Information content of cluster-period cells in stepped wedge trials

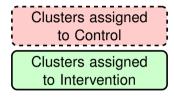
Jessica Kasza: jessica.kasza@monash.edu

Andrew Forbes: andrew.forbes@monash.edu



International Biometric Society Journal Club, February 2020

The standard cluster randomised trial



- Clusters (groups) of participants assigned to treatments. (Why?)
- Clusters could be hospitals, intensive care units, schools, neighbourhoods...

The standard cluster randomised trial

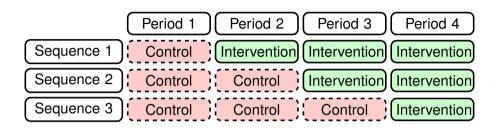
Clusters assigned to Control

Clusters assigned to Intervention

- Clusters (groups) of participants assigned to treatments. (Why?)
- Clusters could be hospitals, intensive care units, schools, neighbourhoods...

Can increase efficiency by considering *longitudinal (multiple period)* cluster randomised trials.

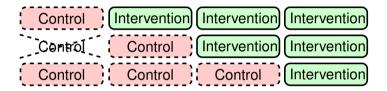
The stepped wedge cluster randomised trial design



- Stepped wedge designs can be useful when all clusters need to receive the intervention, or the intervention is going to be rolled out anyway.
- K clusters are randomised to T-1 sequences; $K \times T$ cluster-period cells;
- m participants in each cluster in each period.

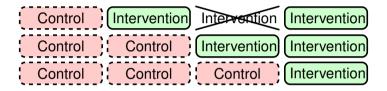
Each cluster-period pair is a **cell** of the design.

Does each *cell* contribute the same amount of information?



- Which participants contribute the most information about the treatment effect?
- Which cells can be omitted with the smallest acceptable decrease in power (or precision)?

Does each *cell* contribute the same amount of information?



- Which participants contribute the most information about the treatment effect?
- Which cells can be omitted with the smallest acceptable decrease in power (or precision)?

Models for continuous outcomes

A simple model for continuous outcomes:

Outcome = Period effect + Treatment effect + random effects + error

Models for continuous outcomes

A simple model for continuous outcomes:

Outcome = Period effect + Treatment effect + random effects + error

For participant i = 1, ..., m in cluster k = 1, ..., K, in period t = 1, ..., T:

$$egin{aligned} \mathbf{Y}_{kti} &= \mu + eta_t + \mathbf{X}_{kt} \theta + CP_{kt} + \epsilon_{kti}, \quad \epsilon_{kti} \sim N(0, \sigma_\epsilon^2) \ \mathbf{CP}_k &= (CP_{k1}, \dots, CP_{kT}) \sim N_T(0, \mathbf{V}_{CP}) \end{aligned}$$

 X_{kt} is the treatment indicator for cluster k in period t.

Models for continuous outcomes

A simple model for continuous outcomes:

Outcome = Period effect + Treatment effect + random effects + error

For participant i = 1, ..., m in cluster k = 1, ..., K, in period t = 1, ..., T:

$$egin{aligned} Y_{kti} &= \mu + eta_t + X_{kt} heta + CP_{kt} + \epsilon_{kti}, \quad \epsilon_{kti} \sim N(0, \sigma_\epsilon^2) \ \mathbf{CP}_k &= (CP_{k1}, \dots, CP_{kT}) \sim N_T(0, \mathbf{V}_{CP}) \end{aligned}$$

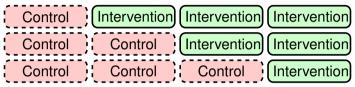
 X_{kt} is the treatment indicator for cluster k in period t.

 θ is the treatment effect: this is what we want to estimate.

- $\hat{\theta}$ the weighted least squares estimator of the treatment effect θ .
- $var(\hat{\theta})$ of interest: used in sample size calculations.

How much does $var(\hat{\theta})$ increase if observations from a given cell are omitted?

