



APPROXIMATIONS TO THE DISTRIBUTION OF CONDITIONAL MOMENT TEST STATISTICS

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Introduction

Objectives

Cross-Section/Short Panels.

Parametric Likelihood Framework.

Conditional Moment Tests.

- $O(T^{-1})$ Edgeworth-type approximations to OPG CM test distribution.

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- Analytic evidence of poor nominal chi-square asymptotic null distribution.

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- Analytical comparison with FE CM test.

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Conditional Moment Tests.

- $O(T^{-1})$ Edgeworth-type approximations to OPG CM test distribution.
- Analytic evidence of poor nominal chi-square asymptotic null distribution.
- Analytical comparison with FE CM test.
- Simulation experiments.

Introduction

Example

$X \sim N(\mu, \sigma^2)$. σ^2 known.

Invariance. Set $\sigma^2 = 1$.

Null hypothesis $H_0 : \mu = 0$.

FE Score Test Statistic.

$$T_{FE} = Tm_1^2.$$

OPG Score Test Statistic.

$$T_{OPG} = Tm_1^2/m_2.$$

REMARK. m_i i th sample moment about the hypothesised mean.

Introduction

Example (Cont.)

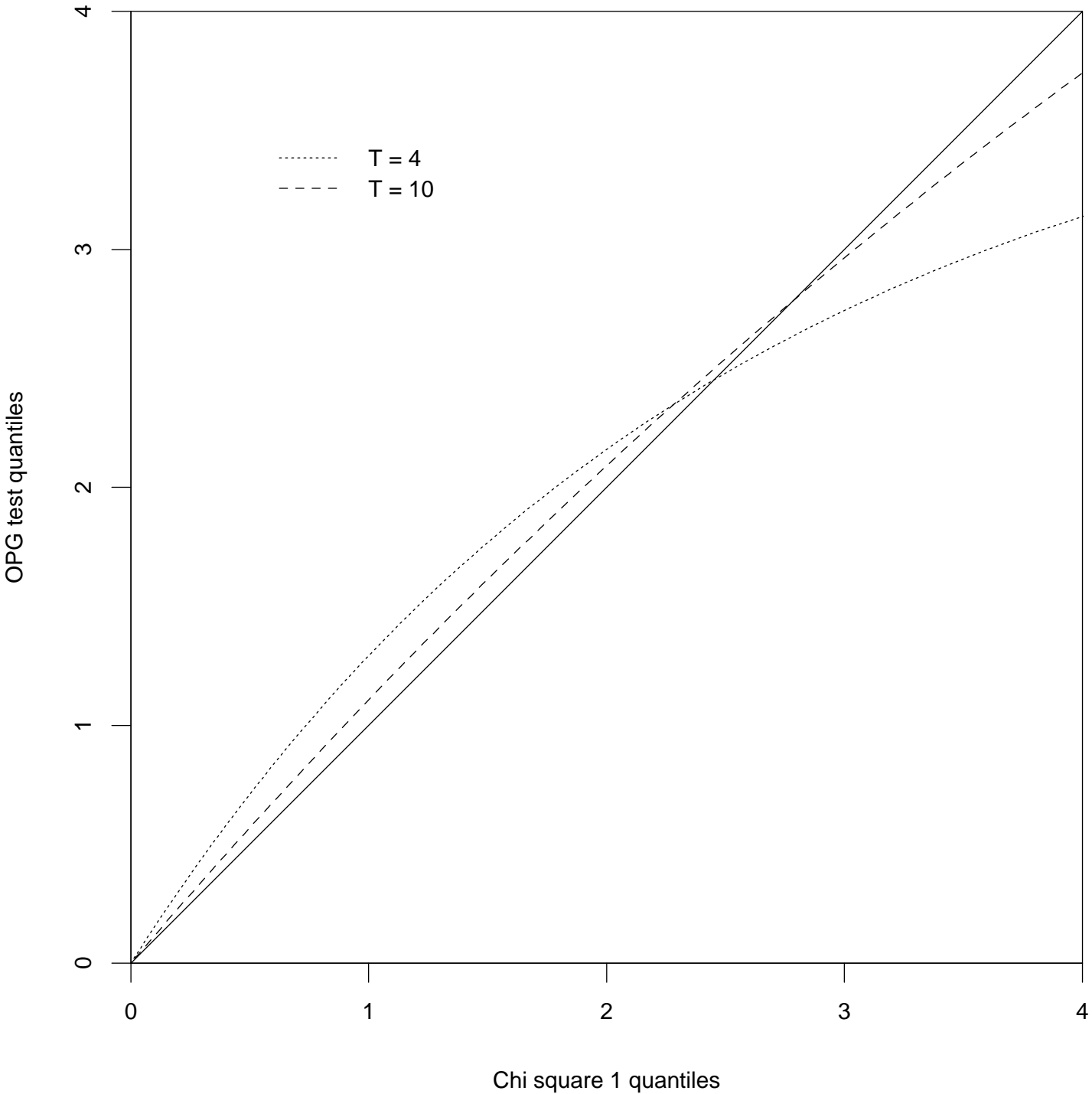
REMARK. T_{FE} exact $\chi^2(1)$.

REMARK. T_{OPG} exact $T\mathcal{B}(\frac{1}{2}, \frac{T-1}{2})$.

Exact and $O(T^{-2})$ approximate cumulants.

Cumulant	Exact	$O(T^{-2})$
κ_1	1	1
κ_2	$2 - \frac{6}{T+2}$	$2 - \frac{6}{T} + \frac{12}{T^2}$
κ_3	$8 - \frac{24(3T+2)}{(T+4)(T+2)}$	$8 - \frac{72}{T} + \frac{384}{T^2}$
κ_4	$48 - \frac{432(2T^3+8T^2+13T+12)}{(T+6)(T+4)(T+2)^2}$	$48 - \frac{864}{T} + \frac{8640}{T^2}$

$$X \sim N(\mu, 1), H_0 : \mu = 0$$



Introduction

Outline

- CM tests as LM tests for additional conditional moments.

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- CM tests as LM tests for additional conditional moments.
- Stochastic approximations.
- Edgeworth approximation.
- Censored regression model. Omitted variables.

Conditional Moment Tests

Definitions

Data vector $x^T = (x_1, \dots, x_T)$.

Independent sampling.

Density function $f_t(\cdot, \theta_0)$.

Fixed design conditional on $z_t, (t = 1, \dots, T), (T = 1, 2, \dots)$.

Conditional Moment Tests

Asymptotics

x sampled conditional on z .

Fixed in repeated samples.

Define $T = dR$.

d : fixed d -point design in z .

R : number of design replications.

$R \rightarrow \infty$. Thus $T \rightarrow \infty$.

Conditional Moment Tests

MLE

$$\hat{\theta}_T = \arg \max_{\theta \in \Theta} \sum_{t=1}^T \log f_t(x_t, \theta).$$

Conditional Moment Tests

Misspecification Test

Test validity of

$$f^T(x^T, \theta_0) = \prod_{t=1}^T f_t(x_t, \theta_0).$$

Finite number of *implied* moment conditions.

$$E_{\theta_0}[m_t^i(x_t, \theta_0)] = 0, (i = 1, \dots, m).$$

$E_{\theta_0}[\cdot]$: expectation w.r.t. $f^T(x^T, \theta_0)$.

REMARK: pure significance test.

Conditional Moment Tests

Chesher-Smith (1997)

Carrier function $h(\cdot)$.

REMARK: scalar; $h(w) > 0$, $dh(w)/dw > 0$; $h(0) = dh(0)/dw = 1$.

Let $m_t(x_t, \theta) = (m_t^1(x_t, \theta), \dots, m_t^m(x_t, \theta))'$, ($t = 1, \dots, T$).

Augmented density function

$$r_t(x_t, \varphi) = f_t(x_t, \theta)h(\lambda' m_t(x_t, \theta)) / q_t(\varphi), (t = 1, \dots, T).$$

REMARK: $\varphi = (\theta', \lambda')'$. $q_t(\varphi) = E_\theta[h(\lambda' m_t(x_t, \theta))]$.

Conditional Moment Tests

Chesher-Smith (1997) (Cont.)

$$\lambda = 0 \Leftrightarrow E_{\theta_0}[m_t(x_t, \theta_0)] = 0.$$

Score/LM test statistic for $\lambda = 0$ identical to CM test based on

$$E_{\theta_0}[m_t(x_t, \theta_0)] = 0.$$

Conditional Moment Tests

CM Test Statistic

r -vector $y_t(\theta)$.

$$r = p + m.$$

First p elements $\partial \log f_t(x_t, \theta) / \partial \theta$.

Last m elements $m_t(x_t, \theta)$.

Let $\hat{y}_T = T^{-1/2} \sum_{t=1}^T y_t(\hat{\theta}_T)$.

CM test statistic

$$S_T = \hat{y}_T' \hat{G}_T^{-1} \hat{y}_T.$$

Conditional Moment Tests

CM Test Statistic (Cont.)

Under $f^T(x^T, \theta_0)$, ($T = 1, 2, \dots$),

$$\hat{G}_T \xrightarrow{p} G_0 = \lim_{T \rightarrow \infty} T^{-1} \sum_{t=1}^T E_{\theta_0} [y_t(\theta_0) y_t(\theta_0)'].$$

G_0 positive definite.

Under $f^T(x^T, \theta_0)$, ($T = 1, 2, \dots$),

$$\mathcal{S}_T \xrightarrow{d} \chi_m^2.$$

REMARK: \mathcal{S}_T invariant to $h(\cdot)$ choice.

