Supplementary materials for $Small\ sample\ methods\ for$ $cluster\ robust\ variance\ estimation\ and\ hypothesis\ testing\ in$ $fixed\ effects\ models$

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S1 Proof of Theorem 1

The Moore-Penrose inverse of \mathbf{B}_i can be computed from its eigen-decomposition. Let $b \leq n_i$ denote the rank of \mathbf{B}_i . Let Λ be the $b \times b$ diagonal matrix of the positive eigenvalues of \mathbf{B}_i and \mathbf{V} be the $n_i \times b$ matrix of corresponding eigen-vectors, so that $\mathbf{B}_i = \mathbf{V}\Lambda\mathbf{V}'$. Then $\mathbf{B}_i^+ = \mathbf{V}\Lambda^{-1}\mathbf{V}'$ and $\mathbf{B}_i^{+1/2} = \mathbf{V}\Lambda^{-1/2}\mathbf{V}'$. Now, observe that

$$\ddot{\mathbf{R}}_{i}'\mathbf{W}_{i}\mathbf{A}_{i}\left(\mathbf{I}-\mathbf{H}_{\mathbf{X}}\right)_{i}\boldsymbol{\Phi}\left(\mathbf{I}-\mathbf{H}_{\mathbf{X}}\right)_{i}'\mathbf{A}_{i}'\mathbf{W}_{i}\ddot{\mathbf{R}}_{i} = \ddot{\mathbf{R}}_{i}'\mathbf{W}_{i}\mathbf{D}_{i}\mathbf{B}_{i}^{+1/2}\mathbf{B}_{i}\mathbf{B}_{i}^{+1/2}\mathbf{D}_{i}'\mathbf{W}_{i}\ddot{\mathbf{R}}_{i} = \ddot{\mathbf{R}}_{i}'\mathbf{W}_{i}\mathbf{D}_{i}\mathbf{V}\mathbf{V}'\mathbf{D}_{i}'\mathbf{W}_{i}\ddot{\mathbf{R}}_{i}.$$

$$(1)$$

Because \mathbf{D}_i , and $\mathbf{\Phi}$ are positive definite and \mathbf{B}_i is symmetric, the eigen-vectors \mathbf{V} define an orthonormal basis for the column span of $(\mathbf{I} - \mathbf{H}_{\mathbf{X}})_i$. We now show that $\ddot{\mathbf{U}}_i$ is in the column space of $(\mathbf{I} - \mathbf{H}_{\mathbf{X}})_i$. Let \mathbf{Z}_i be an $n_i \times (r+s)$ matrix of zeros. Let $\mathbf{Z}_k = -\ddot{\mathbf{U}}_k \mathbf{L}^{-1} \mathbf{M}_{\ddot{\mathbf{U}}}^{-1}$, for $k \neq i$ and take $\mathbf{Z} = (\mathbf{Z}_1', ..., \mathbf{Z}_m')'$. Now observe that $(\mathbf{I} - \mathbf{H}_{\mathbf{T}}) \mathbf{Z} = \mathbf{Z}$. It follows that

$$\begin{split} \left(\mathbf{I} - \mathbf{H}_{\mathbf{X}}\right)_i \mathbf{Z} &= \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}}\right)_i \left(\mathbf{I} - \mathbf{H}_{\mathbf{T}}\right) \mathbf{Z} = \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}}\right)_i \mathbf{Z} \\ &= \mathbf{Z}_i - \ddot{\mathbf{U}}_i \mathbf{M}_{\ddot{\mathbf{U}}} \sum_{k=1}^m \ddot{\mathbf{U}}_k' \mathbf{W}_k \mathbf{Z}_k \\ &= \ddot{\mathbf{U}}_i \mathbf{M}_{\ddot{\mathbf{U}}} \left(\sum_{k \neq i} \ddot{\mathbf{U}}_k' \mathbf{W}_k \ddot{\mathbf{U}}\right) \mathbf{L}^{-1} \mathbf{M}_{\ddot{\mathbf{U}}}^{-1} = \ddot{\mathbf{U}}_i. \end{split}$$

Thus, there exists an $N \times (r+s)$ matrix \mathbf{Z} such that $(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{X}}})_i \mathbf{Z} = \ddot{\mathbf{U}}_i$, i.e., $\ddot{\mathbf{U}}_i$ is in the column span of $(\mathbf{I} - \mathbf{H}_{\mathbf{X}})_i$. Because $\mathbf{D}_i \mathbf{W}_i$ is positive definite and $\ddot{\mathbf{R}}_i$ is a sub-matrix of $\ddot{\mathbf{U}}_i$, $\mathbf{D}_i \mathbf{W}_i \ddot{\mathbf{R}}_i$ is also in the column span of $(\mathbf{I} - \mathbf{H}_{\mathbf{X}})_i$. It follows that

$$\ddot{\mathbf{R}}_{i}^{\prime}\mathbf{W}_{i}\mathbf{D}_{i}\mathbf{V}\mathbf{V}^{\prime}\mathbf{D}_{i}^{\prime}\mathbf{W}_{i}\ddot{\mathbf{R}}_{i} = \ddot{\mathbf{R}}_{i}^{\prime}\mathbf{W}_{i}\mathbf{\Phi}_{i}\mathbf{W}_{i}\ddot{\mathbf{R}}_{i}.$$
(2)

Substituting (2) into (1) demonstrates that \mathbf{A}_i satisfies the generalized BRL criterion (Eq. 6 of the main paper).

Under the working model, the residuals from cluster i have mean $\mathbf{0}$ and variance

$$\operatorname{Var}\left(\mathbf{\ddot{e}}_{i}\right)=\left(\mathbf{I}-\mathbf{H}_{\mathbf{X}}\right)_{i}\mathbf{\Phi}\left(\mathbf{I}-\mathbf{H}_{\mathbf{X}}\right)_{i}',$$

It follows that

$$\begin{split} \mathbf{E}\left(\mathbf{V}^{CR2}\right) &= \mathbf{M}_{\ddot{\mathbf{K}}} \left[\sum_{i=1}^{m} \ddot{\mathbf{R}}_{i}' \mathbf{W}_{i} \mathbf{A}_{i} \left(\mathbf{I} - \mathbf{H}_{\mathbf{X}} \right)_{i} \mathbf{\Phi} \left(\mathbf{I} - \mathbf{H}_{\mathbf{X}} \right)_{i}' \mathbf{A}_{i} \mathbf{W}_{i} \ddot{\mathbf{R}}_{i} \right] \mathbf{M}_{\ddot{\mathbf{K}}} \\ &= \mathbf{M}_{\ddot{\mathbf{K}}} \left[\sum_{i=1}^{m} \ddot{\mathbf{R}}_{i}' \mathbf{W}_{i} \mathbf{\Phi}_{i} \mathbf{W}_{i} \ddot{\mathbf{R}}_{i} \right] \mathbf{M}_{\ddot{\mathbf{K}}} \\ &= \operatorname{Var}\left(\hat{\boldsymbol{\beta}}\right) \end{split}$$

