Analysis of Poisson frequency data under a simple crossover trial



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Outline

01 Introduction

- Goal
- Crossover Design
- Non-equality, Non-inferiority and Equivalence
- Monte Carlo Simulation and Result
 - Non-equality
 - Non-inferiority
 - Interval Estimation

04

Example

• Double-Blind Crossover Trial for Asthma patients

- 05 Discussion
 - Contribution
 - Conclusion of asymptotic test procedure and exact test procedure

02

Notation, model assumption and methods

- Notation
- Model assumption
- Asymptotic Test procedure and Exact Test Procedure

Introduction

Introduction

01

The Goal of This Article

- Frequency of patient response follows the commonly-assumed Poisson distribution under a crossover design.
- Present asymptotic and exact procedures for testing non-equality, non-inferiority and equivalence.
- Develop asymptotic and exact interval estimators for evaluate.
- 02

Crossover Design

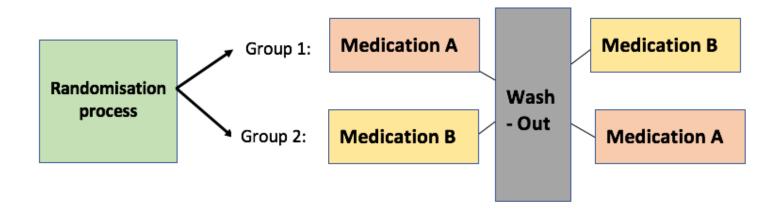
- What is crossover design?
- Advantage & Disadvantage
- 03

Non-equality, Non-inferiority and Equivalence

- Relationship among non-equality, non-inferiority and equivalence
- Testing for non-equality, non-inferiority and equivalence

Crossover Design

What's Crossover Design?



Treatment	Period 1	Period 2
Sequence AB	A	В
Sequence BA	В	A

Crossover Design

Advantage

- Sometimes more efficient than parallel design.
- Require fewer patients than a parallel study.
- The treatment are compared 'within subjects'.

Disadvantage

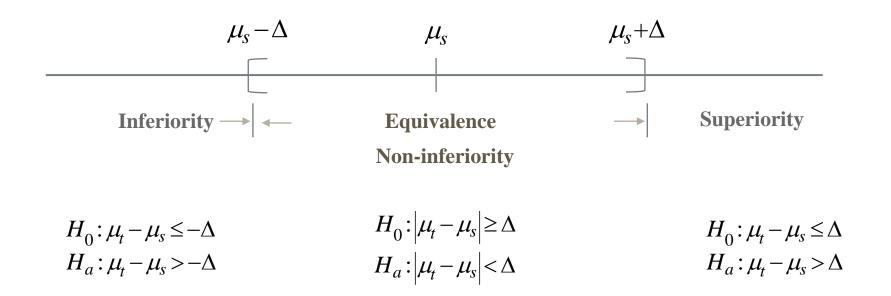
- Carryover effect
- Wash out period

Constraint

- In medical clinical trials, the disease should be chronic and stable.
- The treatments should not result in total cures but only alleviate the disease condition.

Non-equality · Non-inferiority and Equivalence

Relationship among non-inferiority, superiority, and equivalence



Ref: https://ntuhmc.ntuh.gov.tw/epaper-70th.htm

Contribution

- Present asymptotic and exact procedures for testing non-equality, non-inferiority and equivalence.
- Develop asymptotic and exact interval estimators for evaluate.
- Provide asymptotic and exact test procedures to do testing no matter sample size is small, moderate or large.
- Asymptotic interval estimator with logarithmic transform will be more precise than exact interval estimator.

Notation, model assumption and methods

Notation

 Y_{ist} -frequency of the response on patient I assigned to sequence s at period t

patient $i=1,...,n_s$ sequence s=1, 2

period t=1, 2

 X_{ist} -covariate of treatment receipt

$$x_{ist} = \begin{cases} 1, & \text{treatment B} \\ 0, & o.w. \end{cases}$$

 Z_{it} -covariate of period

$$z_{it} = \begin{cases} 1, & \text{period } 2 \\ 0, & o.w. \end{cases}$$

$$Y_{ist} \sim Poisson(E(Y_{ist}))$$
 $E(Y_{ist}) = u_{is} \exp(x_{ist} \eta + z_{it} \gamma)$

 u_{is} -the effect due to the underlying characteristics of the i^{th} patient assigned to sequence s