REMARK: Approximations invariant to $h(\cdot)$ choice.

Conditional Moment Tests

CM Test Statistic (Cont.)

Choice of \hat{G}_T .

- Fully efficient (FE).

$$\hat{G}_T = T^{-1} \sum_{t=1}^T E_{\hat{\theta}_T} [y_t(\theta) y_t(\theta)'].$$

Conditional Moment Tests

CM Test Statistic (Cont.)

Choice of \hat{G}_T .

- Fully efficient (FE).

$$\hat{G}_T = T^{-1} \sum_{t=1}^T E_{\hat{\theta}_T} [y_t(\theta) y_t(\theta)'].$$

- Outer-Product of Gradients (OPG).

$$\hat{G}_T = T^{-1} \sum_{t=1}^T y_t(\hat{\theta}_T) y_t(\hat{\theta}_T)'$$

REMARK: $T\mathcal{R}^2$ from $1 = y_t(\hat{\theta}_T)' \zeta + v_t$, ($t = 1, \dots, T$).

REMARK: Classical score/LM statistics also included.

Stochastic Approximation

Derivatives

Require first four derivatives of $y_t(\theta)$.

Let

$$y_i^t = \frac{\partial \log r_t(x_t, \varphi_0)}{\partial \varphi_i}, \quad y_{ij}^t = \frac{\partial^2 \log r_t(x_t, \varphi_0)}{\partial \varphi_i \partial \varphi_j},$$

$$y_{ijk}^t = \frac{\partial^3 \log r_t(x_t, \varphi_0)}{\partial \varphi_i \partial \varphi_j \partial \varphi_k}, \quad y_{ijkl}^t = \frac{\partial^4 \log r_t(x_t, \varphi_0)}{\partial \varphi_i \partial \varphi_j \partial \varphi_k \partial \varphi_l}.$$

$(i, j, k, l = 1, \dots, r), (t = 1, \dots, T)$.

Stochastic Approximation

Derivatives (Cont.)

Define

$$y_i = T^{-1/2} \sum_{t=1}^T y_i^t, \quad y_{ij} = T^{-1} \sum_{t=1}^T y_{ij}^t,$$

$$y_{ijk} = T^{-3/2} \sum_{t=1}^T y_{ijk}^t, \quad y_{ijkl} = T^{-2} \sum_{t=1}^T y_{ijkl}^t$$

$(i, j, k, l = 1, \dots, r), (T = 1, 2, \dots)$.

REMARK: Cf. usual LR and W stochastic expansion components.

Stochastic Approximation

Conditional Cumulants

Conditional cumulants.

$$\kappa_{ij}^t = E_{\theta_0}[\mathbf{y}_{ij}^t], \quad \kappa_{i,j}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_j^t],$$

$$\kappa_{ijk}^t = E_{\theta_0}[\mathbf{y}_{ijk}^t], \quad \kappa_{i,jk}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_{jk}^t], \quad \kappa_{i,j,k}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_j^t \mathbf{y}_k^t],$$

$$\kappa_{ijkl}^t = E_{\theta_0}[\mathbf{y}_{ijkl}^t], \quad \kappa_{i,jkl}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_{jkl}^t],$$

$$\kappa_{ij,kl}^t = E_{\theta_0}[\mathbf{y}_{ij}^t \mathbf{y}_{kl}^t] - \kappa_{ij}^t \kappa_{kl}^t, \quad \kappa_{i,j,kl}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_{j,kl}^t] - \kappa_{i,j}^t \kappa_{kl}^t,$$

$$\kappa_{i,j,k,l}^t = E_{\theta_0}[\mathbf{y}_i^t \mathbf{y}_j^t \mathbf{y}_k^t \mathbf{y}_l^t] - \kappa_{i,j}^t \kappa_{k,l}^t - \kappa_{i,k}^t \kappa_{j,l}^t - \kappa_{i,l}^t \kappa_{j,k}^t,$$

$(i, j, k, l = 1, \dots, r), (t = 1, \dots, T).$

Stochastic Approximation

Averaged Conditional Cumulants

Averaged conditional cumulants. E.g.

$$\kappa_{ij} = T^{-1} \sum_{t=1}^T \kappa_{ij}^t, \quad \kappa_{i,j} = T^{-1} \sum_{t=1}^T \kappa_{i,j}^t.$$

Other averaged conditional cumulants.

$$\begin{aligned} &\kappa_{ijk}, \quad \kappa_{i,jk}, \quad \kappa_{i,j,k}, \quad \kappa_{ijkl}, \\ &\kappa_{i,jkl}, \quad \kappa_{ij,kl}, \quad \kappa_{i,j,kl}, \quad \kappa_{i,j,k,l}, \end{aligned}$$

$(T = 1, 2, \dots)$.

Stochastic Approximation

Additional Cumulants

Plus

Additional averaged cumulant

$$\kappa_{i,j;k,l} = T^{-1} \sum_{t=1}^T \kappa_{i,j}^t \kappa_{k,l}^t.$$

REMARK: peculiar to Edgeworth expansion of OPG CM form.

REMARK: arises because conditioning variables $\{z_t\}_{t=1}^T$ present.

Stochastic Approximation

Additional Derivatives

CM test statistic

$$S_T = \hat{g}^{ij} \hat{y}_i \hat{y}_j.$$

Let

$$g_{ab} = [T^{-1} \sum_{t=1}^T y_t(\theta_0) y_t(\theta_0)']_{ab}.$$

Additional derivatives.

$$g_{ab,k} = T^{-1/2} \sum_{t=1}^T \frac{\partial g_{ab}}{\partial \varphi_k} = T^{-3/2} \sum_{t=1}^T (y_a^t y_{bk}^t + y_{ak}^t y_b^t).$$

$$\begin{aligned} g_{ab,kl} &= T^{-1} \sum_{t=1}^T \frac{\partial^2 g_{ab}}{\partial \varphi_k \partial \varphi_l} \\ &= T^{-2} \sum_{t=1}^T (y_{al}^t y_{bk}^t + y_{ak}^t y_{bl}^t + y_a^t y_{bkl}^t + y_{akl}^t y_b^t). \end{aligned}$$

Stochastic Approximation

Stochastic Expansions

Let $\Delta\hat{\varphi}_{T_i} = \hat{\theta}_{T_i} - \theta_{0i}$, ($i = 1, \dots, p$), and 0 , ($i = p + 1, \dots, r$).

- \hat{g}^{ij} .

$$\begin{aligned}\hat{g}^{ij} &= g^{ij} - g^{ia} g^{jb} g_{ab,k} (T^{1/2} \Delta\hat{\varphi}_{T_k}) \\ &\quad + g^{ia} g_{ab,k} (T^{1/2} \Delta\hat{\varphi}_{T_k}) g^{bc} g_{cd,l} (T^{1/2} \Delta\hat{\varphi}_{T_l}) g^{dj} \\ &\quad - \frac{1}{2} g^{ia} g_{ab,kl} (T^{1/2} \Delta\hat{\varphi}_{T_k}) (T^{1/2} \Delta\hat{\varphi}_{T_l}) g^{bj} + O_p(T^{-3/2}),\end{aligned}$$

($i, j = 1, \dots, r$).

Stochastic Approximation

Stochastic Expansions

Let $\Delta\hat{\varphi}_{Ti} = \hat{\theta}_{Ti} - \theta_{0i}$, ($i = 1, \dots, p$), and 0 , ($i = p + 1, \dots, r$).

- \hat{g}^{ij} .

$$\begin{aligned}\hat{g}^{ij} &= g^{ij} - g^{ia} g^{jb} g_{ab,k} (T^{1/2} \Delta\hat{\varphi}_{Tk}) \\ &\quad + g^{ia} g_{ab,k} (T^{1/2} \Delta\hat{\varphi}_{Tk}) g^{bc} g_{cd,l} (T^{1/2} \Delta\hat{\varphi}_{Tl}) g^{dj} \\ &\quad - \frac{1}{2} g^{ia} g_{ab,kl} (T^{1/2} \Delta\hat{\varphi}_{Tk}) (T^{1/2} \Delta\hat{\varphi}_{Tl}) g^{bj} + O_p(T^{-3/2}),\end{aligned}$$

($i, j = 1, \dots, r$).

- \hat{y}_i .

$$\begin{aligned}\hat{y}_i &= y_i + y_{ij} (T^{1/2} \Delta\hat{\varphi}_{Tj}) + \frac{1}{2} y_{ijk} (T^{1/2} \Delta\hat{\varphi}_{Tj}) (T^{1/2} \Delta\hat{\varphi}_{Tk}) \\ &\quad + \frac{1}{6} y_{ijkl} (T^{1/2} \Delta\hat{\varphi}_{Tj}) (T^{1/2} \Delta\hat{\varphi}_{Tk}) (T^{1/2} \Delta\hat{\varphi}_{Tl}) + O_p(T^{-3/2}),\end{aligned}$$

($i = 1, \dots, r$).

Stochastic Approximation

Stochastic Expansions (Cont.)

