No Analytical Power Formula? No Problem. A General Model-Implied Simulation-Based Approach to Power Estimation for Likelihood Ratio Tests with Applications in Complex SEM

HUMBOLDT-UNIVERSITÄT ZU BERLIN

Conference of the DGPs Methods and Evaluation Section 2025, Berlin

Julien P. Irmer
and
Manuel C. Voelkle

29.09.2025

Power Analysis for *Continuous-Time* SEM (CTSEM)

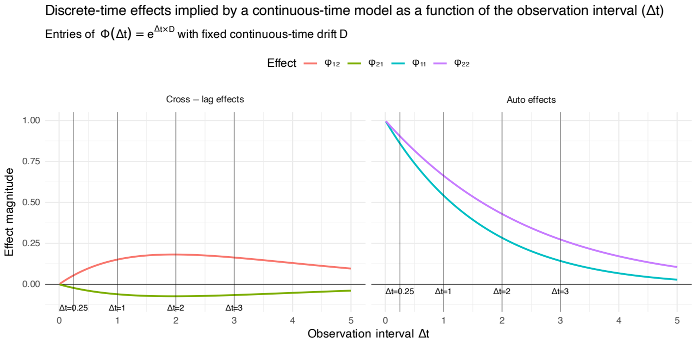

Figure. Discrete-time effects implied by a fixed continuous-time drift D as a function of the observation interval Δt: left panel $\{\phi_{12}(\Delta t), \phi_{21}(\Delta t)\}$, right panel $\{\phi_{11}(\Delta t), \phi_{22}(\Delta t)\}$ where $\Phi(\Delta t) = \exp(\Delta t\, D)$.

Hypotheses to test in CTSEM

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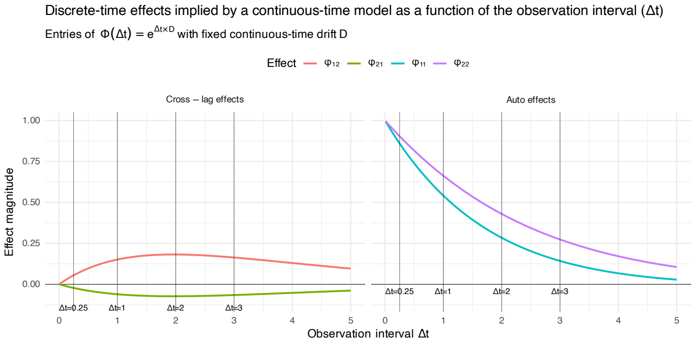

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(A) Single-parameter focus

- Tests like $H_0 : D_{12} = 0$, $H_0 : D_{21} = 0$
- Issue: Interpretation depends on Δt via $\Phi(\Delta t) = \exp(\Delta t \cdot D)$ $\Rightarrow$ Apparent "cross-lag size" changes with sampling rate

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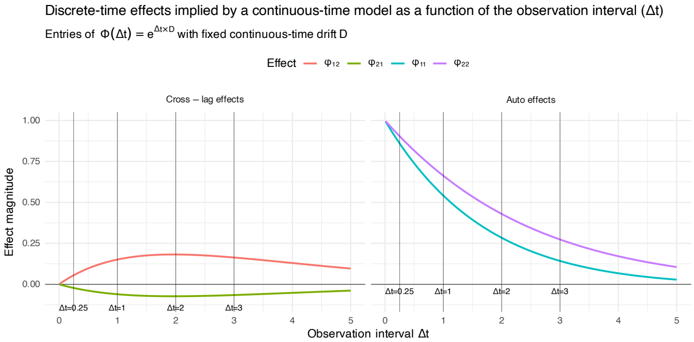

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(B) Likelihood-Ratio Tests

- Test meaningful *CT* structure, e.g. $H_0 :\ D_{12} = D_{21} = 0$ (no dynamic coupling)
- Communicates a clear scientific hypothesis independent of a specific Δt

Previous Research (on Power Analysis in [CT]SEM)

Linear SEM

- Analytical power for LRT and parameter tests (Satorra & Saris, 1985; see also implementations)
  - Implemented in `semPower` (Moshagen & Bader, 2024), `semTools` (Jorgensen et al., 2022), and Shiny `power4SEM` (Jak et al., 2021)
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Continuous-Time SEM (CTSEM)

- Framework & software: `ctsem` for panel and time-series CT models (Voelkle et al., 2012, Driver, et al., 2017; Driver & Voelkle, 2018)
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Open Problems

- No analytical solution for one parameter z-Test or LRT in CTSEM
- Not many power analyses for CT models, only approximations (e.g., Hecht, Walther, Arnold, & Zitzmann, 2024)

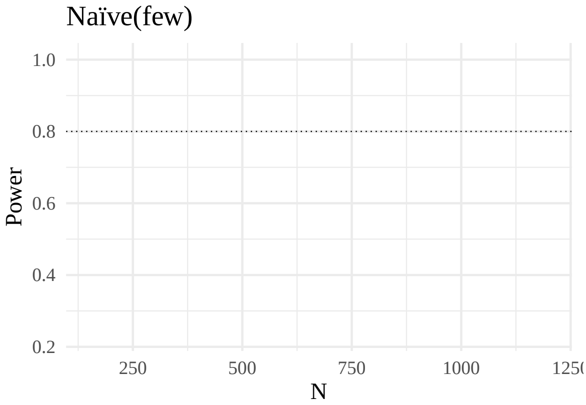
Open Problem: No General Analytical Power Solution for CTSEM

