# CAUSAL INFERENCE FROM POSSIBLY UNBALANCED SPLIT-PLOT DESIGNS: A RANDOMIZATION-BASED PERSPECTIVE 

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## Supplementary Material

## Proof of all results

In what follows, $E_{1}$ and $\operatorname{cov}_{1}$ denote unconditional expectation and covariance with respect to the randomization at the WP stage, while $E_{2}$ and $\operatorname{cov}_{2}$ denote expectation and covariance with respect to the randomization at the SP stage, conditional on the WP stage assignment.

Proof of Proposition 1. Follows from straightforward conditioning arguments.

Proof of Theorem 2. Recall that

$$
\begin{aligned}
\bar{U}_{w}^{\mathrm{obs}}\left(z_{1} z_{2}\right) & =\frac{1}{r_{w 2}\left(z_{2}\right)} \sum_{i \in T_{w 2}\left(z_{2}\right)} U_{i}\left(z_{1} z_{2}\right), w \in T_{1}\left(z_{1}\right) \\
\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right) & =\frac{1}{r_{1}\left(z_{1}\right)} \sum_{w \in T_{1}\left(z_{1}\right)} \bar{U}_{w}^{\mathrm{obs}}\left(z_{1} z_{2}\right)
\end{aligned}
$$

Consequently,

$$
E_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right)\right\}=\frac{1}{r_{1}\left(z_{1}\right)} \sum_{w \in T_{1}\left(z_{1}\right)} \bar{U}_{w}\left(z_{1} z_{2}\right)
$$

and,

$$
E_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\}=\frac{1}{r_{1}\left(z_{1}^{*}\right)} \sum_{w \in T_{1}\left(z_{1}^{*}\right)} \bar{U}_{w}\left(z_{1}^{*} z_{2}^{*}\right)
$$

Defining $\delta\left(z_{1}, z_{1}^{*}\right)$ as an indicator that equals one if $z_{1}=z_{1}^{*}$ and zero otherwise, we have

$$
\begin{aligned}
& \operatorname{cov}_{1}\left[E_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right)\right\}, E_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\}\right] \\
= & \frac{1}{(W-1) W r_{1}\left(z_{1}\right)} \sum_{w=1}^{W}\left\{\bar{U}_{w}\left(z_{1} z_{2}\right)-\bar{U}\left(z_{1} z_{2}\right)\right\}\left\{\bar{U}_{w}\left(z_{1}^{*} z_{2}^{*}\right)-\bar{U}\left(z_{1}^{*} z_{2}^{*}\right)\right\}\left\{W \delta\left(z_{1}, z_{1}^{*}\right)-r_{1}\left(z_{1}\right)\right\} \\
= & \frac{1}{W \bar{M} r_{1}\left(z_{1}\right)} S_{\mathrm{bt}}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)\left\{W \delta\left(z_{1}, z_{1}^{*}\right)-r_{1}\left(z_{1}\right)\right\} .
\end{aligned}
$$

Next,

$$
\begin{aligned}
& \operatorname{cov}_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right), \bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\} \\
= & \delta\left(z_{1}, z_{1}^{*}\right) \sum_{w \in T_{1}\left(z_{1}\right)} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)\left\{M_{w} \delta\left(z_{2}, z_{2}^{*}\right)-r_{w 2}\left(z_{2}\right)\right\}}{M_{w} r_{w 2}\left(z_{2}\right)\left\{r_{1}\left(z_{1}\right)\right\}^{2}} .
\end{aligned}
$$

so that

$$
\begin{aligned}
& E_{1}\left[\operatorname{cov}_{2}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right), \bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\}\right] \\
= & \delta\left(z_{1}, z_{1}^{*}\right) \sum_{w=1}^{W} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)\left\{M_{w} \delta\left(z_{2}, z_{2}^{*}\right)-r_{w 2}\left(z_{2}\right)\right\}}{W M_{w} r_{1}\left(z_{1}\right) r_{w 2}\left(z_{2}\right)} .
\end{aligned}
$$