- $\Delta \hat{\phi}_{Ti}$. Successive back-substitution in $\hat{y}_i = 0$, ($i = 1, \dots, p$).

$$\begin{aligned}
 T^{1/2} \Delta \hat{\phi}_{Ti} &= -[c_{iw} y_w] - \frac{1}{2} c_{ij} y_{jkl} [c_{kw} y_w] [c_{lw} y_w] \\
 &\quad - \frac{1}{2} c_{ij} y_{jkl} [c_{kw} y_w] c_{lm} y_{mno} [c_{mw} y_w] [c_{ow} y_w] \\
 &\quad + \frac{1}{6} c_{ij} y_{jklm} [c_{kw} y_w] [c_{lw} y_w] [c_{mw} y_w] + O_p(T^{-3/2});
 \end{aligned}$$

($i = 1, \dots, r$).

$$\begin{aligned}
 c_{ij} &= y^{ij}, (i, j = 1, \dots, p) \\
 &= 0 \text{ otherwise.}
 \end{aligned}$$

Stochastic Approximation

Stochastic Expansions (Cont.)

REMARK.

$$y_{ijkl} - E_{\theta_0}[y_{ijkl}] = O_p(T^{-3/2}), \quad g_{ij,kl} - E_{\theta_0}[g_{ij,kl}] = O_p(T^{-3/2}),$$

$(i, j, k, l = 1, \dots, r)$.

Replace terms $\{y_{ijkl}\}$ and $\{g_{ij,kl}\}$ by

$$E_{\theta_0}[y_{ijkl}] = T^{-1}\kappa_{ijkl},$$

$$E_{\theta_0}[g_{ij,kl}] = T^{-1}(\kappa_{ik,jl} + \kappa_{il,jk} + \kappa_{i,jkl} + \kappa_{j,ikl} + \kappa_{i,l;jk} + \kappa_{i,k;jl}).$$

Validity of the stochastic approximation unaffected to $O_p(T^{-3/2})$.

Likewise Edgeworth-type expansion to $o(T^{-1})$.

REMARK. Stochastic expansion for OPG CM form \mathcal{S}_T involves $\{\kappa_{ij;kl}\}$.
Cf. FE CM statistic.

Stochastic Approximation

Stochastic Expansions (Cont.)

Combine stochastic expansions for \hat{g}^{ij} , \hat{y}_i and $\Delta\hat{\phi}_{Ti}$.

$$\mathcal{S}_T = O_p(1) + O_p(T^{-1/2}) + O_p(T^{-1}) + o_p(T^{-1}).$$

REMARK. Remainder $O_p(T^{-3/2})$.

Edgeworth Approximation

Edgeworth Series Distribution

Require Edgeworth density to $O(T^{-3/2})$ for

$$y_i = T^{-1/2} \sum_t y_i^t, \quad y_{ij} = T^{-1} \sum_t y_{ij}^t, \quad y_{ijk} = T^{-3/2} \sum_t y_{ijk}^t.$$

Plus

$$g_{ij} = T^{-1} \sum_t g_{ij}^t, \quad g_{ij,k} = T^{-3/2} \sum_t g_{ij,k}^t.$$

REMARK.

$$g_{ij}^t = y_i^t y_j^t, \quad g_{ij,k}^t = \partial g_{ij}^t / \partial \varphi_k = y_i^t y_{jk}^t + y_{ik}^t y_j^t,$$

$(t = 1, \dots, T), (T = 1, 2, \dots).$

Edgeworth Approximation

Edgeworth Series Distribution (Cont.)

Edgeworth series distribution $h(\{y_i\}, \{y_{ij}\}, \{y_{ijk}\}, \{g_{ij}\}, \{g_{ij,k}\})$

$$\begin{aligned} & \exp\left(\sum (-1)^{r+s+t+u+v} (r, s, t, u, v)\right) \\ & \times \frac{(\partial/\partial y_i)^r (\partial/\partial y_{jk})^s (\partial/\partial y_{lmo})^t (\partial/\partial g_{ij})^u (\partial/\partial g_{kl,m})^v}{r! s! t! u! v!} \\ & \times g(\{y_i\}, \{y_{jk}\}, \{y_{lmo}\}, \{g_{ij}\}, \{g_{kl,m}\}). \end{aligned}$$

REMARK. Sum over $r + 2s + 3t + 2u + 3v \geq 3$.

Omit $t = 1$ or $v = 1$ when $r = s = u = 0$.

REMARK. Truncate at $r + 2s + 3t + 2u + 3v = 4$ for $O(T^{-3/2})$.

REMARK. $\kappa(r, s, t, u, v)$ cumulant associated with $(y_i)^r (y_{jk})^s (y_{lmo})^t (g_{ij})^u (g_{kl,m})^v$.

Edgeworth Approximation

Edgeworth Series Distribution (Cont.)

$$\begin{aligned}
 & g(\{y_i\}, \{y_{jk}\}, \{y_{lmo}\}, \{g_{ij}\}, \{g_{ij,k}\}) \\
 &= (2\pi)^{-r/2} (\det \kappa_{i,j})^{-1/2} \exp\{-(1/2)\kappa^{ij}y_i y_j\} \\
 &\quad \times \prod_{j,k} \delta(y_{jk} - \kappa_{jk}) \prod_{l,m,o} \delta(y_{lmo} - T^{-1/2}\kappa_{lmo}) \\
 &\quad \times \prod_{i,j} \delta(g_{ij} - \kappa_{i,j}) \prod_{k,l,m} \delta(g_{kl,m} - T^{-1/2}(\kappa_{k,lm} + \kappa_{l,km})).
 \end{aligned}$$

Dirac delta function $\delta(\cdot)$.

E.g. $\delta(y_{jk} - \kappa_{jk}) = 0$ if $y_{jk} \neq \kappa_{jk}$ and 1 if $y_{jk} = \kappa_{jk}$.

Edgeworth Approximation

Characteristic Function

Let $q = 2\iota s / (1 - 2\iota s)$ and $\iota = \sqrt{-1}$.

Characteristic function.

$$\begin{aligned} \varphi_{S_T}(s) &= \int \dots \int \exp(\iota s S_T) h(\{y_i\}, \{y_{ij}\}, \{y_{ijk}\}, \{g_{ij}\}, \{g_{ij,k}\}) \\ &\quad \times dy_i dy_{ij} dy_{ijk} dg_{ij} dg_{ij,k} + O(T^{-3/2}). \end{aligned}$$

REMARK. Integrate w.r.t $\{y_{ij}\}, \{y_{ijk}\}, \{g_{ij}\}, \{g_{ij,k}\}$. Then $\{y_i\}$.

Let

$$\begin{aligned} a_{ij} &= \kappa^{ij}, (i, j = 1, \dots, p) \\ &= 0 \text{ otherwise.} \end{aligned}$$

and

$$m_{ij} = \kappa^{ij} - a_{ij}, (i, j = 1, \dots, r).$$

Edgeworth Approximation

Characteristic Function (Cont.)

Characteristic function.

$$\varphi_{S_T}(s) = (1 - 2is)^{-\frac{m}{2}} \left(1 + \frac{1}{24T} (\mathcal{B}_1 q + \mathcal{B}_2 q^2 + \mathcal{B}_3 q^3) \right) + O(T^{-3/2}).$$

Edgeworth Approximation

Characteristic Function (Cont.)

$$\begin{aligned}
 \mathcal{B}_1 &= 3(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}m_{kp}(\kappa_{pqr} + 2\kappa_{p,q,r})a_{qr} - 12(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}m_{kp}\kappa_{p,q,r}m_{qr} \\
 &\quad + 12\kappa_{i,j,k}m_{ij}\kappa^{k,p}\kappa_{p,q,r}m_{qr} + 12\kappa_{i,j,k,l}a_{ij}m_{kl} - 6\kappa_{ij,k}a_{ip}a_{jq}m_{kr}\kappa_{p,q,r} \\
 &\quad - 6\kappa_{i,j,k}a_{ip}a_{jq}m_{kr}\kappa_{p,q,r} + 12\kappa_{i,j,k}m_{ip}m_{jq}\kappa^{k,r}\kappa_{p,q,r} \\
 &\quad + 24\kappa_{i,j;k,l}a_{ik}m_{jl} + 12\kappa_{i,j;k,l}a_{ij}m_{kl}, \\
 \mathcal{B}_2 &= 24\kappa_{i,j,k}m_{ij}m_{kp}\kappa_{p,q,r}m_{qr} - 12(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}m_{kp}\kappa_{p,q,r}m_{qr} - 6\kappa_{i,j,k,l}m_{ij}m_{kl} \\
 &\quad + 12\kappa_{i,j,k}m_{ij}a_{kp}\kappa_{p,q,r}m_{qr} + 24\kappa_{i,j,k}m_{ip}m_{jq}\kappa^{k,r}\kappa_{p,q,r} \\
 &\quad - 6\kappa_{i,j;k,l}m_{ij}m_{kl} - 12\kappa_{i,j;k,l}m_{ik}m_{jl}, \\
 \mathcal{B}_3 &= 12\kappa_{i,j,k}m_{ij}m_{kp}\kappa_{p,q,r}m_{qr} + 8\kappa_{i,j,k}m_{ip}m_{jq}m_{kr}\kappa_{p,q,r}.
 \end{aligned}$$

REMARK. i.i.d. case

$$\mathcal{B}_1 : \kappa_{i,j;k,l}a_{ij}m_{kl} = mp;$$

$$\mathcal{B}_2 : \kappa_{i,j;k,l}m_{ik}m_{jl} = \frac{1}{2}m(m+2).$$

Edgeworth Approximation

Characteristic Function (Cont.)

FE CM Test.