S2 Proof of Theorem 2

From the fact that $\ddot{\mathbf{U}}_{i}'\mathbf{W}_{i}\mathbf{T}_{i} = \mathbf{0}$ for i = 1, ..., m, it follows that

$$\begin{split} \mathbf{B}_{i} &= \mathbf{D}_{i} \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}} \right)_{i} \left(\mathbf{I} - \mathbf{H}_{\mathbf{T}} \right) \mathbf{\Phi} \left(\mathbf{I} - \mathbf{H}_{\mathbf{T}} \right)' \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}} \right)'_{i} \mathbf{D}'_{i} \\ &= \mathbf{D}_{i} \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}} - \mathbf{H}_{\mathbf{T}} \right)_{i} \mathbf{\Phi} \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}} - \mathbf{H}_{\mathbf{T}} \right)'_{i} \mathbf{D}'_{i} \\ &= \mathbf{D}_{i} \left(\mathbf{\Phi}_{i} - \ddot{\mathbf{U}}_{i} \mathbf{M}_{\ddot{\mathbf{U}}} \ddot{\mathbf{U}}'_{i} - \mathbf{T}_{i} \mathbf{M}_{\mathbf{T}} \mathbf{T}'_{i} \right) \mathbf{D}'_{i} \end{split}$$

and

$$\mathbf{B}_{i}^{+} = \left(\mathbf{D}_{i}^{\prime}\right)^{-1} \left(\mathbf{\Phi}_{i} - \ddot{\mathbf{U}}_{i} \mathbf{M}_{\ddot{\mathbf{U}}} \ddot{\mathbf{U}}_{i}^{\prime} - \mathbf{T}_{i} \mathbf{M}_{\mathbf{T}} \mathbf{T}_{i}^{\prime}\right)^{+} \mathbf{D}_{i}^{-1}.$$
(3)

Let $\Psi_i = \left(\Phi_i - \ddot{\mathbf{U}}_i \mathbf{M}_{\ddot{\mathbf{U}}} \ddot{\mathbf{U}}_i'\right)^+$. Using a generalized Woodbury identity (Henderson and Searle, 1981),

$$oldsymbol{\Psi}_i = oldsymbol{\mathbf{W}}_i + oldsymbol{\mathbf{W}}_i \ddot{f U}_i oldsymbol{\mathbf{M}}_{\ddot{f U}} \left(oldsymbol{\mathbf{M}}_{\ddot{f U}} - oldsymbol{\mathbf{M}}_{\ddot{f U}} \ddot{f U}_i' oldsymbol{\mathbf{W}}_i \ddot{f U}_i oldsymbol{\mathbf{M}}_{\ddot{f U}} \ddot{f U}_i' oldsymbol{\mathbf{W}}_i.$$

It follows that $\Psi_i \mathbf{T}_i = \mathbf{W}_i \mathbf{T}_i$. Another application of the generalized Woodbury identity gives

$$\begin{split} \left(\mathbf{\Phi}_{i} - \ddot{\mathbf{U}}_{i}\mathbf{M}_{\ddot{\mathbf{U}}}\ddot{\mathbf{U}}_{i}' - \mathbf{T}_{i}\mathbf{M}_{\mathbf{T}}\mathbf{T}_{i}'\right)^{+} &= \mathbf{\Psi}_{i} + \mathbf{\Psi}_{i}\mathbf{T}_{i}\mathbf{M}_{\mathbf{T}}\left(\mathbf{M}_{\mathbf{T}} - \mathbf{M}_{\mathbf{T}}\mathbf{T}_{i}'\mathbf{\Psi}_{i}\mathbf{T}_{i}\mathbf{M}_{\mathbf{T}}\right)^{+}\mathbf{M}_{\mathbf{T}}\mathbf{T}_{i}'\mathbf{\Psi}_{i} \\ &= \mathbf{\Psi}_{i} + \mathbf{W}_{i}\mathbf{T}_{i}\mathbf{M}_{\mathbf{T}}\left(\mathbf{M}_{\mathbf{T}} - \mathbf{M}_{\mathbf{T}}\mathbf{T}_{i}'\mathbf{W}_{i}\mathbf{T}_{i}\mathbf{M}_{\mathbf{T}}\right)^{+}\mathbf{M}_{\mathbf{T}}\mathbf{T}_{i}'\mathbf{W}_{i} \\ &= \mathbf{\Psi}_{i}. \end{split}$$

The last equality follows from the fact that

$$\mathbf{T}_i \mathbf{M_T} \left(\mathbf{M_T} - \mathbf{M_T} \mathbf{T}_i' \mathbf{W}_i \mathbf{T}_i \mathbf{M_T} \right)^{-} \mathbf{M_T} \mathbf{T}_i' = \mathbf{0}$$

because the fixed effects are nested within clusters. Substituting into (3), we then have that $\mathbf{B}_i^+ = (\mathbf{D}_i')^{-1} \Psi_i \mathbf{D}_i^{-1}$. But

$$\tilde{\mathbf{B}}_{i} = \mathbf{D}_{i} \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}}\right)_{i}^{} \mathbf{\Phi} \left(\mathbf{I} - \mathbf{H}_{\ddot{\mathbf{U}}}\right)_{i}^{\prime} \mathbf{D}_{i}^{\prime} = \mathbf{D}_{i} \left(\mathbf{\Phi}_{i} - \ddot{\mathbf{U}}_{i} \mathbf{M}_{\ddot{\mathbf{U}}} \ddot{\mathbf{U}}_{i}^{\prime}\right) \mathbf{D}_{i}^{\prime} = \mathbf{D}_{i} \mathbf{\Psi}_{i}^{+} \mathbf{D}_{i}^{\prime},$$

and so $\mathbf{B}_{i}^{+} = \tilde{\mathbf{B}}_{i}^{+}$. It follows that $\mathbf{A}_{i} = \tilde{\mathbf{A}}_{i}$ for i = 1, ..., m.

Table S1: Simulation design parameters

Parameter	levels
Design	RB, CR, DD
Balance	Balanced, Unbalanced
Outcome missingness	Complete data, 15% missing
Clusters (m)	15, 30, 50
Units per cluster (n)	12, 18, 30
Intra-class correlation (τ^2)	.05, .15, .25
Treatment effect variability (σ_{δ}^2)	.00, .04, .09
Correlation among outcomes (ρ)	.2, .8

S3 Details of simulation study

This section provides further details regarding the design of the simulations reported in Section 4 of the main text. Table S1 summarizes the factors manipulated in the simulation.