Hence,

$$
\begin{align*}
& \operatorname{cov}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right), \bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\} \\
= & \delta\left(z_{1}, z_{1}^{*}\right)\left\{\frac{S_{\mathrm{bt}}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)}{\bar{M} r_{1}\left(z_{1}\right)}-\sum_{w=1}^{W} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)}{W M_{w} r_{1}\left(z_{1}\right)}\right\} \\
+ & \delta\left(z_{1}, z_{1}^{*}\right) \delta\left(z_{2}, z_{2}^{*}\right) \sum_{w=1}^{W} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)}{W r_{1}\left(z_{1}\right) r_{w 2}\left(z_{2}\right)}-\frac{S_{\mathrm{bt}}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right)}{N} . \tag{S1.1}
\end{align*}
$$

Since $\widehat{\bar{\tau}}=\sum_{z_{1} \in Z_{1}} \sum_{z_{2} \in Z_{2}} g\left(z_{1} z_{2}\right) \bar{U}^{\text {obs }}\left(z_{1} z_{2}\right)$, we have that

$$
\operatorname{var}(\widehat{\bar{\tau}})=\sum_{z_{1} \in Z_{1}} \sum_{z_{2} \in Z_{2}} \sum_{z_{1}^{*} \in Z_{1}} \sum_{z_{2}^{*} \in Z_{2}} g\left(z_{1} z_{2}\right) g\left(z_{1}^{*} z_{2}^{*}\right) \operatorname{cov}\left\{\bar{U}^{\mathrm{obs}}\left(z_{1} z_{2}\right), \bar{U}^{\mathrm{obs}}\left(z_{1}^{*} z_{2}^{*}\right)\right\} .
$$

Substituting the expression of $\operatorname{cov}\left\{\bar{U}^{\text {obs }}\left(z_{1} z_{2}\right), \bar{U}^{\text {obs }}\left(z_{1}^{*} z_{2}^{*}\right)\right\}$ from S1.1 in the above, the first two terms in the expression of $\operatorname{var}(\hat{\bar{\tau}})$ in Theorem 1
follow immediately. The last term can be explained as

$$
\begin{aligned}
& \sum_{z_{1} \in Z_{1}} \sum_{z_{2} \in Z_{2}} \sum_{z_{1}^{*} \in Z_{1}} \sum_{z_{2}^{*} \in Z_{2}} g\left(z_{1} z_{2}\right) g\left(z_{1}^{*} z_{2}^{*}\right) S_{\mathrm{bt}}\left(z_{1} z_{2}, z_{1}^{*} z_{2}^{*}\right) / N \\
= & \frac{\bar{M}}{(W-1) N} \sum_{w=1}^{W}\left[\sum_{z_{1} \in Z_{1}} \sum_{z_{2} \in Z_{2}} g\left(z_{1} z_{2}\right)\left\{\bar{U}_{w}\left(z_{1} z_{2}\right)-\bar{U}\left(z_{1} z_{2}\right)\right\}\right]^{2} \\
= & \frac{1}{W(W-1)} \sum_{w=1}^{W}\left[\sum_{z_{1} \in Z_{1}} \sum_{z_{2} \in Z_{2}} g\left(z_{1} z_{2}\right)\left\{\left(M_{w} / \bar{M}\right) \bar{Y}_{w}\left(z_{1} z_{2}\right)-\bar{Y}\left(z_{1} z_{2}\right)\right\}\right]^{2} \\
= & \frac{1}{W(W-1)} \sum_{w=1}^{W}\left\{\left(M_{w} / \bar{M}\right) \bar{\tau}_{w}-\bar{\tau}\right\}^{2}=\Delta .
\end{aligned}
$$

Proof of Theorem 3.