Replace $\{\mathcal{B}_i\}$ by

$$\begin{aligned} \mathcal{A}_1 &= 3(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}m_{kp}(\kappa_{pqr} + 2\kappa_{p,q,r})a_{qr} - 6(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}a_{kp}\kappa_{p,q,r}m_{qr} \\ &\quad + 6(\kappa_{i,jk} - \kappa_{i,j,k})m_{ip}a_{jq}a_{kr}(\kappa_{pqr} + 2\kappa_{p,q,r}) - 6(\kappa_{i,j,k,l} + \kappa_{i,j,kl})a_{ij}m_{kl}, \\ \mathcal{A}_2 &= -3\kappa_{i,j,k}m_{ij}a_{kp}\kappa_{p,q,r}m_{qr} + 6(\kappa_{ijk} + 2\kappa_{i,jk})a_{ij}m_{kp}\kappa_{p,q,r}m_{qr} + 3\kappa_{i,j,k,l}m_{ij}m_{kl} \\ &\quad - 6\kappa_{i,j,k}m_{ip}m_{jq}a_{kr}\kappa_{p,q,r}, \\ \mathcal{A}_3 &= 3\kappa_{i,j,k}m_{ij}m_{kp}\kappa_{p,q,r}m_{qr} + 2\kappa_{i,j,k}m_{ip}m_{jq}m_{kr}\kappa_{p,q,r}. \end{aligned}$$

REMARK. Typically coefficients of $\{\mathcal{B}_i\}$ cumulants greater than $\{\mathcal{A}_i\}$.
 E.g. $\mathcal{B}_3 = 4\mathcal{A}_3$. Affects $O(n^{-1})$ skewness/kurtosis expressions.
 Deviations from $\chi^2(m)$ greater for OPG than FE.

Edgeworth Approximation

Cumulants

$O(T^{-1})$ OPG CM cumulants.

$$\kappa_1^{S_T} = m + \frac{1}{12T} \mathcal{B}_1,$$

$$\kappa_2^{S_T} = 2m + \frac{1}{3T} (\mathcal{B}_1 + \mathcal{B}_2),$$

$$\kappa_3^{S_T} = 8m + \frac{2}{T} (\mathcal{B}_1 + 2\mathcal{B}_2 + \mathcal{B}_3),$$

$$\kappa_4^{S_T} = 48m + \frac{16}{T} (\mathcal{B}_1 + 3\mathcal{B}_2 + 3\mathcal{B}_3)$$

REMARK. Remainders $O(T^{-3/2})$.

REMARK. First term $\chi^2(m)$.

Edgeworth Approximation

C.D.F.

Let $F_{S_T}(x) = \mathcal{P}\{S_T \leq x\}$.

Fourier inversion.

$$F_{S_T}(x) = P_m(x) + \frac{1}{24T} [(\mathcal{B}_2 - \mathcal{B}_1 - \mathcal{B}_3)P_m(x) + (3\mathcal{B}_3 - 2\mathcal{B}_2 + \mathcal{B}_1)P_{m+2}(x) + (\mathcal{B}_2 - 3\mathcal{B}_3)P_{m+4}(x) + \mathcal{B}_3P_{m+6}(x)] + O(T^{-3/2}).$$

REMARK. $\mathcal{P}_r(x) = \mathcal{P}\{\chi^2(r) \leq x\}$.

Edgeworth Approximation

C.D.F. (Cont.)

Alternative formulation.

$$F_{S_T}(x) = P_m(x) - \frac{1}{12T}\beta(x)p_m(x) + O(T^{-3/2}).$$

REMARK. $p_m(\cdot)$ p.d.f. of $\chi^2(m)$.

REMARK. $\beta(x) = \sum_{i=1}^3 \beta_i x^i$ and

$$\beta_1 = \frac{(\mathcal{B}_3 - \mathcal{B}_2 + \mathcal{B}_1)}{m}, \beta_2 = \frac{(\mathcal{B}_2 - 2\mathcal{B}_3)}{m(m+2)}, \beta_3 = \frac{\mathcal{B}_3}{m(m+2)(m+4)}.$$

REMARK. Enables investigation of monotonicity properties.

Edgeworth Approximation

C.D.F. (Cont.)

Also

$$F_{S_T}(x) = P_m \left(x - \frac{1}{12T} \beta(x) \right) + O(T^{-3/2}).$$

REMARK. Basis for Cornish-Fisher inverse expansion.

Let c_α denote $O(1)$ approximating $\chi^2(m)$ α -quantile.

Corresponding CM statistic S_T critical value c_α^* to $O(T^{-3/2})$.

$$c_\alpha^* - \frac{1}{12T} \beta(c_\alpha^*) = c_\alpha$$

Approximated by

$$c_\alpha^* = c_\alpha + \frac{1}{12T} \beta(c_\alpha).$$

Censored Regression

Design

Censored regression

$$y = \max[0, N(\beta_0 + \beta_1 z, \sigma^2)].$$

REMARK. Set $\sigma^2 = 1$.

Intercept β_0 adjusted for expected 25% or 50% censoring.

REMARK. Slope β_1 set for expected latent regression model \mathcal{R}^2 of 0.75.

Censored Regression

Covariate Design

Sample size $d = 50$.

- Design 1. Expected $U(0,1)$ order statistics.
- Design 2. Expected $N(0,1)$ order statistics.
- Design 3. Expected log normal $\Lambda(0,0.3)$ order statistics.
- Design 4. Replace Design 1 lowest and highest values by -1 and $+2$.

REMARK. Designs 1, 2 and 4 symmetric. Design 3 asymmetric.

REMARK. Designs 3 and 4 points of relatively high leverage.

Censored Regression

Omitted Variable Design

- W_1 : squared Design 2 covariate.

Censored Regression

Omitted Variable Design

- W_1 : squared Design 2 covariate.
- W_2 : $i^2/50$, ($i = 1, \dots, 50$).

Censored Regression

Simulation Experiments

10000 replications.

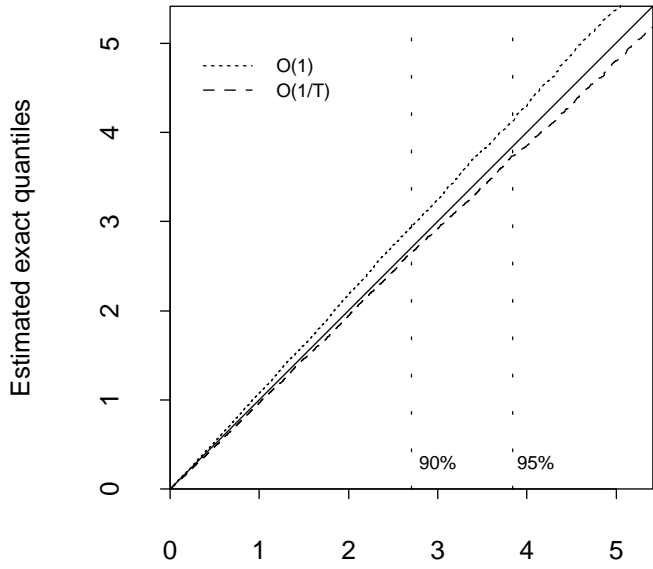
Design replication. $R = 5$ and 10 .

$T = 250$ and 500 .

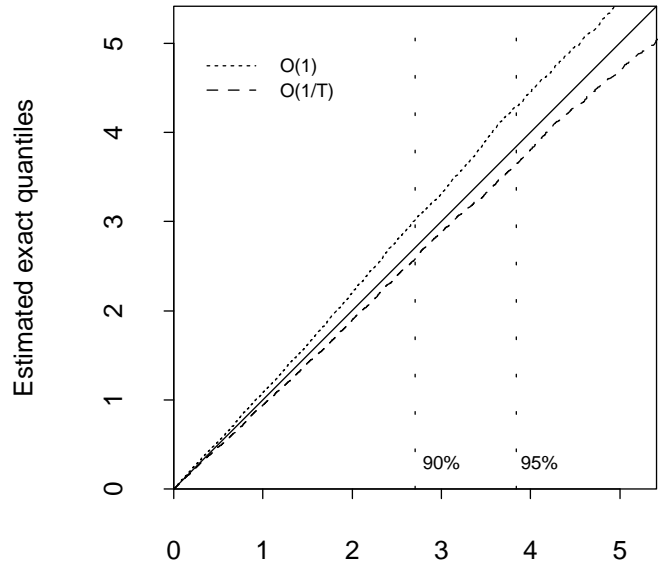
QQ plots. $T = 250$.

REMARK. Clear regression design effects.