-the effect of treatment B relative to treatment A

-the effect for period 2 v.s. period 1

Model assumption

$$Y_{i12}|Y_{i1+} = y_{i1+} \sim Bin(y_{i1+}, \exp(\eta + \gamma)/(1 + \exp(\eta + \gamma)))$$

$$P(Y_{+12} = y_{+12} | y_{1+}, \eta, \gamma) = \begin{pmatrix} y_{+1+} \\ y_{+12} \end{pmatrix} p_1^{y_{+12}} (1 - p_1)^{y_{+1+} - y_{+12}}$$

$$Y_{+12} (= \sum_{i=1}^{n_1} Y_{i12}) \qquad \qquad y_{1+}^{'} = (y_{11+}, y_{21+}, \dots, y_{n_11+}) \qquad \qquad y_{+1+} = \sum_{i=1}^{n_1} y_{i1+} \qquad \qquad p_1 = \exp(\eta + \gamma) / (1 + \exp(\eta + \gamma))$$

$$Y_{i22}|Y_{i2+} = y_{i2+} \sim Bin(y_{i2+}, \exp(\gamma)/(\exp(\eta) + \exp(\gamma)))$$

$$P(Y_{+22} = y_{+22} | y_{2+}, \eta, \gamma) = \begin{pmatrix} y_{+2+} \\ y_{+22} \end{pmatrix} p_2^{y_{+22}} (1 - p_2)^{y_{+2+} - y_{+22}}$$

$$Y_{+22} (= \sum_{i=1}^{n_2} Y_{i22}) \qquad \qquad y_{2+}^{'} = (y_{12+}, y_{22+}, \dots, y_{n_22+}) \qquad \qquad y_{+2+} = \sum_{i=1}^{n_2} y_{i2+} \qquad p_2 = \exp(\gamma) / (\exp(\eta) + \exp(\gamma))$$

$$\text{Conditional MLE of} \quad p_s \quad \text{is} \quad \hat{p}_s = \frac{y_{+s2}}{y_{+s+}} \quad , (s = 1, 2)$$

Model assumption

$$RM_T = \exp(\eta)$$

given a fixed period, the ratio of two mean frequencies of responses on a given patient between treatment B and A

$$RM_P = \exp(\gamma)$$

given a fixed treatment, the ratio of two mean frequencies for period 2 versus period 1 on a given patient

Conditional MLE of
$$p_s$$
 is $\hat{p}_s = \frac{y_{+s2}}{y_{+s+}}$, $(s=1,2)$

$$RM_T^2 = p_1(1-p_2)/p_2(1-p_1)$$

$$Var(\log(RM_T)) = \frac{1}{4} \left(\frac{1}{y_{+1+}p_1(1-p_1)} + \frac{1}{y_{+2+}p_2(1-p_2)} \right)$$

$$RM_T = \left(\frac{\hat{p}_1(1-\hat{p}_2)}{\hat{p}_2(1-\hat{p}_1)}\right)^{1/2} = \left(\frac{Y_{+12}Y_{+21}}{Y_{+11}Y_{+22}}\right)^{1/2}$$

$$Var(\log(RM_T)) = \frac{1}{4} \left(\frac{1}{Y_{+12}} + \frac{1}{Y_{+11}} + \frac{1}{Y_{+21}} + \frac{1}{Y_{+22}} \right)$$

Methods-Fieller's Theorem

- For skewed distribution, use delta method we may obtained asymmetric confidence limits.
- While $o_p(1)$ is small, then the large-sample confidence limits will be close to those given by Fieller's theorem.