$$
\begin{aligned}
E_{2}\left\{\widehat{S}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\right\} & =\frac{1}{r_{1}\left(z_{1}\right)} \sum_{w \in T_{1}\left(z_{1}\right)} \operatorname{cov}_{2}\left\{\bar{U}_{w}^{\text {obs }}\left(z_{1} z_{2}\right), \bar{U}_{w}^{\mathrm{obs}}\left(z_{1} z_{2}^{*}\right)\right\} \\
& +\frac{1}{r_{1}\left(z_{1}\right)-1} \sum_{w \in T_{1}\left(z_{1}\right)}\left\{\bar{U}_{w}\left(z_{1} z_{2}\right)-\tilde{\bar{U}}\left(z_{1} z_{2}\right)\right\}\left\{\bar{U}_{w}\left(z_{1} z_{2}^{*}\right)-\tilde{\bar{U}}\left(z_{1} z_{2}^{*}\right)\right\}
\end{aligned}
$$

where $\widetilde{\bar{U}}\left(z_{1} z_{2}\right)=\sum_{w \in T_{1}\left(z_{1}\right)} \bar{U}_{w}\left(z_{1} z_{2}\right) / r_{1}\left(z_{1}\right)$, and $\widetilde{\bar{U}}\left(z_{1} z_{2}^{*}\right)$ is similarly defined. For any $w \in T_{1}\left(z_{1}\right)$,
$\operatorname{cov}_{2}\left\{\bar{U}_{w}^{\mathrm{obs}}\left(z_{1} z_{2}\right), \bar{U}_{w}^{\mathrm{obs}}\left(z_{1} z_{2}^{*}\right)\right\}=\frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\left\{M_{w} \delta\left(z_{2}, z_{2}^{*}\right)-r_{w 2}\left(z_{2}\right)\right\}}{M_{w} r_{w 2}\left(z_{2}\right)}$.
Thus,

$$
\begin{aligned}
E\left\{\widehat{S}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\right\} & =E_{1} E_{2}\left\{\widehat{S}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\right\} \\
& =\sum_{w=1}^{W} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\left\{M_{w} \delta\left(z_{2}, z_{2}^{*}\right)-r_{w 2}\left(z_{2}\right)\right\}}{W M_{w} r_{w 2}\left(z_{2}\right)} \\
& +\frac{1}{W-1} \sum_{w=1}^{W}\left\{\bar{U}_{w}\left(z_{1} z_{2}\right)-\bar{U}\left(z_{1} z_{2}\right)\right\}\left\{\bar{U}_{w}\left(z_{1} z_{2}^{*}\right)-\bar{U}\left(z_{1} z_{2}^{*}\right)\right\} \\
& =\sum_{w=1}^{W} \frac{S_{\mathrm{in}, w}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)\left\{M_{w} \delta\left(z_{2}, z_{2}^{*}\right)-r_{w 2}\left(z_{2}\right)\right\}}{W M_{w} r_{w 2}\left(z_{2}\right)}+\frac{S_{\mathrm{bt}}\left(z_{1} z_{2}, z_{1} z_{2}^{*}\right)}{\bar{M}} .
\end{aligned}
$$

The result stated in Theorem 3 is evident from the above.

Proof of Proposition 2. Because $w \neq w^{*}$, by (2.5) and the definition of $G_{w}^{\text {obs }}$, conditionally on the assignment of the WPs to the level combinations of the

WP factors, $G_{w}^{\mathrm{obs}}$ and $G_{w^{*}}^{\mathrm{obs}}$ are independent and the conditional expectation of their product equals

$$
\left\{\sum_{z_{2} \in Z_{2}} g\left(z_{1 w} z_{2}\right) \bar{Y}_{w}\left(z_{1 w} z_{2}\right)\right\}\left\{\sum_{z_{2} \in Z_{2}} g\left(z_{1 w^{*}} z_{2}\right) \bar{Y}_{w^{*}}\left(z_{1 w^{*}} z_{2}\right)\right\} .
$$

The result now follows from (3.2), noting that the pair $\left(z_{1 w}, z_{1 w^{*}}\right)$ equals any $\left(z_{1}, z_{1}^{*}\right)$ with probability $\frac{r_{1}\left(z_{1}\right)\left\{r_{1}\left(z_{1}^{*}\right)-\delta\left(z_{1}, z_{1}^{*}\right)\right\}}{W(W-1)}$.