Solution: Simulation-based methods

- Simulation under model and apply z-Test or LRT for single or multiple parameters
- Use link functions between significance decisions and sample size
- E.g., use model-implied simulation-based power estimation (MSPE) method (Irmer et al., 2024a,2024b) for z-Test
- There are also alternatives (Constantin et al., 2023, Zimmer & Debelak, 2025, Zimmer et al., 2024)

Example: Naïve Simulation Based Power Estimation for Single Parameter z-Test

Select all parameter values from theory

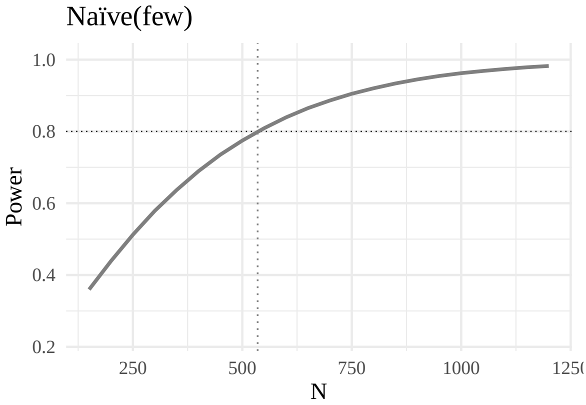


Example: Naïve Simulation Based Power Estimation for Single Parameter z-Test

Select all parameter values from theory

$\longrightarrow$ Solve for power $\rho = 80\%$, here for parameter of interest (POI) "true"

$N_{\rho=.8} = 535$



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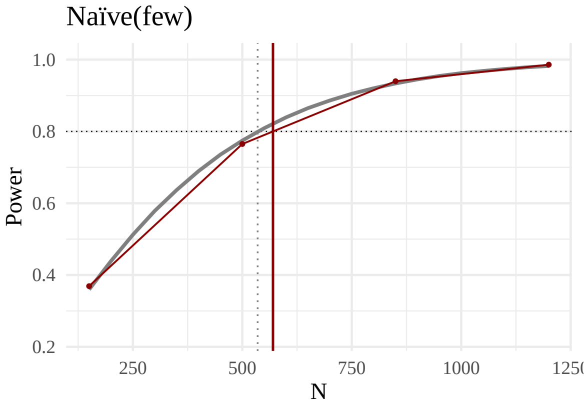
- Selection of few sample sizes (150, 500, 850, 1200) and simulate (500 each)
- Interpolate power: $\hat{N}_{\text{Power}=.80} = 570$



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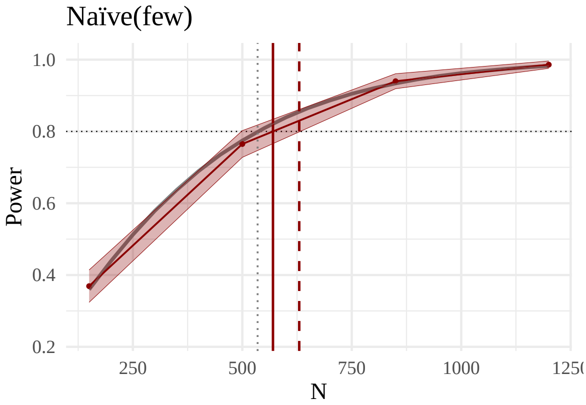

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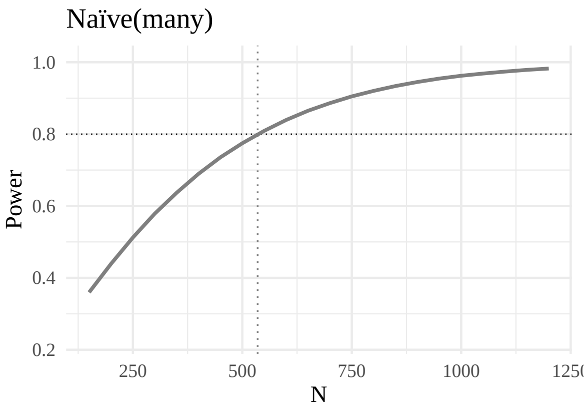

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Approaches to Model Power for $R = 2000$

- Selection of many sample sizes (150, ..., 1200) and simulate (100 each)
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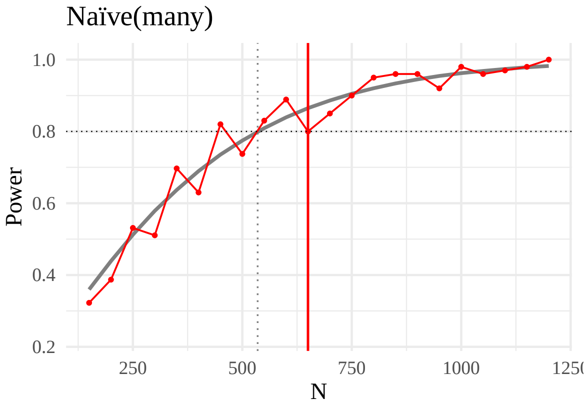