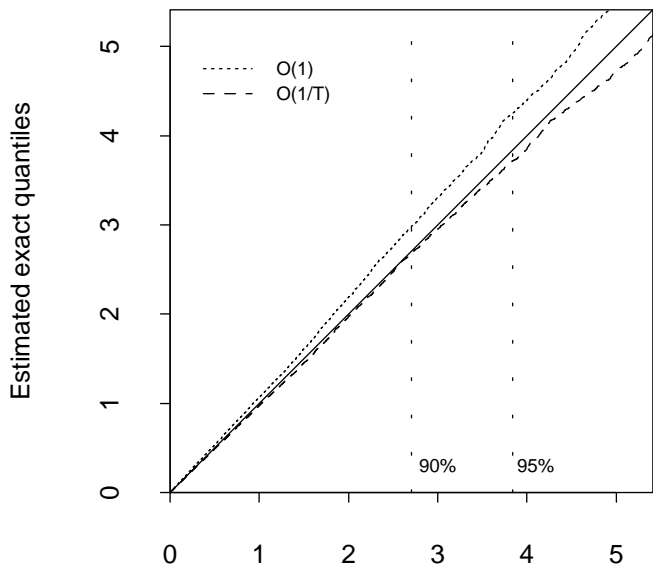
Design 1



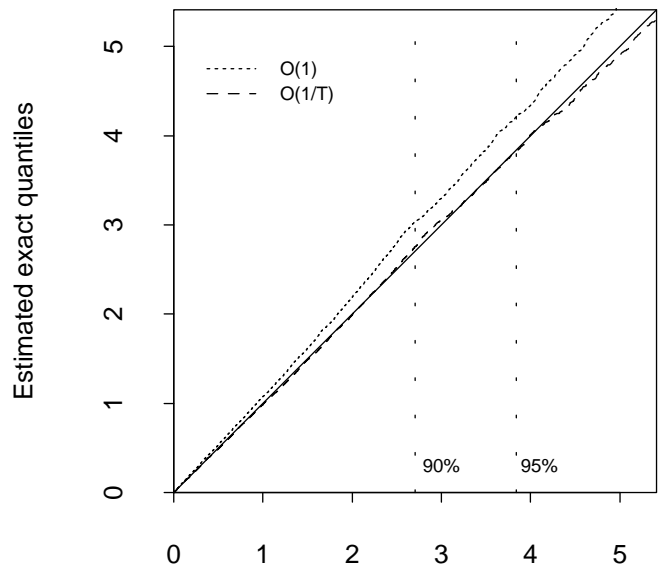
Design 2



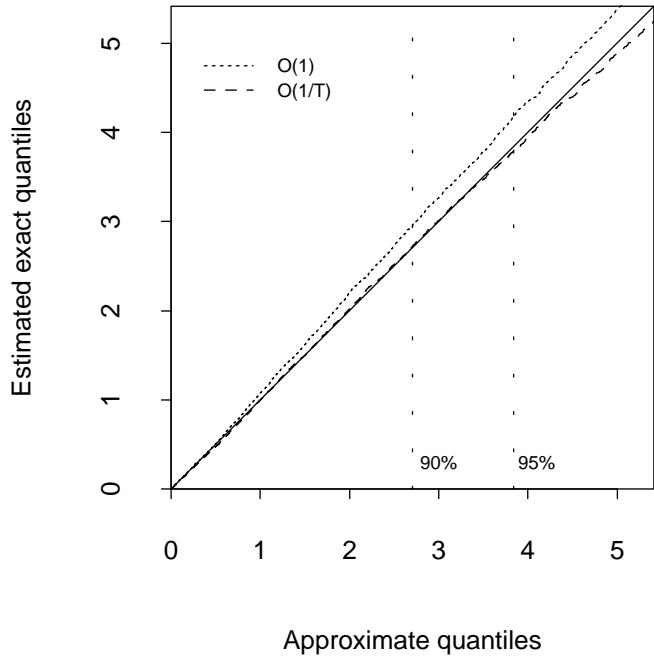
Design 3



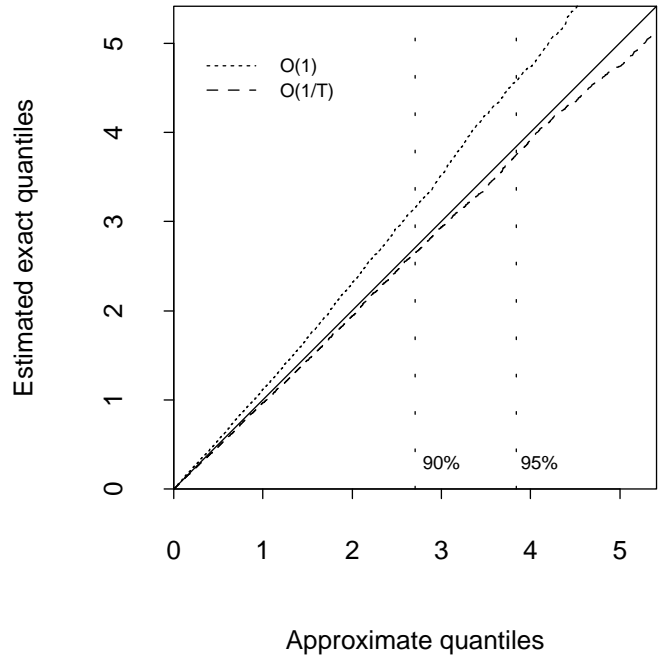
Design 4



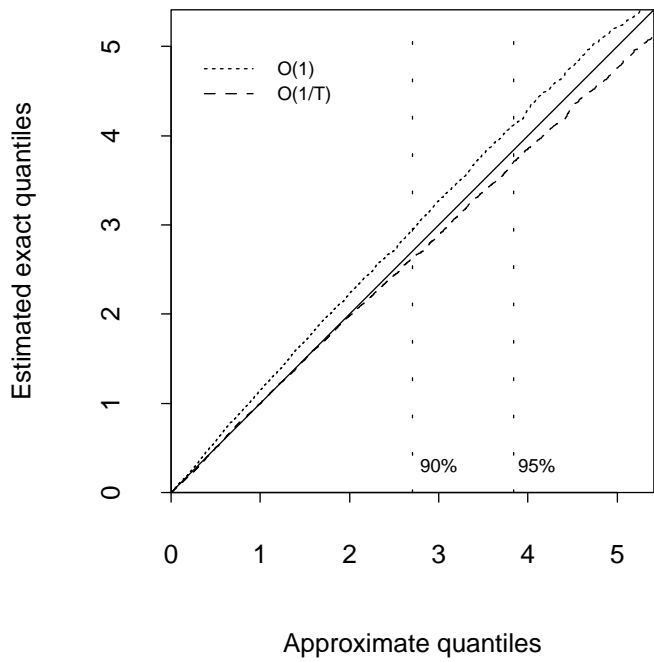
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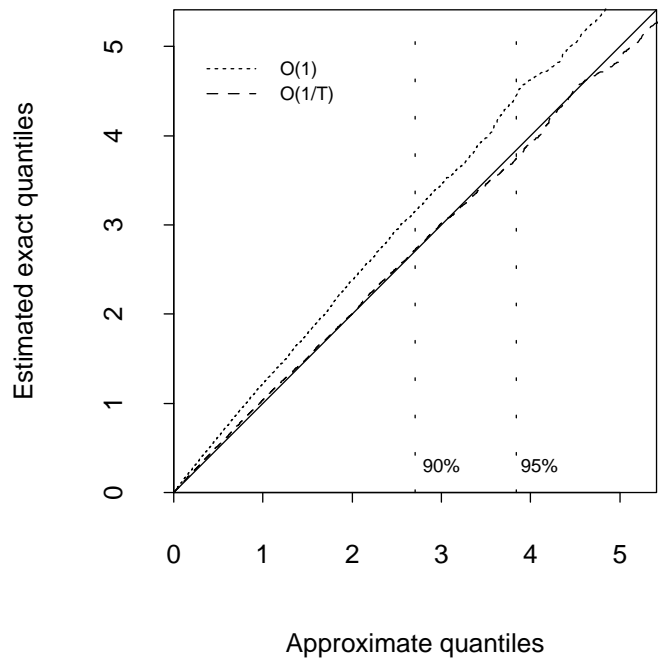
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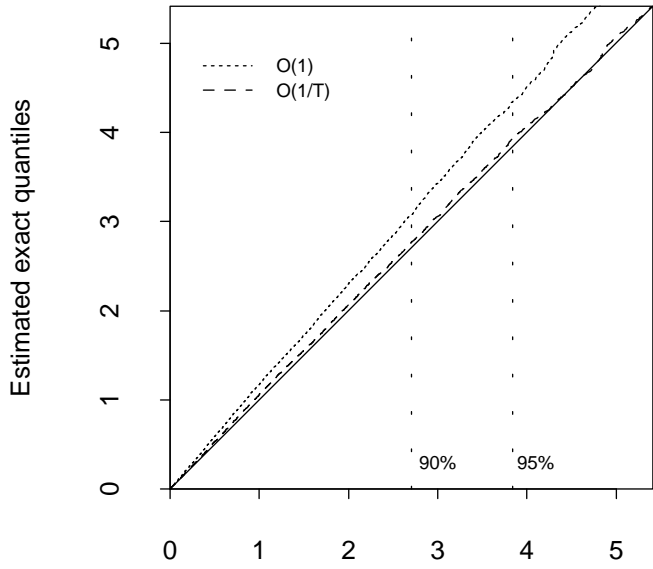
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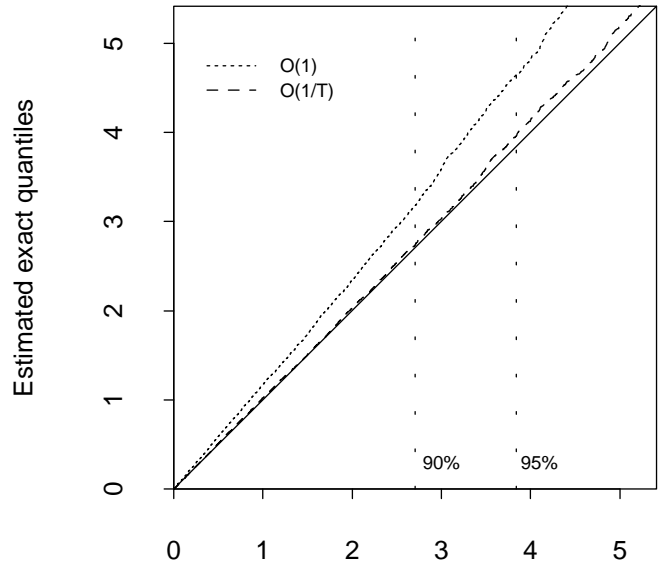
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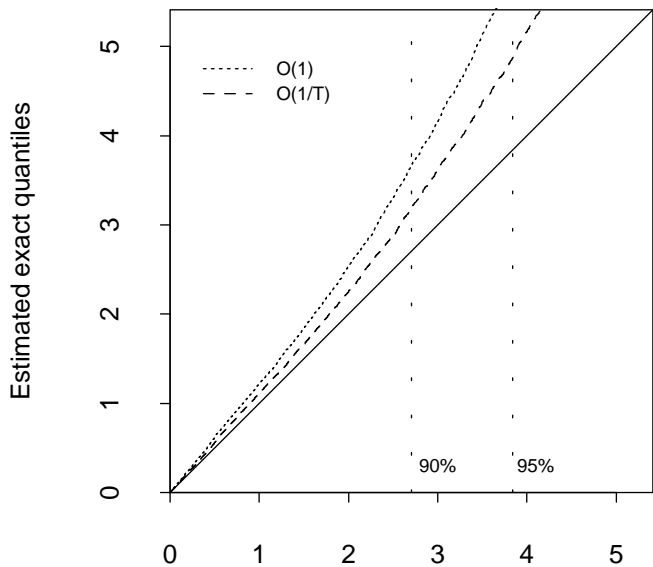
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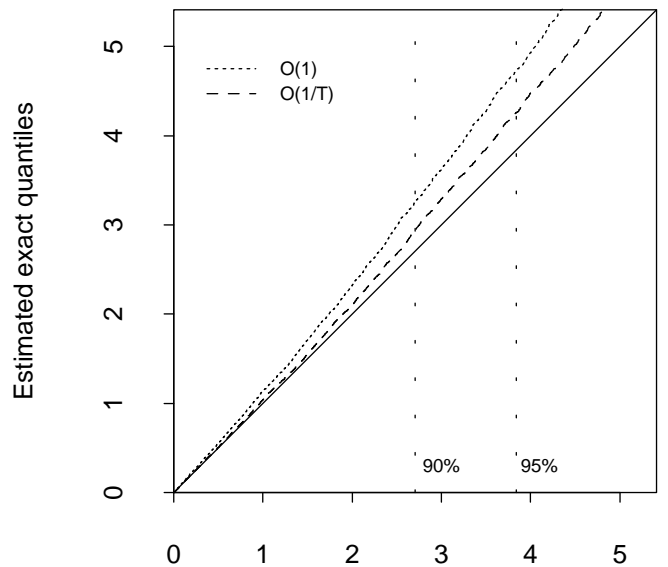