Proof of the necessity part of Theorem 5. Suppose a psd matrix $B=\left(b_{w w^{*}}\right)$ of order $W$ and satisfying (c1)-(c3) exists. Then by (c1),

$$
\begin{equation*}
\left|b_{w w^{*}}\right| \leq M_{w} M_{w^{*}}, \quad w, w^{*}=1, \ldots, W, \quad w \neq w^{*} \tag{S1.2}
\end{equation*}
$$

Hence using (c2), S1.2), and (c1) in succession,
$0=b_{W 1}+\ldots+b_{W W} \geq b_{W W}-M_{W}\left(M_{1}+\ldots+M_{W-1}\right)=M_{W}\left(M_{W}-M_{1}-\ldots-M_{W-1}\right)$,
which implies $M_{W} \leq M_{1}+\ldots+M_{W-1}$. If possible, let equality hold here. Then equality holds throughout in (S1.3), and invoking (S1.2), this yields

$$
\begin{equation*}
b_{W w}=-M_{W} M_{w}, \quad w=1, \ldots, W-1 \tag{S1.4}
\end{equation*}
$$

For any $w, w^{*}$ such that $w<w^{*}<W$, by ( c 1 ) and (S1.4), the principal minor of $B$, as given by its $w$ th, $w^{*}$ th and $W$ th rows and columns turns out to be $-M_{W}^{2}\left(b_{w w^{*}}-M_{w} M_{w^{*}}\right)^{2}$. Because this principal minor is nonnegative due
to psd-ness of $B$, it follows that $b_{w w^{*}}=M_{w} M_{w^{*}}$. This, in conjunction with (c1) and S1.4), implies that $B=b b^{\prime}$, where $b=\left(M_{1}, \ldots, M_{W-1},-M_{W}\right)^{\prime}$. But then $\operatorname{rank}(B)=1<W-1$, and (c3) is violated. This contradiction proves the necessity of the condition $M_{W}<M_{1}+\ldots+M_{W-1}$.

To prove the sufficiency part of Theorem 5, we first state a lemma that is crucial in this proof and also leads to the algorithm for construction of the symmetric psd matrix $B$ of order $W$ that satisfies conditions (c1)-(c3).

Lemma 1. Let $W \geq 3$. Suppose $M_{1}, \ldots, M_{W}$ are not all equal and $M_{1} \leq$ $\ldots \leq M_{W}$, as per (5.1). Let e denote the $(W-1) \times 1$ vector of ones and $\mu=\left(M_{1}, \ldots, M_{W-1}\right)^{\prime}$.
(a) Then there exists a $(W-1) \times 1$ vector $x$ with elements $\pm 1$ such that $\left|\mu^{\prime} x\right|<M_{W}$.
(b) If, in addition, condition (5.3) holds, i.e., $M_{W}<M_{1}+\ldots+M_{W-1}$, then, with the vector $x$ as in (a) above, there exist nonnegative constants $a_{1}, a_{2}$ satisfying $a_{1}+a_{2}<1$, such that equation (5.6) holds, i.e.,

$$
a_{1}\left\{\left(\mu^{\prime} x\right)^{2}-\mu^{\prime} \mu\right\}+a_{2}\left\{\left(\mu^{\prime} e\right)^{2}-\mu^{\prime} \mu\right\}=M_{W}^{2}-\mu^{\prime} \mu
$$

Proof of Lemma 1. Part (a). It will suffice to show that there exist $x_{1}, \ldots, x_{W-1}$, each +1 or -1 , such that $\left|\sum_{w=1}^{W-1} M_{w} x_{w}\right|<M_{W}$. One can then simply take $x=\left(x_{1}, \ldots, x_{W-1}\right)^{\prime}$. Recall that $M_{1} \leq M_{2} \leq \ldots \leq M_{W}$, as per (5.1).

Because $M_{1} \ldots, M_{W}$ are not all equal, this yields

$$
\begin{equation*}
M_{1}<M_{W} \tag{S1.5}
\end{equation*}
$$

Let $h$ be the largest nonnegative integer such that

$$
\begin{equation*}
M_{W-2 h}=M_{W} \tag{S1.6}
\end{equation*}
$$

By (S1.5), $W-2 h \geq 2$. If $h \geq 1$, define

$$
\begin{equation*}
x_{W-h}=\ldots=x_{W-1}=1, \quad x_{W-2 h}=\ldots=x_{W-h-1}=-1, \tag{S1.7}
\end{equation*}
$$

and note that

$$
\begin{equation*}
\sum_{w=W-2 h}^{W-1} M_{w} x_{w}=0 \tag{S1.8}
\end{equation*}
$$

because by (5.1) and S1.6), $M_{w}=M_{W}$ for $w=W-2 h, \ldots, W-1$.
Now, if $W-2 h=2$, then with $x_{1}=1$ and $x_{2}, \ldots, x_{W-1}$ as in (S1.7, $\left|\sum_{w=1}^{W-1} M_{w} x_{w}\right|=M_{1}<M_{W}$, by S1.5 and S1.8.