Calculate $var(\hat{\theta})$ given the complete design:



Calculate $var(\hat{\theta})$ given the complete design:

```
Control Intervention Intervention Intervention

Control Control Intervention Intervention

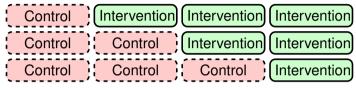
Control Control Intervention Intervention

Control Control Intervention
```

Calculate $var(\hat{\theta})_{[kt]}$ from the incomplete design, omitting period t of cluster k:

```
Control (Intervention) (Intervention) (Intervention) (Control (Intervention) (Int
```

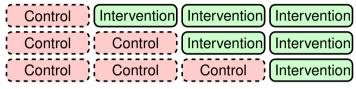
Calculate $var(\hat{\theta})$ given the complete design:



Calculate $var(\hat{\theta})_{[kt]}$ from the incomplete design, omitting period t of cluster k:

Information content of cell (k, t): $IC(k, t) = var(\hat{\theta})_{[kt]}/var(\hat{\theta})$

Calculate $var(\hat{\theta})$ given the complete design:



Calculate $var(\hat{\theta})_{[kt]}$ from the incomplete design, omitting period t of cluster k:

Information content of cell (k, t): $IC(k, t) = var(\hat{\theta})_{[kt]}/var(\hat{\theta})$

IC(k, t) = 1 implies no information loss; IC(k, t) > 1 implies loss of information.

Can obtain a closed-form expression for $IC(k,t) = var(\hat{\theta})_{[kt]}/var(\hat{\theta})$ for certain models¹

Depends on the within-cluster correlation structure.

$$Y_{kti} = \mu + \beta_t + X_{kt}\theta + CP_{kt} + \epsilon_{kti}, \quad \epsilon_{kti} \sim N(0, \sigma_{\epsilon}^2)$$

$$\mathbf{CP}_k = (CP_{k1}, \dots, CP_{kT}) \sim N_T(0, \mathbf{V}_{CP})$$

 V_{CP} is the covariance matrix for the random effects

- We will consider three structures, and what these say about correlations between subjects in the same cluster...
 - in the same or in different periods.

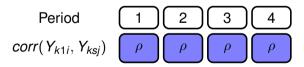
 $^{^{1}}$ A closed form expression for IC(k, t) is available whenever the inverse of the covariance matrix of observations from a cluster has a closed form.

Within-cluster correlation structure

Model 1: Hussey and Hughes (2007)

$$CP_{kt} = CP_{ks} = CP_k \sim N(0, \tau^2)$$
 $ho = corr(Y_{kti}, Y_{ksj}) = rac{ au^2}{ au^2 + \sigma_\epsilon^2}$

Correlation between the outcomes of any pair of participants is identical.

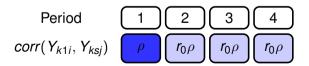


Within-cluster correlation structure

Model 2: "Constant between-period correlation model"

$$extbf{CP}_k \sim extbf{N}_T \left(0, au^2 \left[r_0 J_T + (1-r_0) I_T
ight]
ight)$$
 $ho = corr(Y_{kti}, Y_{ktj}) = rac{ au^2}{ au^2 + \sigma_\epsilon^2}, \quad corr(Y_{kti}, Y_{ksj}) = r_0 rac{ au^2}{ au^2 + \sigma_\epsilon^2} = r_0
ho$

• Participants in the *same* treatment period have more highly correlated outcomes than participants in different treatment periods.

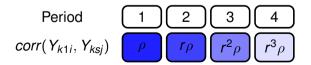


Within-cluster correlation structure

Model 3: "Exponential decay model"

$$extbf{CP}_k \sim N_T\left(0, au^2 R
ight), \quad R[t, s] = r^{|t-s|}$$
 $ho = corr(Y_{kti}, Y_{ktj}) = rac{ au^2}{ au^2 + \sigma^2}, \quad corr(Y_{kti}, Y_{ksj}) = r^{|t-s|} rac{ au^2}{ au^2 + \sigma^2} = r^{|t-s|}
ho$

 The correlation between a pair of participants decreases the further their measurement periods are apart in time.