The simulations examined six distinct study designs. Outcomes are measured for n units (which may be individuals, as in a cluster-randomized or block-randomized design, or time-points, as in a difference-in-differences panel) in each of m clusters under one of three treatment conditions. Suppose that there are G sets of clusters, each of size m_g , where the clusters in each set have a distinct configuration of treatment assignments. Let n_{ghi} denote the number of units at which cluster i in configuration g is observed under condition h, for i = 1, ..., m, g = 1, ..., G, and h = 1, 2, 3. Table S2 summarizes the cluster-level sample sizes and unit-level patterns of treatment allocation for each of the six designs. The simulated designs included the following:

- 1. A balanced, block-randomized design, with an un-equal allocation within each block. In the balanced design, the treatment allocation is identical for each block, so G = 1.
- 2. An unbalanced, block-randomized design, with two different patterns of treatment allocation (G=2).
- 3. A balanced, cluster-randomized design, in which units are nested within clusters and an equal number of clusters are assigned to each treatment condition.
- 4. An unbalanced, cluster-randomized design, in which units are nested within clusters but the number of clusters assigned to each condition is not equal.
- 5. A balanced difference-in-differences design with two patterns of treatment allocation (G = 2), in which half of the clusters are observed under the first treatment condition only and the remaining half are observed under all three conditions.
- 6. An unbalanced difference-in-differences design, again with two patterns of treatment allocation (G = 2), but where 2/3 of the clusters are observed under the first treatment condition only and the remaining 1/3 of clusters are observed under all three conditions.

Table S2: Study designs used for simulation

Study design	Balance	Configuration	Clusters	Treatment allocation
Randomized Block	Balanced	1	$m_1 = m$	$n_{11i} = n/2, n_{12i} = n/3, n_{13i} = n/6$
Randomized Block	Unbalanced	1	$m_1 = m/2$	$n_{11i} = n/2, n_{12i} = n/3, n_{13i} = n/6$
		2	$m_2 = m/2$	$n_{21i} = n/3, n_{22i} = 5n/9, n_{23i} = n/9$
		1	$m_1 = m/3$	$n_{11i} = n$
Cluster-Randomized	Balanced	2	$m_2 = m/3$	$n_{22i} = n$
		3	$m_3 = m/3$	$n_{33i} = n$
Cluster-Randomized	Unbalanced	1	$m_1 = m/2$	$n_{11i} = n$
		2	$m_2 = 3m/10$	$n_{22i} = n$
		3	$m_3 = m/5$	$n_{33i} = n$
Difference-in-Differences	Balanced	1	$m_1 = m/2$	$n_{11i} = n$
		2	$m_2 = m/2$	$n_{21i} = n/2, n_{22i} = n/3, n_{23i} = n/6$
Difference-in-Differences	Unbalanced	1	$m_1 = 2m/3$	$n_{11i} = n$
		2	$m_2 = m/3$	$n_{21i} = n/2, n_{22i} = n/3, n_{23i} = n/6$

S4 Additional simulation results

S4.1 Rejection rates of AHT and standard tests

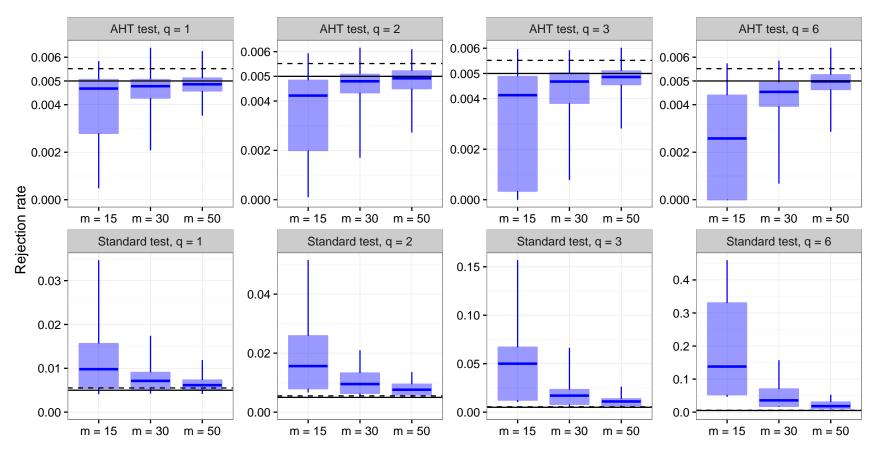


Figure S1: Rejection rates of AHT and standard tests for $\alpha = .005$, by dimension of hypothesis (q) and sample size (m).



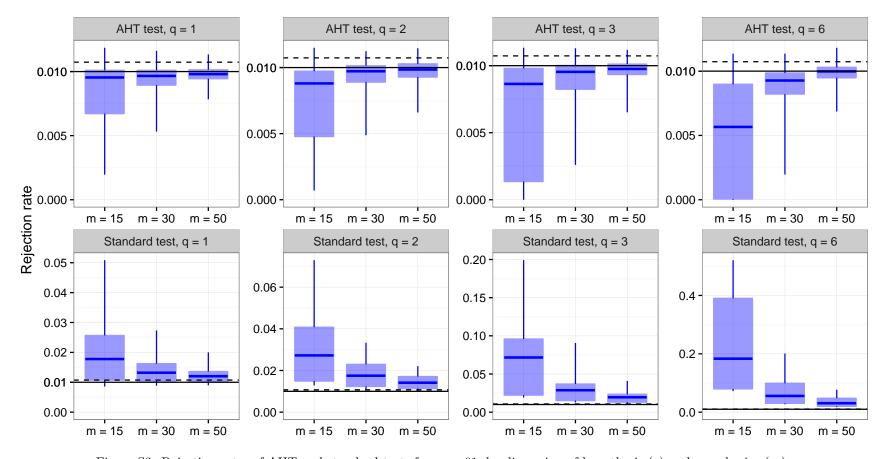


Figure S2: Rejection rates of AHT and standard tests for $\alpha = .01$, by dimension of hypothesis (q) and sample size (m).