Assuming that $\mathbf{L}'\boldsymbol{\theta} \neq 0$, we must have

$$\frac{t^2 \hat{\sigma}^2 [\mathbf{L}'\mathbf{I}^{-1}(\boldsymbol{\theta})\mathbf{L}]}{(\mathbf{L}'\hat{\boldsymbol{\theta}})^2} = o_p(1)$$

t: the appropriate percentile of the t-distribution

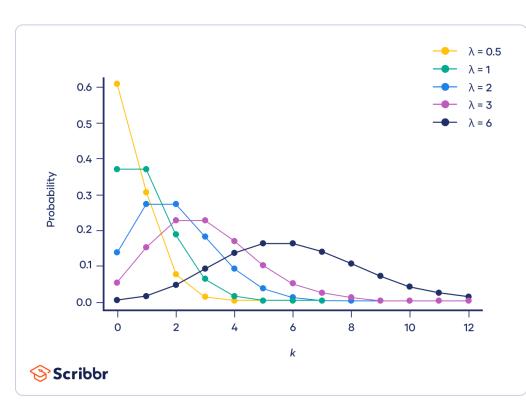
Let
$$\mathbf{g}(\boldsymbol{\theta}) = (g_1(\boldsymbol{\theta}), \dots, g_l(\boldsymbol{\theta}))^T$$

Partial derivatives

$$\mathbf{L} = \left[\frac{\partial g_l(\boldsymbol{\theta})}{\partial \theta_j}\right], i = 1,...,l; j = 1,...,k$$

$$\sqrt{n}(\mathbf{g}(\hat{\boldsymbol{\theta}}_n) - \mathbf{g}(\boldsymbol{\theta})) \rightarrow MN_l(0, \mathbf{L}'\mathbf{I}^{-1}(\boldsymbol{\theta})\mathbf{L}) \text{ as } n \rightarrow \infty$$

$$\mathbf{I}^{-1}(\boldsymbol{g}(\boldsymbol{\theta})) = [\mathbf{L}'\mathbf{I}^{-1}(\boldsymbol{\theta})\mathbf{L}]^{-1}$$



Methods-Fisher Exact Test

Guess					
Actually	Milk	Tea			
Milk	n_{11}	n_{12}	n_{1+}		
Tea	$n_{21}^{}$	n_{22}	n_{2+}		
	n_{+1}	n_{+2}	n_{++}		

 H_0 : the variables are independent

 H_a : the variables are dependent

Reject H_0 if

$$P(X \ge n_{11} \mid n_{+1} = n_{+2} = n_{1+} = n_{2+}) = \sum_{X \ge n_{11}} {n_{1+} \choose n_{11}} {n_{2+} \choose n_{+1} - n_{11}} / {n_{++} \choose n_{+1}} \le \alpha$$

Test non-equality

$$H_0: \eta = 0 \ (RM_T = 1), H_1: \eta \neq 0 \ (RM_T \neq 1)$$

Reject H_0 at the α -level if

$$\log(RM_T)/\sqrt{Var_{H_0}(\log(RM_T))} > Z_{\alpha/2} \text{ or } \log(RM_T)/\sqrt{Var_{H_0}(\log(RM_T))} < -Z_{\alpha/2}$$
 (7)

where
$$Var_{H_0}(\log(RM_T)) = (1/y_{+1+} + 1/y_{+2+})/[4\hat{p}(1-\hat{p})], \hat{p} = (Y_{+12} + Y_{+22})/(y_{+1+} + y_{+2+})$$

To alleviate the concern of our inference directly based on the possibly skewed distribution of RM_T By Filler's Theorem

$$Z(\psi_T) = \hat{p}_1(1 - \hat{p}_2) - \psi_T \hat{p}_2(1 - \hat{p}_1)$$
, where $\psi_T = RM_T^2$, and $E(Z(\psi_T)) = 0$

$$Var(Z(\psi_T)) = Var(\hat{p}_1(1-\hat{p}_2)) + \psi_T^2 Var(\hat{p}_2(1-\hat{p}_1)) - 2\psi_T Cov(\hat{p}_1(1-\hat{p}_2), \hat{p}_2(1-\hat{p}_1))$$

Reject H_0 at the α -level if

$$Z(1)/\sqrt{Var_{H_0}(Z(1))} > Z_{\alpha/2} \text{ or } Z(1)/\sqrt{Var_{H_0}(Z(1))} < -Z_{\alpha/2}$$
 (9)

Test non-equality

$$H_0: \eta = 0 \ (RM_T = 1), H_1: \eta \neq 0 \ (RM_T \neq 1)$$

Two Sample T-Test

Given the total y_{+s+} being reasonably large for both s, reject H_0 at the α -level if

$$(\hat{p}_1 - \hat{p}_2)/\sqrt{\hat{p}(1-\hat{p})(1/y_{++1} + 1/y_{++2})} > Z_{\alpha/2}, \text{ or}$$