Next, let $W-2 h \geq 3$. Then, by (5.1),

$$
\sum_{w=2}^{W-2 h-1} M_{w} \geq(W-2 h-2) M_{2} \geq M_{1}
$$

Let $w_{1}$ be the largest integer in $\{1, \ldots, W-2 h-2\}$ such that $\sum_{w=1}^{w_{1}} M_{w} \leq$ $\sum_{w=w_{1}+1}^{W-2 h-1} M_{w}$. If $w_{1}=W-2 h-2$, then $\sum_{w=1}^{W-2 h-2} M_{w} \leq M_{W-2 h-1}$. So,
with $x_{1}=\ldots=x_{W-2 h-2}=-1, x_{W-2 h-1}=1$ and $x_{W-2 h}, \ldots, x_{W-1}$ as in (S1.7) when $h \geq 1$,

$$
\left|\sum_{w=1}^{W-1} M_{w} x_{w}\right|=M_{W-2 h-1}-\sum_{w=1}^{W-2 h-2} M_{w}<M_{W-2 h-1} \leq M_{W}
$$

by (S1.8).
Now, suppose $1 \leq w_{1} \leq W-2 h-3$, in which case $W-2 h \geq 4$. Then,

$$
\sum_{w=1}^{w_{1}} M_{w} \leq \sum_{w=w_{1}+1}^{W-2 h-1} M_{w}, \quad \text { and } \quad \sum_{w=1}^{w_{1}+1} M_{w}>\sum_{w=w_{1}+2}^{W-2 h-1} M_{w}
$$

As a result, either

$$
\begin{equation*}
\left|\sum_{w=w_{1}+1}^{W-2 h-1} M_{w}-\sum_{w=1}^{w_{1}} M_{w}\right|<M_{W} \quad \text { or (ii) }\left|\sum_{w=1}^{w_{1}+1} M_{w}-\sum_{w=w_{1}+2}^{W-2 h-1} M_{w}\right|<M_{W} . \tag{i}
\end{equation*}
$$

Else,

$$
\sum_{w=w_{1}+1}^{W-2 h-1} M_{w}-\sum_{w=1}^{w_{1}} M_{w} \geq M_{W}, \quad \text { as well as } \quad \sum_{w=1}^{w_{1}+1} M_{w}-\sum_{w=w_{1}+2}^{W-2 h-1} M_{w} \geq M_{W}
$$

Adding these two inequalities, we have $M_{w_{1}+1} \geq M_{W}$, which is impossible by the definition of $h$, because $w_{1}+1 \leq W-2 h-2$.

If (i) holds, then the choice $x_{1}=\ldots=x_{w_{1}}=-1, x_{w_{1}+1}=\ldots=$ $x_{W-2 h-1}=1$, coupled with $x_{W-2 h}, \ldots, x_{W-1}$ as in (S1.7) when $h \geq 1$, entails $\left|\sum_{w=1}^{W-1} M_{w} x_{w}\right|<M_{W}$, by S1.8. Similarly, if (ii) holds, then the choice $x_{1}=\ldots=x_{w_{1}+1}=-1, x_{w_{1}+2}=\ldots=x_{W-2 h-1}=1$, coupled with $x_{W-2 h}, \ldots, x_{W-1}$ as in S1.7 when $h \geq 1$, entails $\left|\sum_{w=1}^{W-1} M_{w} x_{w}\right|<M_{W}$.