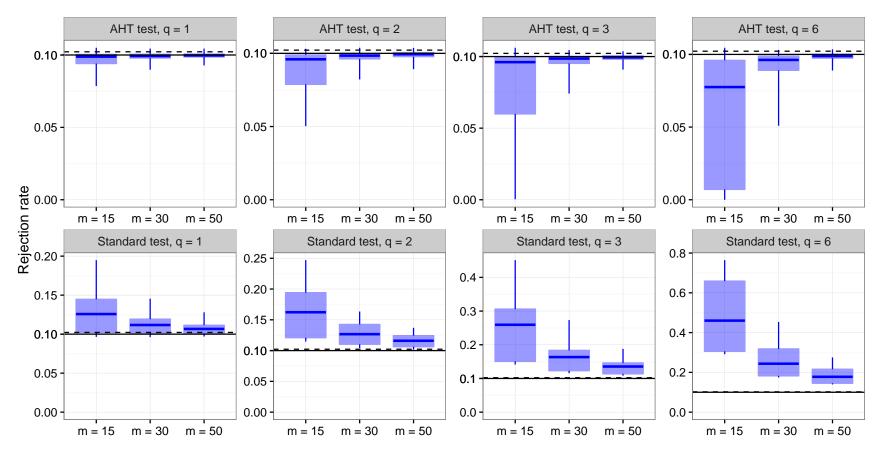


Figure S3: Rejection rates of AHT and standard tests for $\alpha = .10$, by dimension of hypothesis (q) and sample size (m).

S4.2 Rejection rates of AHT and standard tests by study design

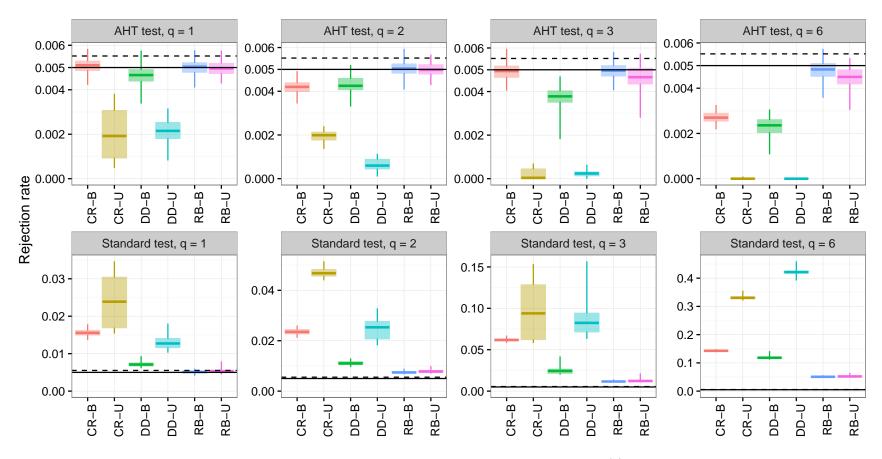


Figure S4: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .005$ and m = 15. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

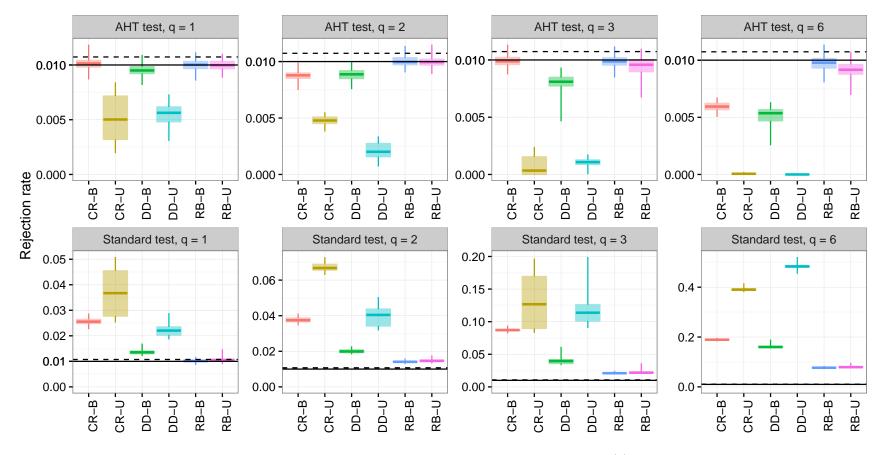


Figure S5: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .01$ and m = 15. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

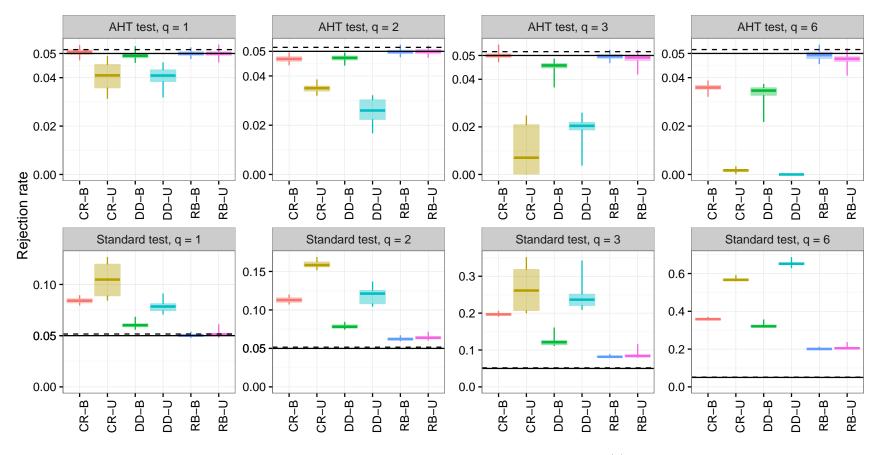


Figure S6: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .05$ and m = 15. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

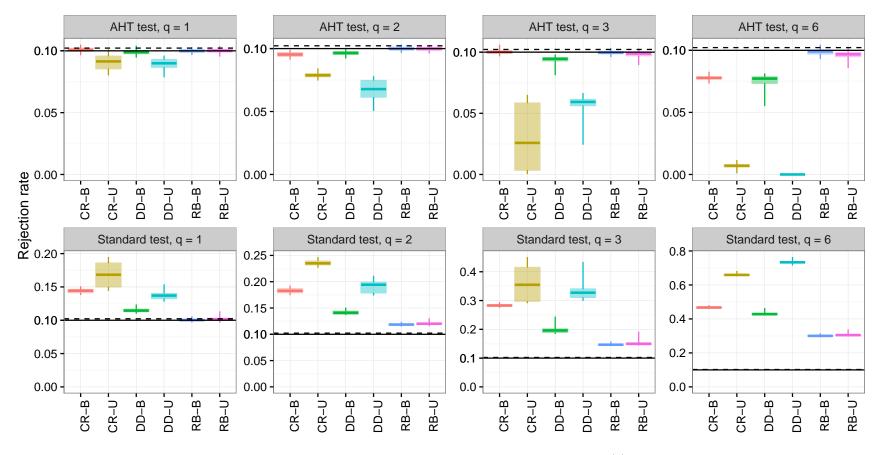


Figure S7: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .10$ and m = 15. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

