eta}_K$ lies on the line segment between $\hat{\eta}_K$ and η^* . Now, define

$$J_K^2 = \frac{\sum_{i=1}^K n_i^2}{\left(\sum_{i=1}^K n_i\right)^2}.$$

Note that $J_K^2 = O(K^{-1})$ by condition (3.12). Then,

$$J_K^2\mathbf{\Gamma}(\tilde{\eta}_K) = J_K^2\mathbf{\Gamma}(\eta^*) + o_p(1).$$

Since we can obtain $J_K^2\mathbf{\Gamma}(\eta^*)$ converges in probability to its mean

$$M_1(\eta^*) = \lim_{K \rightarrow \infty} E\{J_K^2\mathbf{\Gamma}(\eta^*)\},$$

and $B_{2K}^{-1}\Psi_K(\eta^*) = O_p(J_K^{-1})$ by central limit theorem. Therefore, if $M_1(\eta^*)$

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is nonsingular,

$$J_K^{-1}(\hat{\eta}_K - \eta^*) = -\{M_1(\eta^*)\}^{-1} B_{2K}^{-1} \Psi_K(\eta^*) + o_p(1)$$

which establishes the asymptotic normality of $J_K^{-1}(\hat{\eta}_K - \eta^*)$. Since $K^{1/2}(\hat{\eta}_K - \eta^*) = (K J_K^2)^{1/2} J_K^{-1}(\hat{\eta}_K - \eta^*) = C J_K^{-1}(\hat{\eta}_K - \eta^*) + o_p(1)$, where $C^2 = \lim_{K \rightarrow \infty} (K J_K^2)$, the asymptotic normality of $K^{1/2}(\hat{\eta}_K - \eta^*)$ also follows. See Chapter 6.2.1 of Bickel and Doksum (1977) for more details about regularity conditions.

References

Bickel, P.J. and Doksum, K.A. (1977). *Mathematical statistics : basic ideas and selected topics*, Vol 1. Prentice Hall.