 $(\hat{p}_1 - \hat{p}_2)/\sqrt{\hat{p}(1-\hat{p})(1/y_{++1} + 1/y_{++2})} < -Z_{\alpha/2}.$ (10)

where
$$\hat{p} = (Y_{+12} + Y_{+22})/(y_{+1+} + y_{+2+})$$

Fisher Exact Test

$$P(Y_{+12} \ge y_{+12} | y_{++2}, y_{1+}, y_{2+}, RM_T = 1) = \sum_{y \ge y_{+12}} {y_{+1+} \choose y} {y_{+2+} \choose y_{++2} - y} / {y_{+++} \choose y_{++2}} \le \alpha/2 \text{ or}$$

$$P(Y_{+21} \ge y_{+21} | y_{++2}, y_{1+}, y_{2+}, RM_T = 1) = \sum_{y \le y_{+12}} {y_{+1+} \choose y} {y_{+2+} \choose y_{++2} - y} / {y_{+++} \choose y_{++2}} \le \alpha/2$$

$$y_{1+}' = (y_{11+}, y_{21+}, ..., y_{n_11+}) \qquad y_{2+}' = (y_{12+}, y_{22+}, ..., y_{n_22+})$$

15

Test non-inferiority

$$H_0: RM_T \le RM_l (0 < RM_l < 1), H_1: RM_T > RM_l$$

Reject H_0 at the α -level and claim that treatment B is non-inferior to treatment A if the test statistic

$$(\log(RM_T) - \log(RM_I)) / \sqrt{Var(\log(RM_T))} > Z_{\alpha}$$
(14)

$$Z(\psi_l)/\sqrt{Var(Z(\psi_l))} > Z_{\alpha}$$
, where $\psi_l = RM_l^2$ (15)

$$P(Y_{+12} \ge y_{+12} | y_{++2}, y_{1+}, y_{2+}, RM_l) = \sum_{y \ge y_{+12}} {y \choose y} {y_{+1+} \choose y} {y_{+2+} \choose y_{++2} - y} (RM_l^2)^y / \sum_{y} {y \choose y_{+1+} \choose y} {y_{+2+} \choose y_{++2} - y} (RM_l^2)^y < \alpha$$
 (16)

Test equivalence

$$H_0: RM_T \le RM_l \text{ or } RM_T \ge RM_u, H_1: RM_l < RM_T < RM_u$$

$$(\log(RM_T) - \log(RM_I)) / \sqrt{Var(\log(RM_T))} > Z_{\alpha} \text{ and } (\log(RM_T) - \log(RM_u)) / \sqrt{Var(\log(RM_T))} < -Z_{\alpha}$$
(17)

$$Z(\psi_l)/\sqrt{Var(Z(\psi_l))} > Z_{\alpha} \text{ and } Z(\psi_u)/\sqrt{Var(Z(\psi_u))} < -Z_{\alpha}, \text{ where } \psi_l = RM_l^2, \psi_u = RM_u^2$$
(18)

$$P(Y_{+12} \ge y_{+12} | y_{++2}, y_{1+}, y_{2+}, RM_l) < \alpha \text{ and } P(Y_{+12} \le y_{+12} | y_{++2}, y_{1+}, y_{2+}, RM_u) < \alpha$$
 (19)

Interval Estimation

$$\left[RM_T \exp(-Z_{\alpha/2}) \sqrt{Var(\log(RM_T))}, RM_T \exp(Z_{\alpha/2}) \sqrt{Var(\log(RM_T))} \right]$$
 (20)

If A > 0, $B^2 - AC > 0$, asymptotic $100(1 - \alpha)\%$ confidence interval for RM_T as given by

$$\left[\max \left\{ \frac{B - \sqrt{B^2 - AC}}{A}, 0 \right\}^{1/2}, \left(\frac{B + \sqrt{B^2 - AC}}{A} \right)^{1/2} \right]$$
(22)

$$\begin{split} A &= ((1-\hat{p}_1)\hat{p}_2)^2 - Z_{\alpha/2}^2 Var((1-\hat{p}_1)\hat{p}_2) \\ B &= \hat{p}_1(1-\hat{p}_2)(1-\hat{p}_1)\hat{p}_2 - Z_{\alpha/2}^2 Cov(\hat{p}_1(1-\hat{p}_2), \ (1-\hat{p}_1)\hat{p}_2) \\ C &= (\hat{p}_1(1-\hat{p}_2))^2 - Z_{\alpha/2}^2 Var((1-\hat{p}_2)\hat{p}_1) \end{split}$$