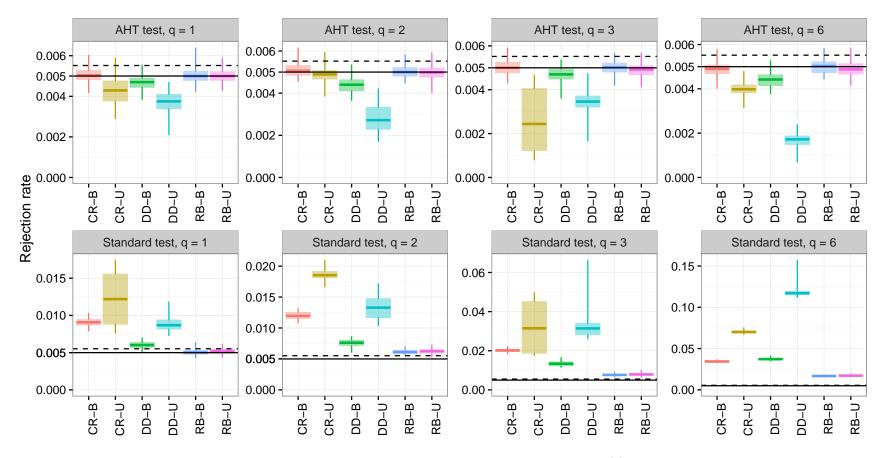


Figure S8: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .005$ and m = 30. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

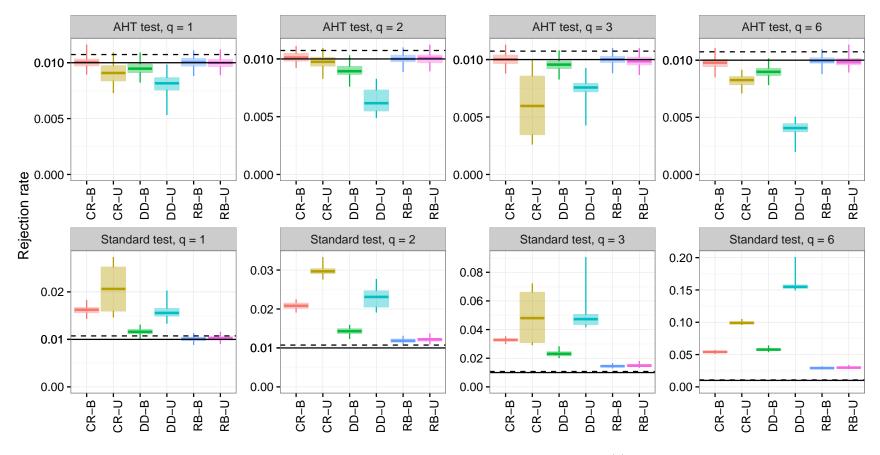


Figure S9: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .01$ and m = 30. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

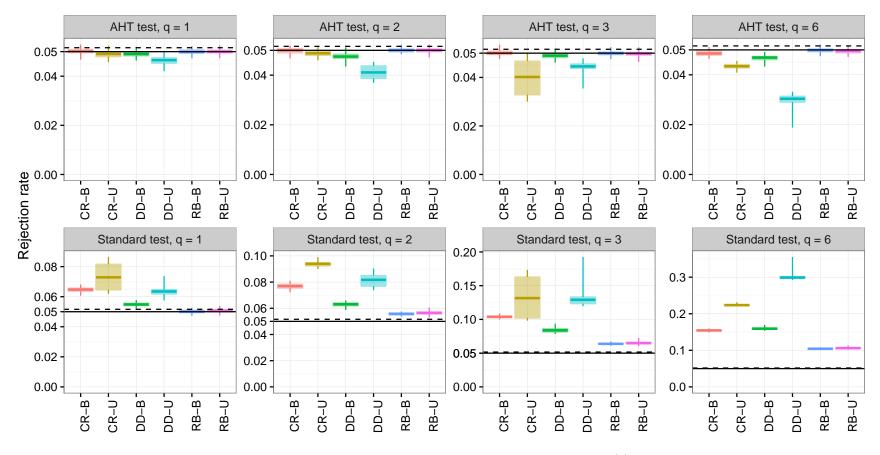


Figure S10: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .05$ and m = 30. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

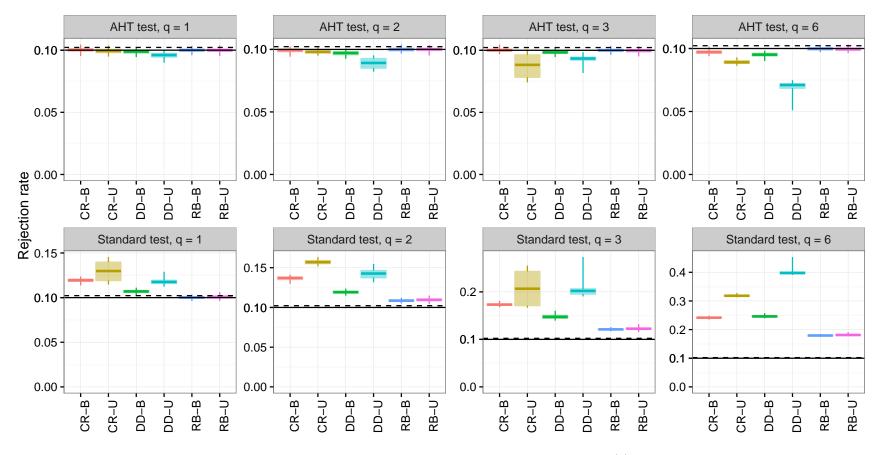


Figure S11: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .10$ and m = 30. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

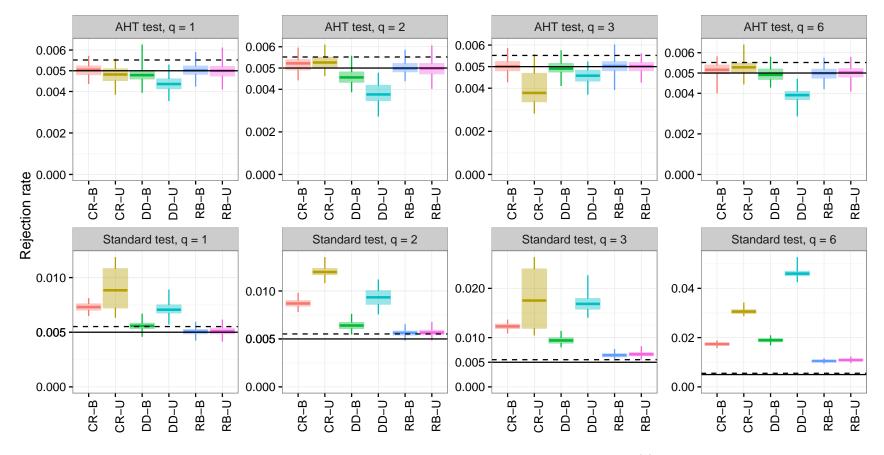


Figure S12: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha=.005$ and m=50. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