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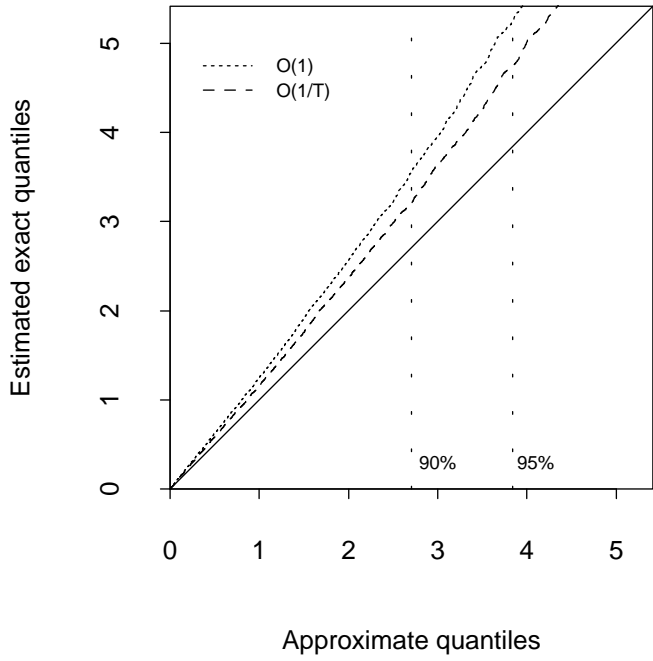
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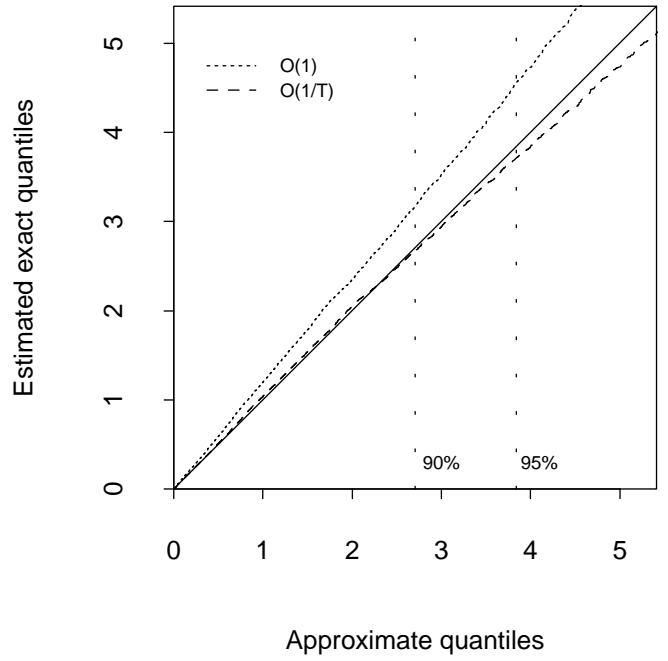
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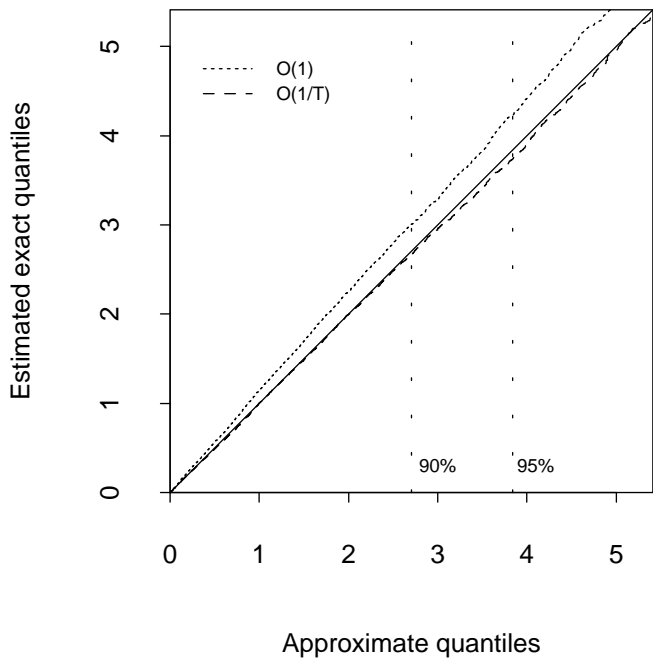
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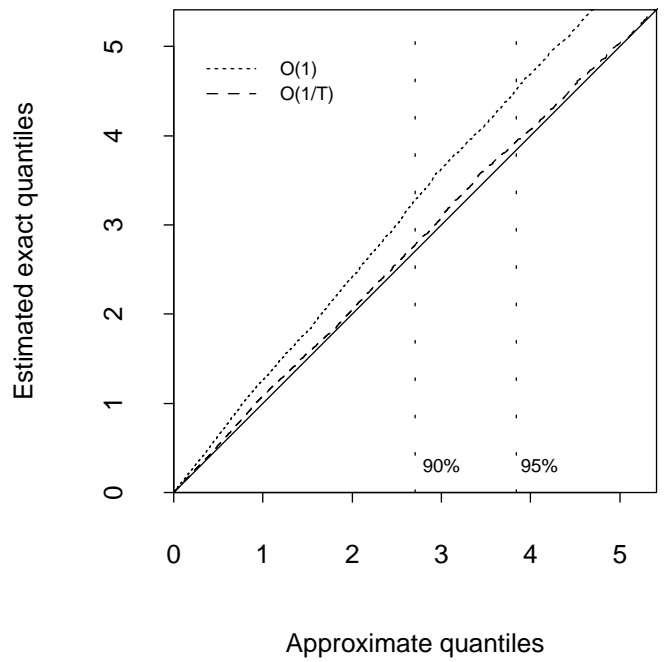
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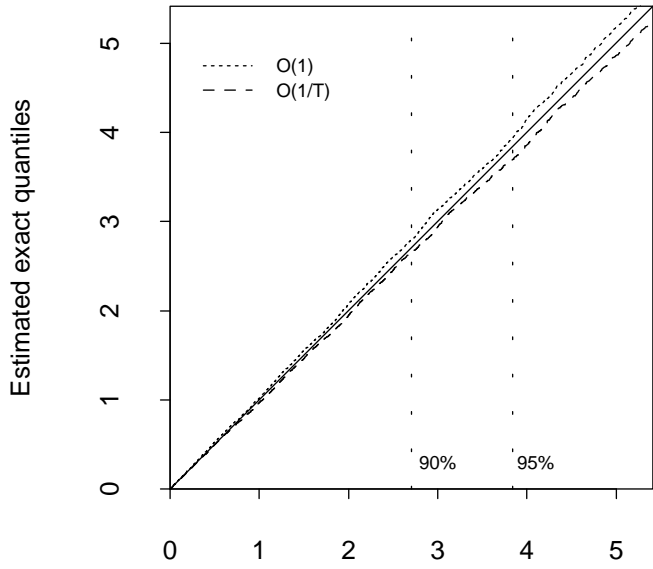
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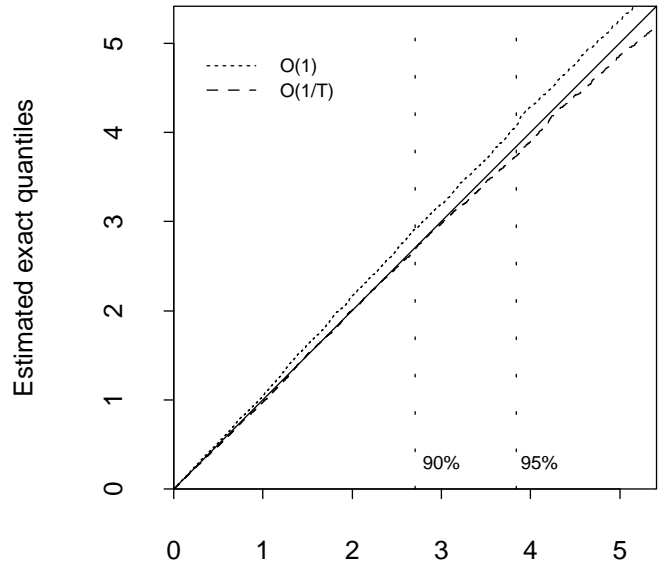
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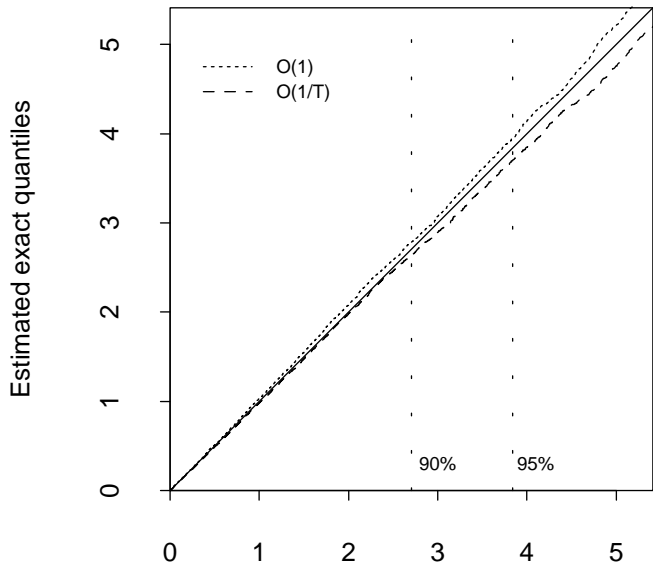
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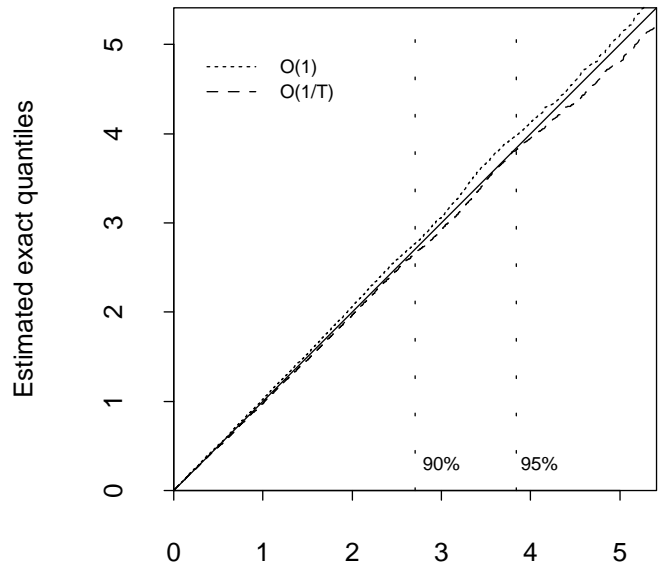
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Design 3