$$[CR_l(\alpha), CR_u(\alpha)] \tag{23}$$

Monte Carlo Simulations and Result

Monte Carlo Simulations

Equivalence

$$Y_{ist} \sim Poisson(E(Y_{ist})), E(Y_{ist}) = u_{is} \exp(x_{ist} \eta + z_{it} \gamma), u_{is} \sim Gamma(\alpha, \beta), E(u_{is}) = \alpha\beta$$

Type I error

$$H_0: \eta = 0 \ (RM_T = 1), H_1: \eta \neq 0 \ (RM_T \neq 1)$$
 $E(u_{is}) = 1, 3, 5, \ \alpha = E(u_{is})/\beta \text{ and } \beta = 1, 2, 5$ $RM_P = 0.5, 2.0$ $n_1 = n_2 = 15, 30, 50$

Power

$$H_0: \eta = 0 \; (RM_T = 1), H_1: \eta \neq 0 \; (RM_T \neq 1)$$
 $E(u_{is}) = 3, \; \alpha = E(u_{is})/\beta \; \text{and} \; \beta = 1, \; 2, \; 5$ $RM_T = 0.5, \; 0.75, \; 1.25, \; 2.0$ $n_1 = n_2 = 15, \; 30, \; 50$ $RM_P = 0.5, \; 2.0$



$$H_0: \eta = 0 \ (RM_T = 1), H_1: \eta \neq 0 \ (RM_T \neq 1)$$

$$\alpha = E(u_{is})/\beta$$
 and $\beta = 1$

Equivalence

	RM	P	=	0	.5	(
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	$E(u_{ig})$	n	(7)	(9)	(10)	(13)
	1	15	0.059	0.044	0.044	0.018
		30	0.059	0.052	0.052	0.031
		50	0.055	0.051	0.051	0.034
	3	15	0.056	0.053	0.053	0.033
		30	0.048	0.047	0.047	0.034
		50	0.054	0.053	0.053	0.042
	5	15	0.055	0.052	0.052	0.037
		30	0.058	0.057	0.057	0.046
		50	0.050	0.049	0.049	0.042
$RM_P = 2.0$	00					
	1	15	0.061 ^a	0.053	0.053	0.032
		30	0.049	0.046	0.046	0.032
		50	0.050	0.048	0.048	0.036
	3	15	0.052	0.049	0.049	0.036
		30	0.052	0.051	0.051	0.040
		50	0.050	0.050	0.050	0.043
	5	15	0.055	0.053	0.053	0.043
		30	0.054	0.053	0.053	0.043
		50	0.046	0.046	0.046	0.038



$$H_0: \eta = 0 \ (RM_T = 1), H_1: \eta \neq 0 \ (RM_T \neq 1)$$
 $E(u_{is}) =$

$$E(u_{is}) = 3$$
, $\alpha = E(u_{is})/\beta$ and $\beta = 1$

$RM_P = 0.50$)					
	RM_T	n	(7)	(9)	(10)	(13)
	0.50	15	0.891	0.890	0.890	0.841
		30	0.994	0.994	0.994	0.991
		50	1.000	1.000	1.000	1.000
	0.75	15	0.318	0.311	0.311	0.245
		30	0.548	0.545	0.545	0.488
		50	0.769	0.768	0.768	0.734
	1.25	15	0.260	0.255	0.255	0.205
		30	0.452	0.450	0.450	0.399
		50	0.650	0.650	0.650	0.614
	1.50	15	0.685	0.683	0.683	0.626
		30	0.932	0.932	0.932	0.914
		50	0.995	0.995	0.995	0.993
$RM_P = 2.00$)					
	0.50	15	0.993	0.993	0.993	0.990
		30	1.000	1.000	1.000	1.000
		50	1.000	1.000	1.000	1.000
	0.75	15	0.552	0.548	0.548	0.496
		30	0.839	0.838	0.838	0.811
		50	0.966	0.966	0.966	0.960
	1.25	15	0.451	0.449	0.449	0.403
		30	0.737	0.736	0.736	0.708
		50	0.916	0.917	0.917	0.906
	1.50	15	0.929	0.928	0.928	0.909
		30	0.998	0.998	0.998	0.997
		50	1.000	1.000	1.000	1.000