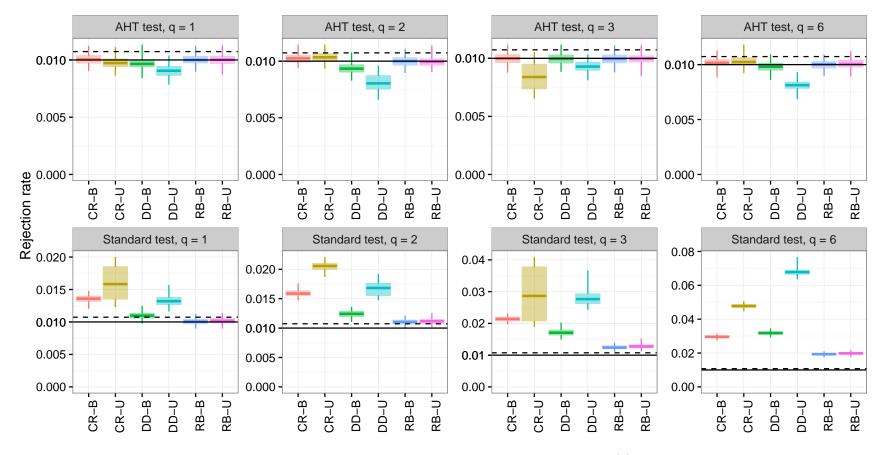


Figure S13: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .01$ and m = 50. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

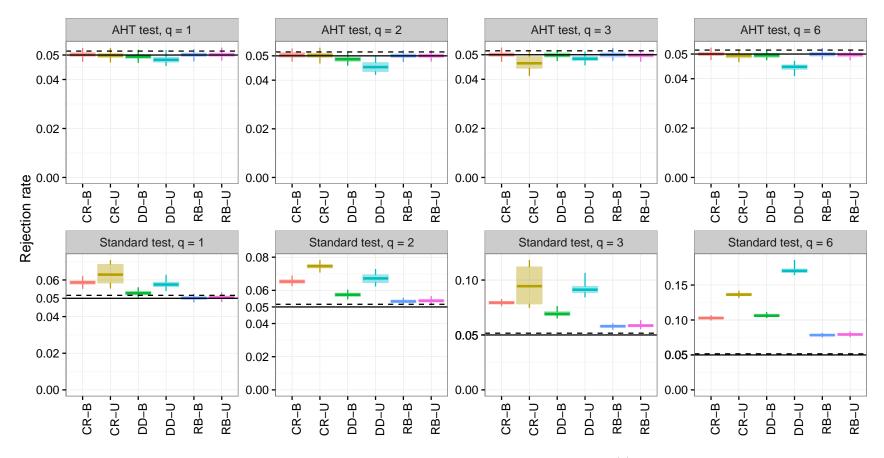


Figure S14: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .05$ and m = 50. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

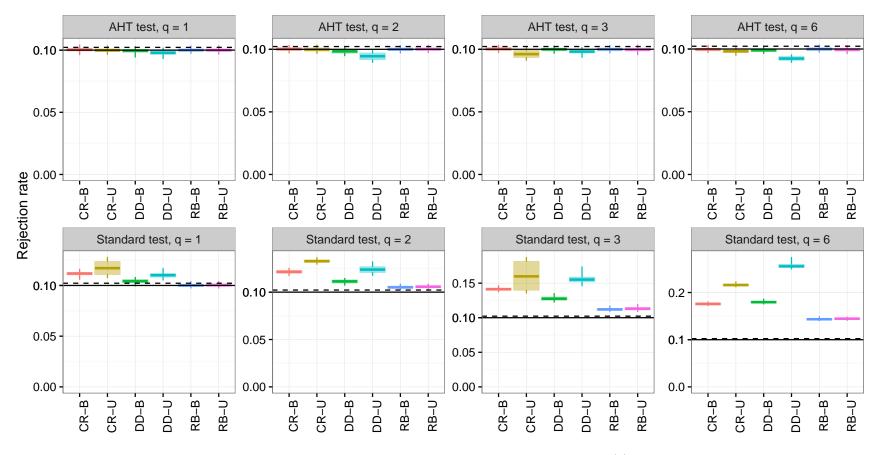


Figure S15: Rejection rates of AHT and standard tests, by study design and dimension of hypothesis (q) for $\alpha = .10$ and m = 50. CR = cluster-randomized design; DD = difference-in-differences design; RB = randomized block design; B = balanced; U = unbalanced.

S4.3 Rejection rates of AHT test using CR1 or CR2, with and without accounting for absorption

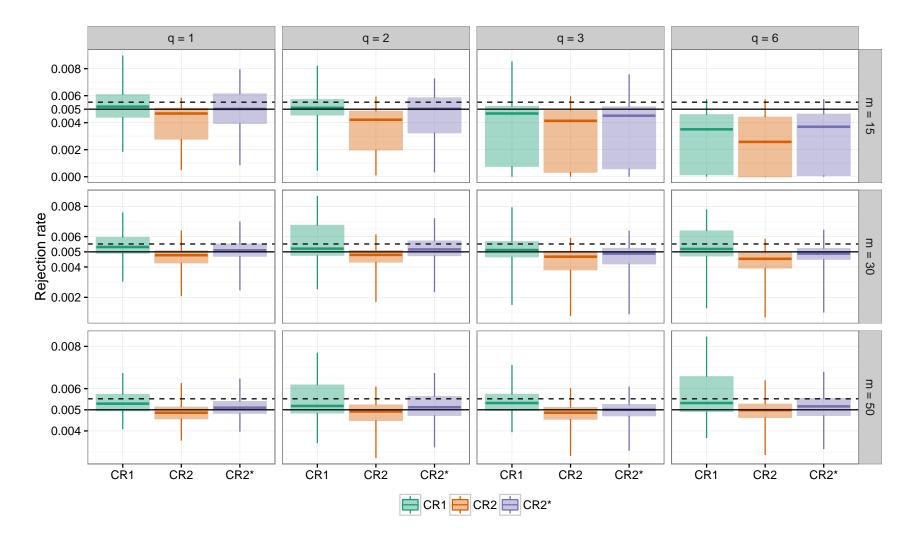


Figure S16: Rejection rates of AHT tests using CR1, CR2, or CR2 calculated without accounting for absorption of fixed effects (CR2*), by sample size (m) and dimension of hypothesis (q), for $\alpha = .005$.