Part (b): Let $M_{W}<M_{1}+\ldots+M_{W-1}=\mu^{\prime} e$, and let the vector $x$ be as in part (a) above, so that $\left|\mu^{\prime} x\right|<M_{W}$. Let $\phi_{1}=\left(\mu^{\prime} x\right)^{2}-\mu^{\prime} \mu, \phi=M_{W}^{2}-\mu^{\prime} \mu$ and $\phi_{2}=\left(\mu^{\prime} e\right)^{2}-\mu^{\prime} \mu$. Then $\phi_{1}<\phi<\phi_{2}$, as $\left|\mu^{\prime} x\right|<M_{W}<\mu^{\prime} e$. As a result, there exist constants $\tilde{a}_{1}$ and $\tilde{a}_{2}$ such that $0 \leq \tilde{a}_{1}, \tilde{a}_{2}<1$ and $\tilde{a}_{1} \phi_{1}<\phi<\tilde{a}_{2} \phi_{2}$. Let $\xi=\left(\tilde{a}_{2} \phi_{2}-\phi\right) /\left(\tilde{a}_{2} \phi_{2}-\tilde{a}_{1} \phi_{1}\right)$. Then $0<\xi<1$. Hence, if we take $a_{1}=\tilde{a}_{1} \xi, a_{2}=\tilde{a}_{2}(1-\xi)$, then $a_{1}, a_{2} \geq 0$ and $a_{1}+a_{2}<1$, because $a_{1}+a_{2}$ is a weighted average of $\tilde{a}_{1}$ and $\tilde{a}_{2}$, both of which are less than one. Moreover, $a_{1} \phi_{1}+a_{2} \phi_{2}=\phi$ by the definition of $\xi$, i.e., $a_{1}$ and $a_{2}$ satisfy (5.6).

Proof of the sufficiency part of Theorem 5. In view of Lemma 1, this follows from steps $1-4$ in Section 5, noting that (i) the matrix $A$ there is positive definite, and hence the matrix $B$ there is psd of rank $W-1$ with each row sum zero, (ii) $A$ has diagonal elements $M_{1}^{2}, \ldots, M_{W-1}^{2}$, and (iii) by (29),

$$
e^{\prime} A e=a_{1}\left(\mu^{\prime} x\right)^{2}+a_{2}\left(\mu^{\prime} e\right)^{2}+\left(1-a_{1}-a_{2}\right) \mu^{\prime} \mu=M_{W}^{2}
$$

because $D e=\mu$.

## UNBALANCED SPLIT PLOT DESIGNS

## Symbol Chart

Table 1: Symbols used in the manuscript and their explanation

| Symbol | Meaning | Symbol | Meaning |
| :---: | :---: | :---: | :---: |
| A | matrix, in sufficiency part of Theorem 4 | $a$ | constant, in sufficiency part of Theorem 4 |
| $B$ | matrix in new variance estimator | $b$ | element of matrix $B$ |
| D | diagonal matrix of whole-plot sizes | $e$ | vector of ones |
| $E$ | expectation | $g$ | function defining treatment contrast |
| $F$ | factor | $h$ | integer, in proving Lemma A.1(a) |
| $G$ | term associated with the new variance estimator | $i$ | dummy subscript for unit |
| H | term used in defining the new variance estimator | $k$ | dummy subscript |
| I | identity matrix | $m$ | number of factors |
| $J$ | matrix of ones | $r$ | treatment replication |
| M | number of sub-plots in a whole plot | $u$ | dummy subscript |
| $N$ | total number of units | $v$ | dummy subscript |
| $S$ | similar to mean square/product component | $w$ | dummy, whole-plot index |
| $T$ | set of whole- or sub-plots | $x$ | vector of $\pm 1$, in sufficiency of Theorem 4 |
| $U$ | transformed outcome | $z$ | treatment combination |
| V | variance estimator |  |  |
| W | number of whole-plots | $\tau$ | treatment contrast |
| $Y$ | potential outcome | $\delta$ | Kronecker delta |
| Z | set of level combinations | $\mu$ | subvector of whole-plot sizes |
|  |  | $\phi$ | in the proof of Lemma A.1(b) |
| $\Omega$ | whole-plot | $\zeta$ | in the proof of Lemma A.1(b) |
| $\Delta$ | bias in variance estimation | $\lambda$ | eigenvalue |