Monte Carlo Simulations

Non-inferiority

$$Y_{ist} \sim Poisson(E(Y_{ist})), E(Y_{ist}) = u_{is} \exp(x_{ist} \eta + z_{it} \gamma), u_{is} \sim Gamma(\alpha, \beta), E(u_{is}) = \alpha \beta$$

Type I error

$$H_0: RM_T \le RM_l (0 < RM_l < 1), \ H_1: RM_T > RM_l$$
 $E(u_{is}) = 1, 3, 5, \ \alpha = E(u_{is})/\beta \text{ and } \beta = 1, 2, 5$
 $RM_P = 0.5, 2.0, RM_l = 0.8$ $n_1 = n_2 = 15, 30, 50$

Power

$$H_0: RM_T \le RM_l (0 < RM_l < 1), \ H_1: RM_T > RM_l$$
 $E(u_{is}) = 1, \ 3, \ 5, \ \alpha = E(u_{is})/\beta \text{ and } \beta = 1, \ 2, \ 5$
$$RM_T = 1.0$$

$$n_1 = n_2 = 15, \ 30, \ 50$$

$$RM_P = 0.5, \ 2.0, \ RM_I = 0.8$$



 $H_0: RM_T \le RM_l (0 < RM_l < 1), \ H_1: RM_T > RM_l$

 $\alpha = E(u_{is})/\beta$ and $\beta = 1, 2, 5$

Non-inferiority

$RM_P = 0.50$				
$E(u_{ig})$	n	(14)	(15)	(16)
I	15	0.045	0.048	0.024
	30	0.051	0.048	0.030
	50	0.052	0.048	0.037
3	15	0.049	0.047	0.034
	30	0.050	0.048	0.039
	50	0.046	0.043	0.038
5	15	0.049	0.047	0.038
	30	0.052	0.049	0.042
	50	0.048	0.046	0.040
$RM_P = 2.0$				
1	15	0.047	0.045	0.028
	30	0.049	0.046	0.034
	50	0.047	0.044	0.038
3	15	0.047	0.045	0.036
	30	0.054	0.051	0.044
	50	0.053	0.052	0.045
5	15	0.049	0.047	0.040
	30	0.051	0.048	0.043
	50	0.050	0.048	0.045



$$H_0: RM_T \le RM_l (0 < RM_l < 1), \ H_1: RM_T > RM_l$$

$\alpha = E(u_{is})/\beta$ and $\beta = 1$

Non-inferiority

$RM_P = 0.50$				
E(u _{ig})	n	(14)	(15)	(16)
T.	15	0.159	0.156	0.100
	30	0.247	0.237	0.187
	50	0.354	0.338	0.294
3	15	0.329	0.315	0.268
	30	0.535	0.520	0.484
	50	0.712	0.701	0.673
5	15	0.468	0.457	0.418
	30	0.716	0.709	0.684
	50	0.891	0.886	0.877
$RM_P = 2.0$				
ī	15	0.248	0.238	0.189
	30	0.401	0.388	0.343
	50	0.559	0.547	0.511
3	15	0.524	0.511	0.472
	30	0.779	0.770	0.753
	50	0.931	0.929	0.923
5	15	0.712	0.704	0.679
	30	0.928	0.924	0.917
	50	0.993	0.992	0.992