For Models 1, 2, and 3 we get the following property:

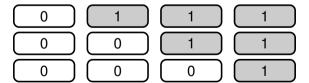
Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$

For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

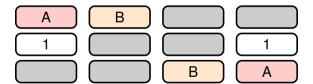
Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

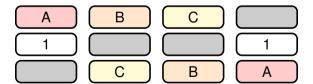
Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

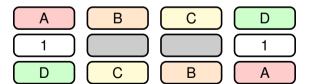
Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$



For Models 1, 2, and 3 we get the following property:

Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

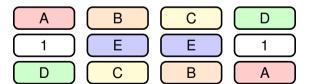
Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$

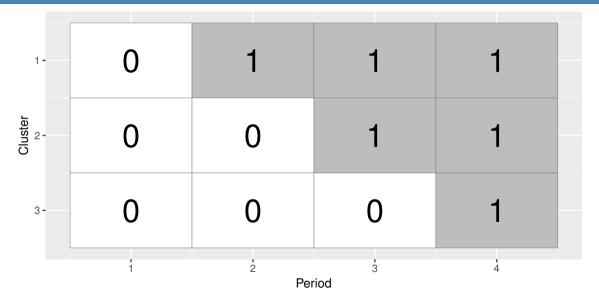


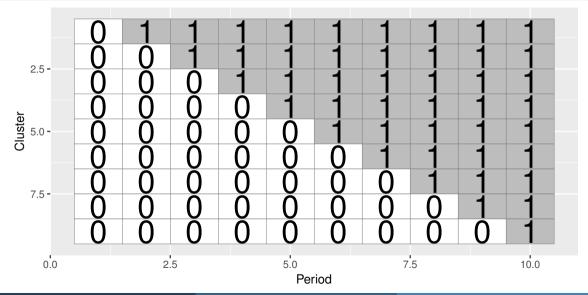
For Models 1, 2, and 3 we get the following property:

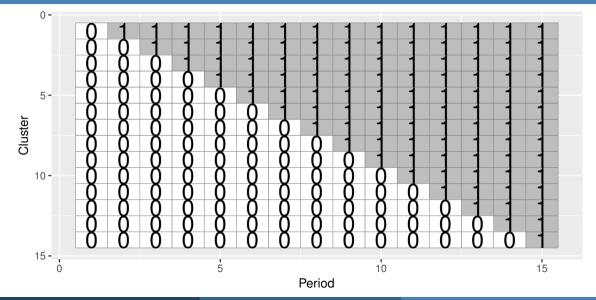
Centrosymmetry:
$$IC(k, t) = IC(K + 1 - k, T + 1 - t)$$

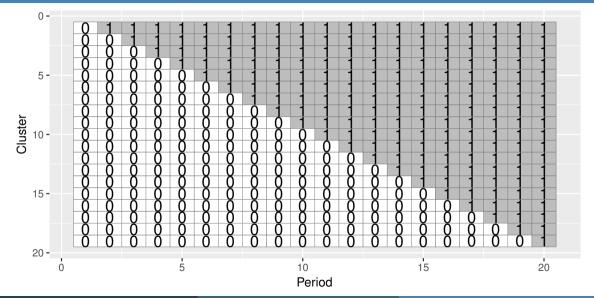
Information-free cells:
$$IC\left(\frac{K+1}{2},1\right)=IC\left(\frac{K+1}{2},T\right)=1$$