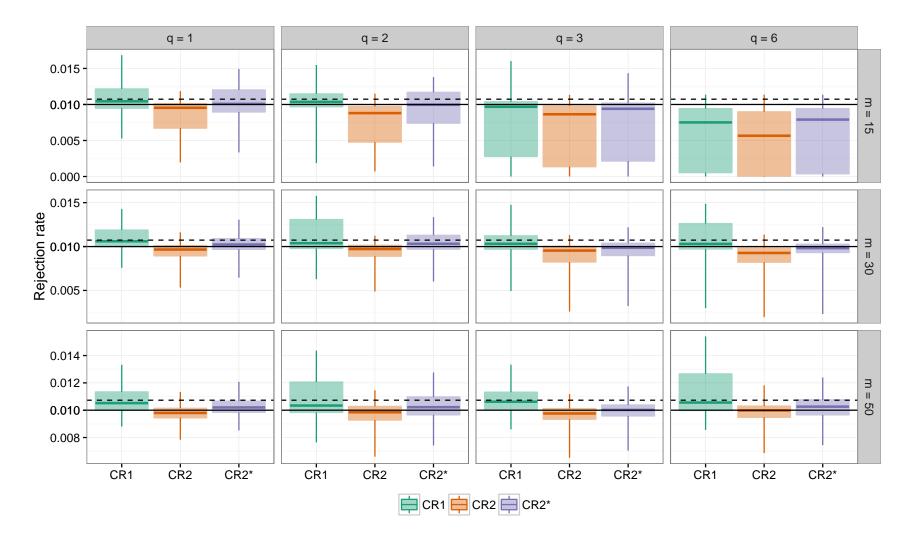


Figure S17: Rejection rates of AHT tests using CR1, CR2, or CR2 calculated without accounting for absorption of fixed effects (CR2*), by sample size (m) and dimension of hypothesis (q), for $\alpha = .01$.

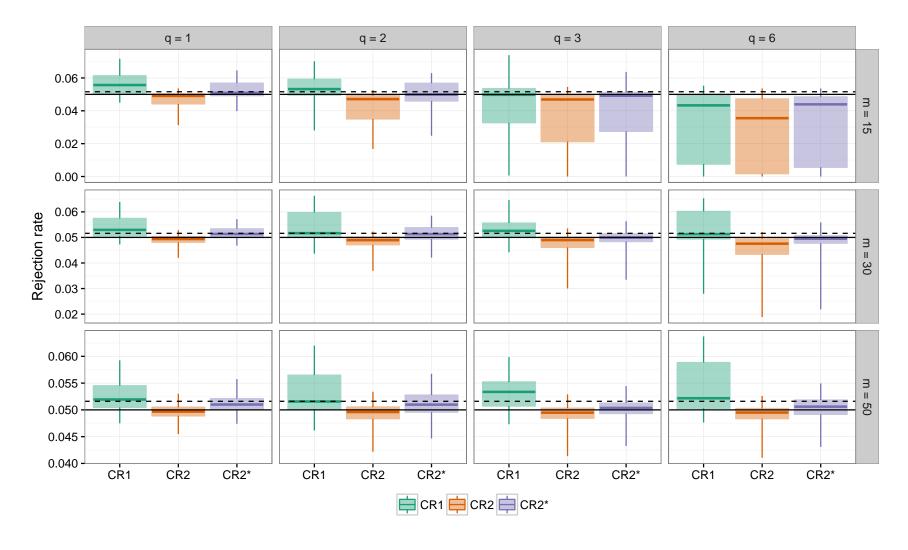


Figure S18: Rejection rates of AHT tests using CR1, CR2, or CR2 calculated without accounting for absorption of fixed effects (CR2*), by sample size (m) and dimension of hypothesis (q), for $\alpha = .05$.

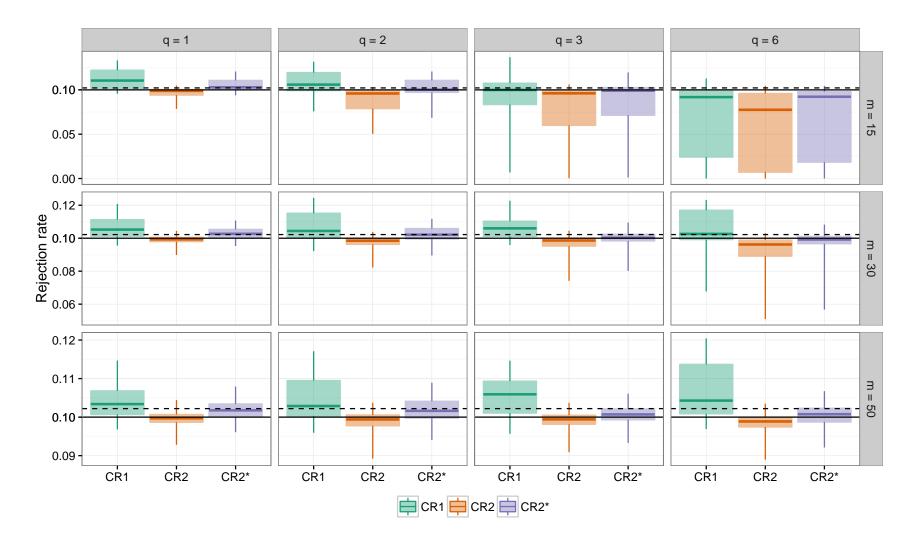


Figure S19: Rejection rates of AHT tests using CR1, CR2, or CR2 calculated without accounting for absorption of fixed effects (CR2*), by sample size (m) and dimension of hypothesis (q), for $\alpha = .10$.

S4.4 Rejection rates of AHT test by degree of working model misspecification

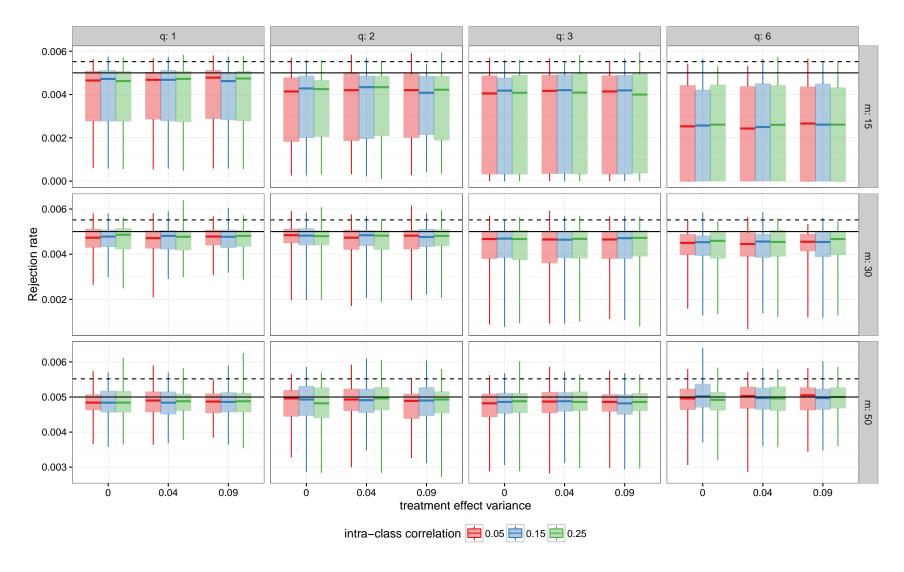


Figure S20: Rejection rates of CR2 AHT test, by treatment effect variance and intra-class correlation for $\alpha = .005$.