Monte Carlo Simulations and Result

Interval Estimator

$$\alpha = E(u_{is})/\beta$$
 and $\beta = 1, 2, 5$

$RM_P = 0.50$						
E(u _{ig})	RM_T	n	(20)	(22)	(23)	
3	0.50	15	0.953 (0.471)	0.989 (0.644)	0.971 (0.522)	
		30	0.954 (0.321)	0.990 (0.429)	0.968 (0.346)	
		50	0.953 (0.245)	0.991 (0.324)	0.966 (0.260)	
	1.00	15	0.951 (0.765)	0.975 (0.955)	0.967 (0.824)	
		30	0.950 (0.524)	0.977 (0.630)	0.963 (0.556)	
		50	0.953 (0.399)	0.979 (0.474)	0.961 (0.419)	
	2.00	15	0.951 (1.329)	0.958 (1.580)	0.966 (1.372)	
		30	0.949 (0.905)	0.960 (1.010)	0.960 (0.934)	
		50	0.949 (0.693)	0.961 (0.758)	0.946 (0.716)	
5	0.50	15	0.951 (0.354)	0.990 (0.475)	0.965 (0.385)	
		30	0.948 (0.245)	0.989 (0.325)	0.960 (0.260)	
		50	0.952 (0.188)	0.991 (0.249)	0.961 (0.197)	
	1.00	15	0.950 (0.576)	0.976 (0.697)	0.964 (0.613)	
		30	0.953 (0.400)	0.980 (0.475)	0.963 (0.420)	
		50	0.946 (0.308)	0.976 (0.363)	0.955 (0.320)	
	2.00	15	0.951 (1.000)	0.960 (1.127)	0.963 (1.032)	
		30	0.952 (0.693)	0.963 (0.758)	0.946 (0.716)	
		50	0.951 (0.532)	0.963 (0.576)	0.958 (0.540)	

Monte Carlo Simulations and Result

Interval Estimator

$$\alpha = E(u_{is})/\beta$$
 and $\beta = 1, 2, 5$

$RM_P = 2.0$					
3	0.50	15	0.951 (0.323)	0.960 (0.351)	0.964 (0.348)
		30	0.952 (0.223)	0.964 (0.240)	0.964 (0.236)
		50	0.948 (0.172)	0.959 (0.184)	0.957 (0.179)
	1.00	15	0.951 (0.526)	0.955 (0.558)	0.962 (0.558)
		30	0.948 (0.365)	0.953 (0.381)	0.956 (0.382)
		50	0.950 (0.280)	0.956 (0.291)	0.958 (0.290)
	2.00	15	0.951 (0.913)	0.949 (0.966)	0.963 (0.942)
		30	0.952 (0.632)	0.953 (0.652)	0.948 (0.652)
		50	0.951 (0.485)	0.952 (0.496)	0.957 (0.488)
5	0.50	15	0.955 (0.246)	0.964 (0.265)	0.965 (0.260)
		30	0.950 (0.172)	0.963 (0.184)	0.960 (0.179)
		50	0.951 (0.132)	0.963 (0.142)	0.958 (0.137)
	1.00	15	0.952 (0.401)	0.957 (0.420)	0.961 (0.421)
		30	0.951 (0.280)	0.957 (0.290)	0.958 (0.290)
		50	0.950 (0.216)	0.957 (0.224)	0.957 (0.222)
	2.00	15	0.951 (0.696)	0.952 (0.722)	0.949 (0.719)
		30	0.953 (0.485)	0.953 (0.496)	0.958 (0.489)
		50	0.951 (0.375)	0.951 (0.381)	0.955 (0.383)

Application

An Example

Double-Blind Crossover Trial for Asthma patients

Treatment A: Placebo

Treatment B: Beta-agonist salmeterol (50g twice daily)

101 participate only 87 patients who completed the trial

Randomized to sequence AB or sequence BA

Sequence AB

24 weeks placebo

Washeout period

24 weeks salmeterol

Sequence BA

24 weeks salmeterol

Washeout period

24 weeks placebo

An Example

Sums of exacerbations in asthma on the 87 patients

$$Y_{+11} = 15$$
, $Y_{+12} = 6$ for sequence 1; $Y_{+21} = 14$, $Y_{+22} = 23$ for sequence 2 $RM_T = 0.493$

Test non-equality	(7)	(9)	(10)	(13)
P-value	0.010	0.014	0.014	0.028

All these suggest that there be significant evidence that taking salmeterol at the 5% level can reduce the mean number of exacerbations in asthma.

Test non-equality	(20)	(22)	(23)
95% confidence interval	[0.227, 0.880]	[0.167, 0.931]	[0.252, 0.937]

Discussions

Discussions

- Asymptotic interval estimators for large sample, exact interval estimator can be use of small sample.
- Asymptotic test procedures can all perform well with respect to the estimated Type I error as n=15, but power is larger than exact test procedures.
- The interval estimator (20) based on \widehat{RM}_T with the logarithmic transformation is probably the best among the three interval estimators discussed here.

Reference

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Thanks!