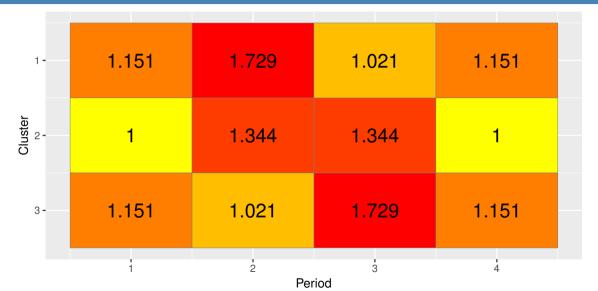


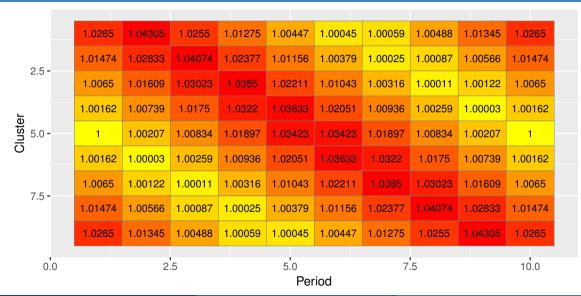


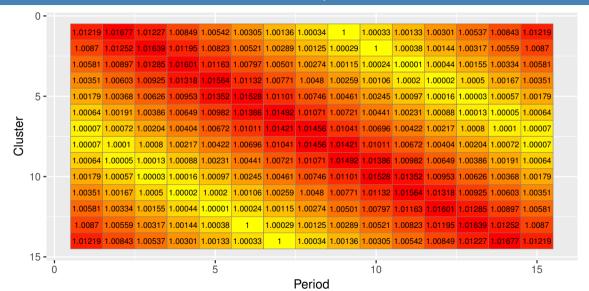


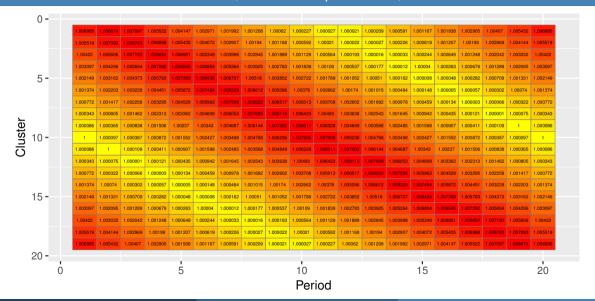


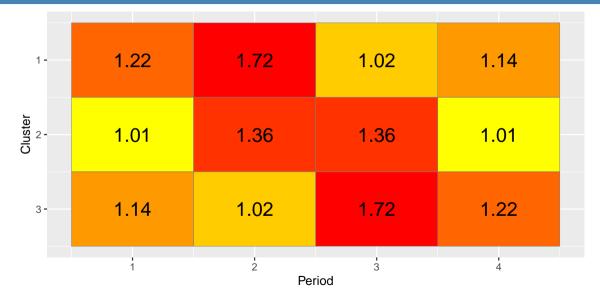


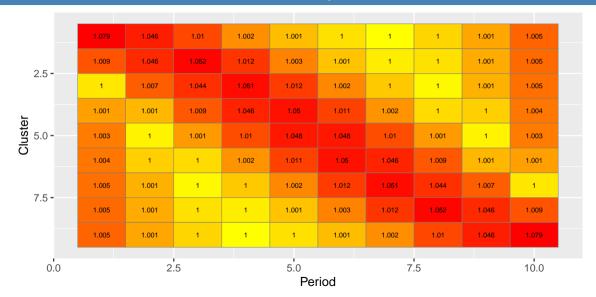


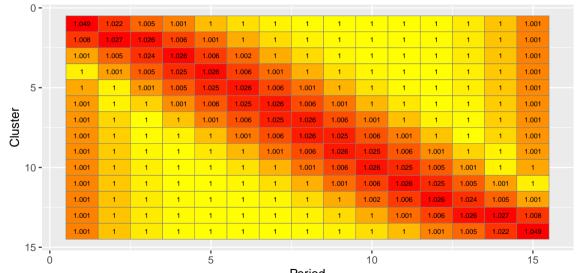


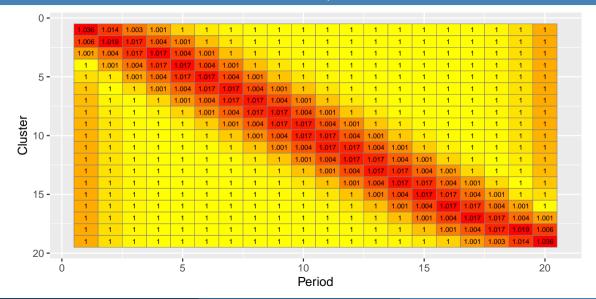












What have we learned about the stepped wedge design?

- Periods near the treatment cross-over tend to be most valuable...
 - But the "hot corners" can add a lot of information (necessary to account for time effects)
 - Pattern of information content depends on the within-cluster correlation structure.
- Logistical vs. statistical value of cells?

Here we assumed a very simple situation. But what if....

- there are transition periods (i.e. periods missing by design)?
- there is treatment effect heterogeneity?
- clusters/cells are of different sizes?
- a different treatment effect estimator is considered?

Future work: development of "optimal" incomplete designs.

You can explore the information content of cells in your own cluster randomised trial at:

https://monash-biostat.shinyapps.io/InformationContentofCells