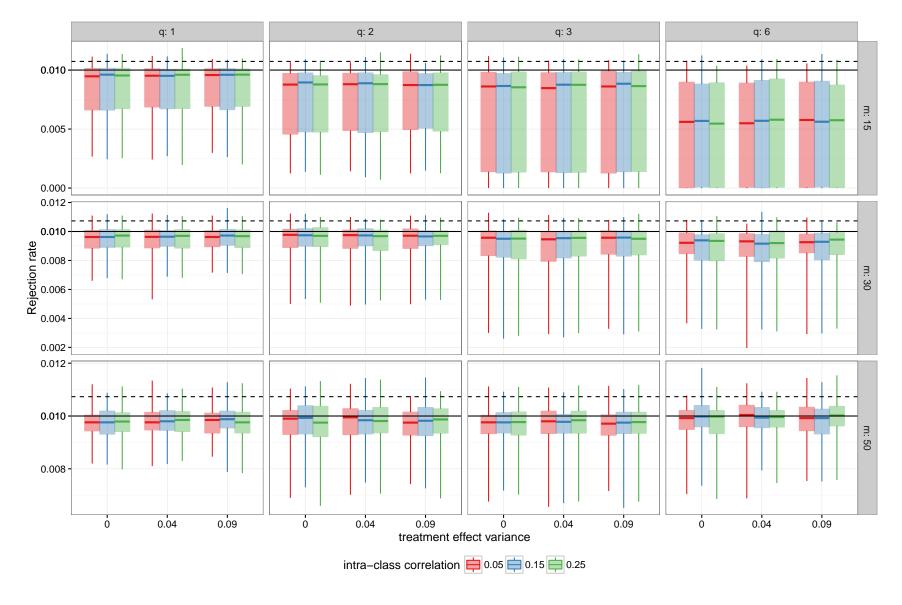


Figure S21: Rejection rates of CR2 AHT test, by treatment effect variance and intra-class correlation for $\alpha = .01$.

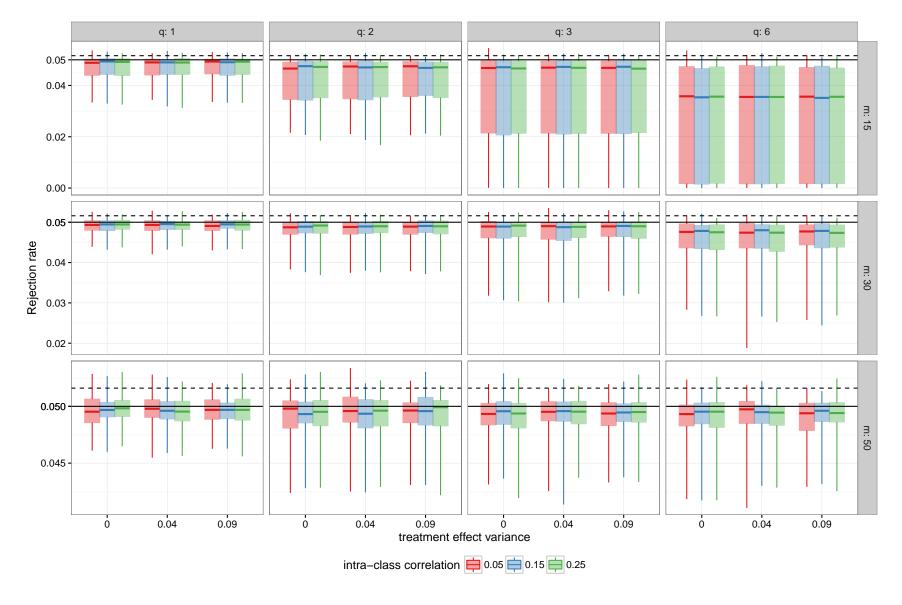


Figure S22: Rejection rates of CR2 AHT test, by treatment effect variance and intra-class correlation for $\alpha = .05$.

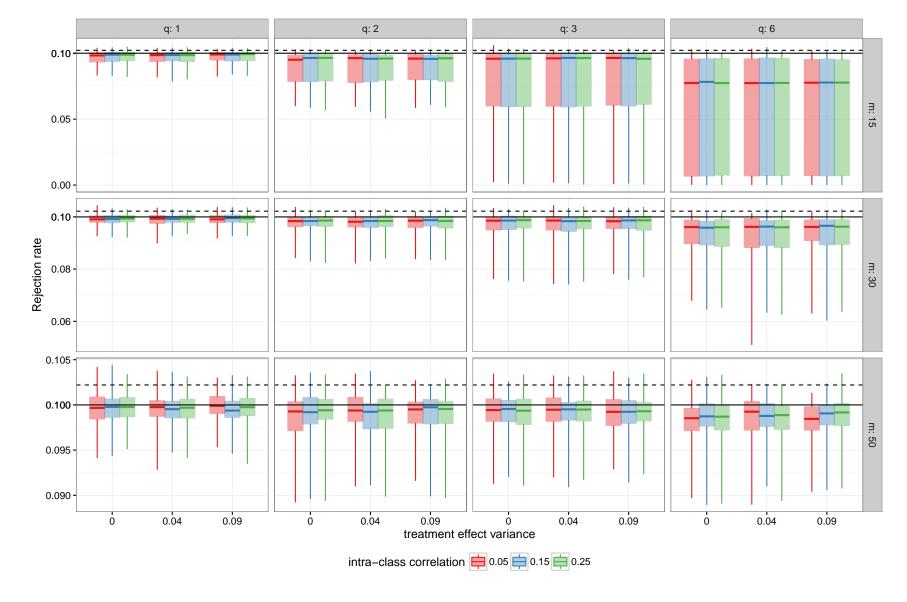


Figure S23: Rejection rates of CR2 AHT test, by treatment effect variance and intra-class correlation for $\alpha = .10$.

References

Henderson, H. V. and Searle, S. R. (1981), 'On deriving the inverse of a sum of matrices', $Siam\ Review\ 23(1),\ 53-60.$