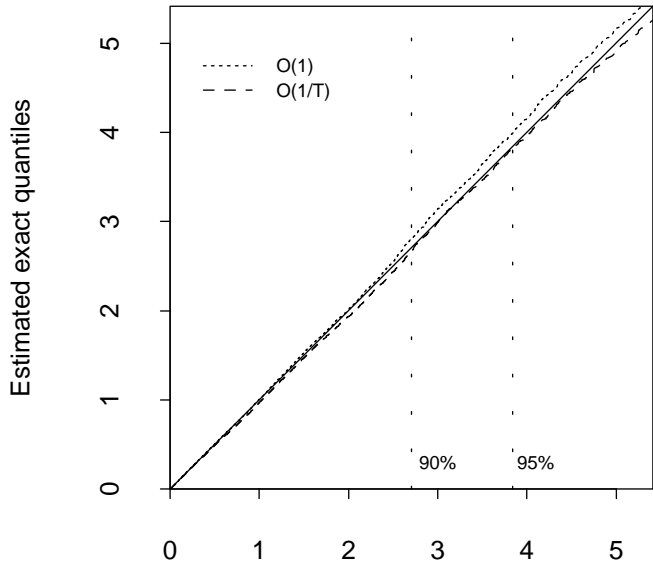
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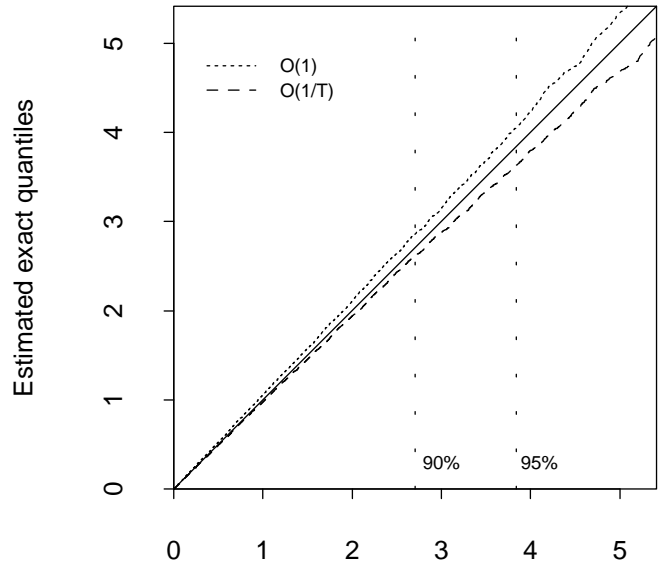
Approximate quantiles

Approximate quantiles

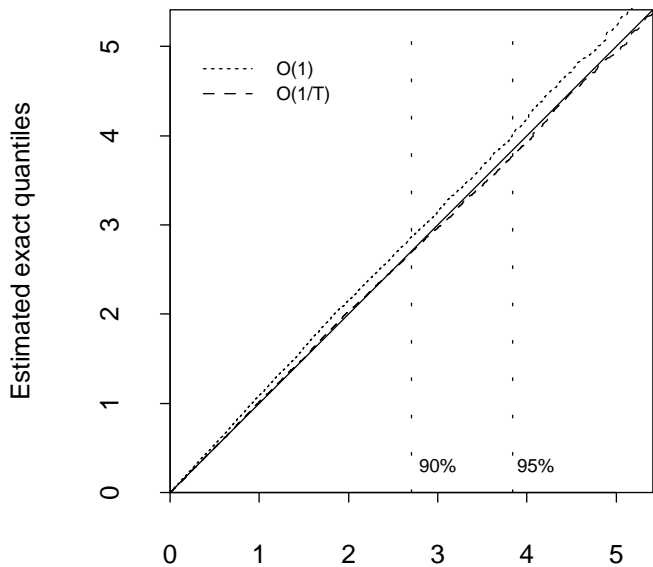
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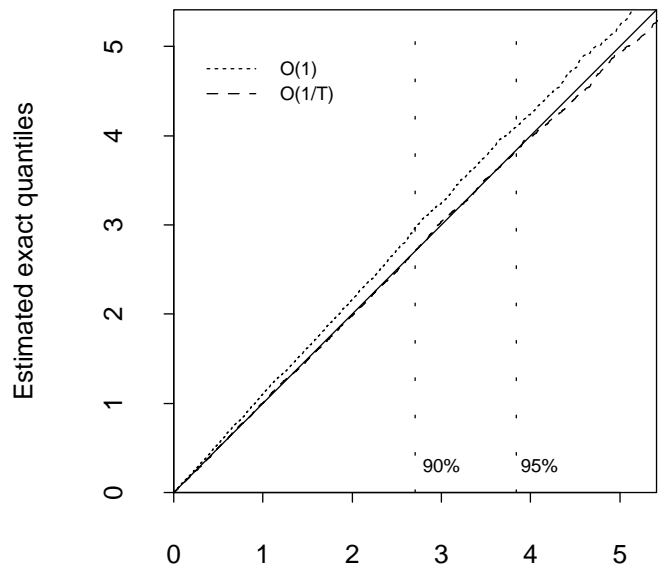
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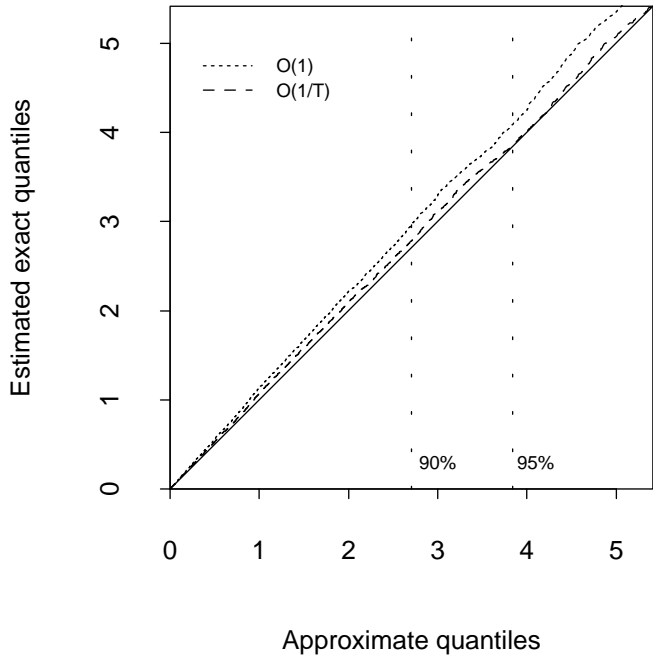
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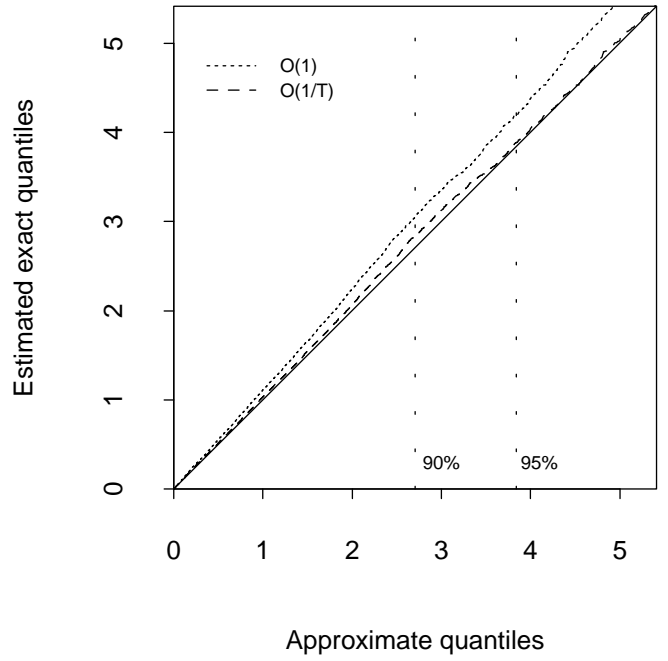
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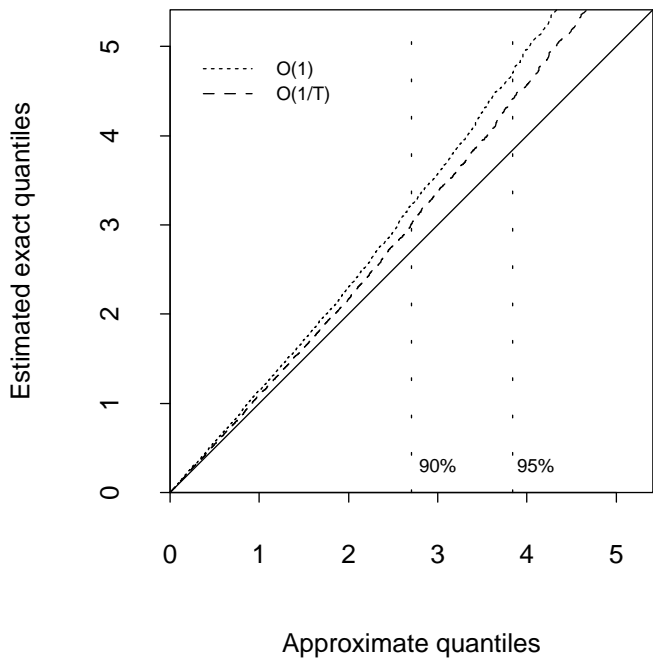
Design 1



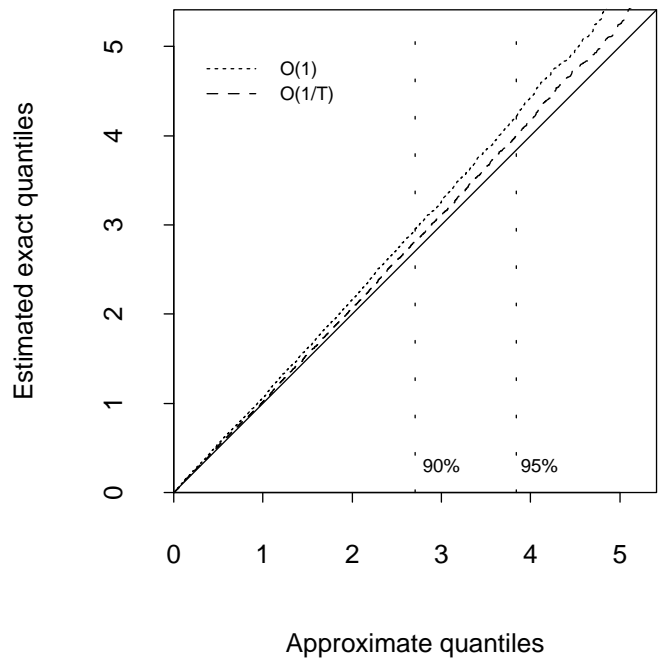
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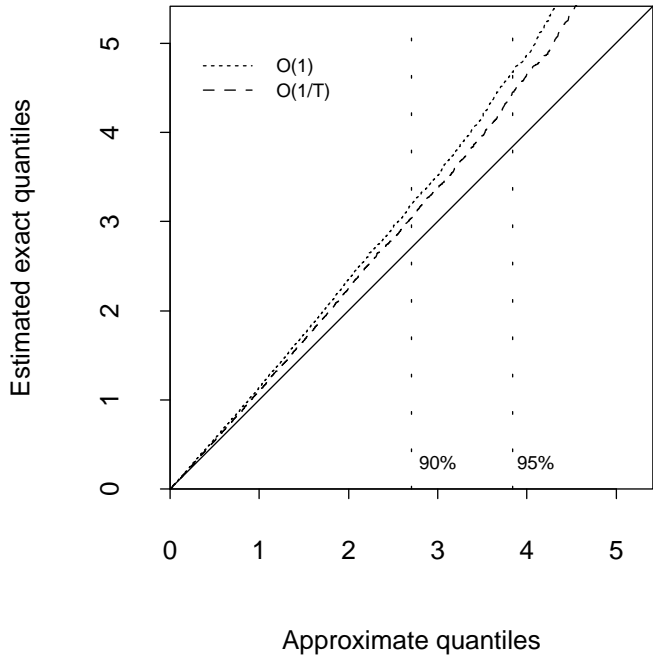
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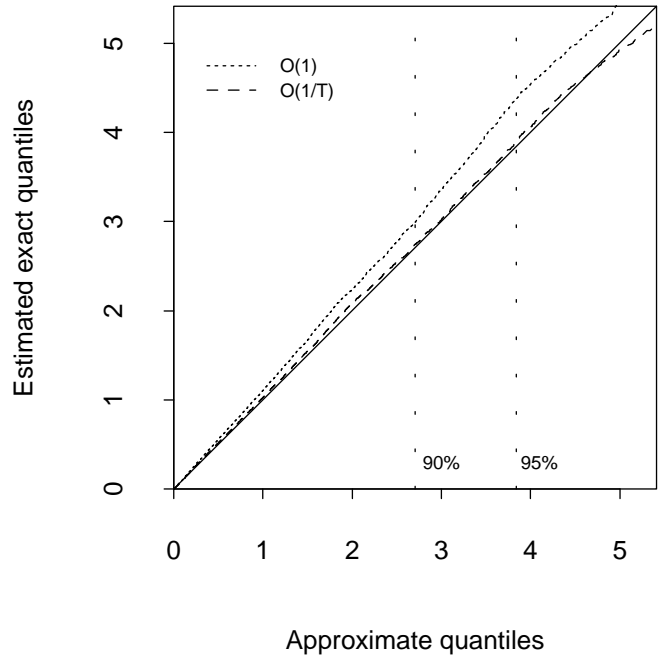
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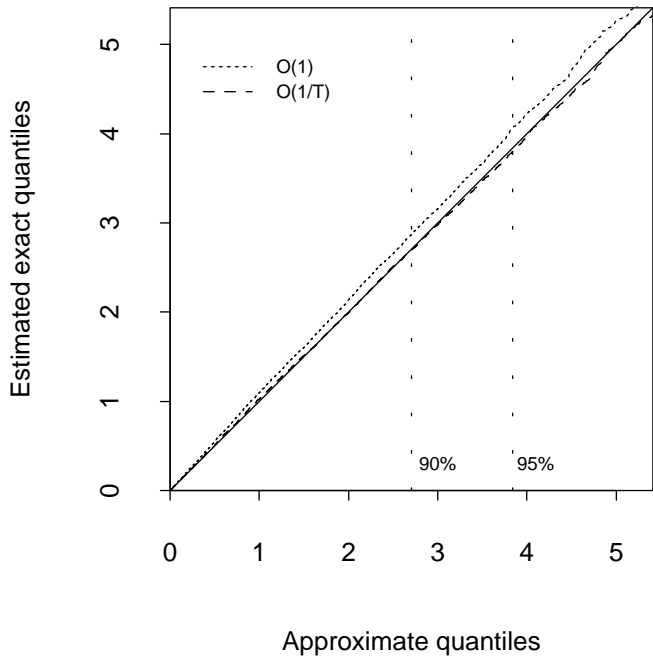
Design 1



Design 2



Design 3



Design 4