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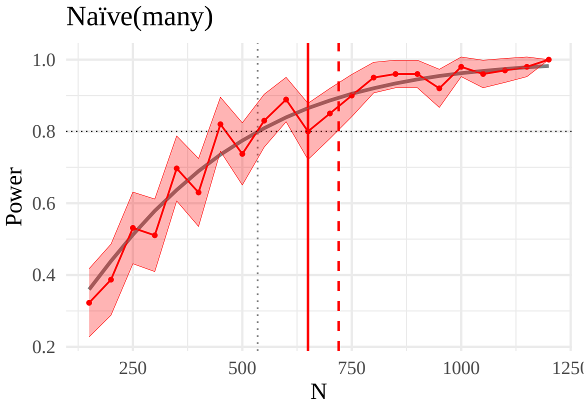

What to do?

Select all parameter values from theory

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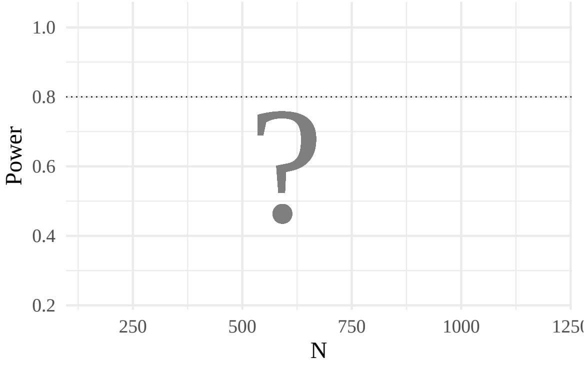
Approaches to Model Power for $R = 2000$

- Non-parametric/Machine Learning estimation?
- Parametric estimation?



Paper 1: Model-Implied Simulation-Based Power Estimation

Behavior Research Methods (2024) 56:8955–8991
https://doi.org/10.3758/s13428-024-02507-z

SPECIAL ISSUE/METHODOLOGICAL CHALLENGES OF COMPLEX LATENT MEDIATOR AND MODERATOR MODELS

Check for updates

Model-implied simulation-based power estimation for correctly specified and distributionally misspecified models: Applications to nonlinear and linear structural equation models

Julien P. Irmer[1] · Andreas G. Klein[1] · Karin Schermelleh-Engel[1]

- Irmer, J. P., Klein, A. G., & Schermelleh-Engel, K. (2024). Model-implied simulation-based power estimation for correctly specified and distributional misspecified models: Applications to nonlinear and linear structural equation models. *Behavior Research Methods, 56*, 8955–8991. `https://doi.org/10.3758/s13428-024-02507-z`

Motivation: From z-Test Power to Model-Implied Simulation-Based Power Estimation (MSPE)

z-Test

- Applicable to wide range of estimators (M-estimators, (Generalized) Method of Moments)
- Requires "only" asymptotic normality of parameter estimates

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Power for a single parameter

- $H_0 : \vartheta = 0,\ H_1 : \vartheta = \vartheta_0 \neq 0$
- z-Test: $\hat{\vartheta}_n / SE(\hat{\vartheta}_n) \ \sim\ \mathcal{N}(0, 1)$ under H_0
- Power depends on ϑ_0, α, and n via $SE(\hat{\vartheta}_n)$

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Problem: no closed form for complex SEMs
$\Longrightarrow$ simulation with interpolation only

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MSPE idea

- Each simulated decision $\mathcal{S}_i \sim \mathrm{Ber}(P(n_i))$
- Model $P(n_i)$ as parametric monotone function of n_i

$$\mathrm{Power}(n) = \Pr(\mathcal{S} = 1|n) = \Phi(\beta_0 + \beta_1\sqrt{n})$$

Invert:

$$N_\rho \approx \left\lceil \left(\frac{\Phi^{-1}(\rho) - \beta_0}{\beta_1}\right)^2 \right\rceil$$

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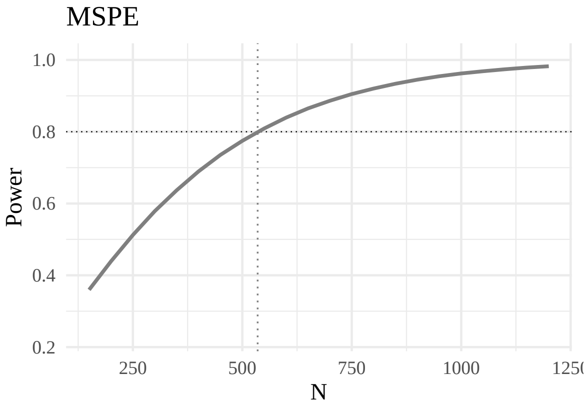
- Fit Probit-Regression Model on $\mathcal{S}_i$ with $\sqrt{n_i}$ as predictor



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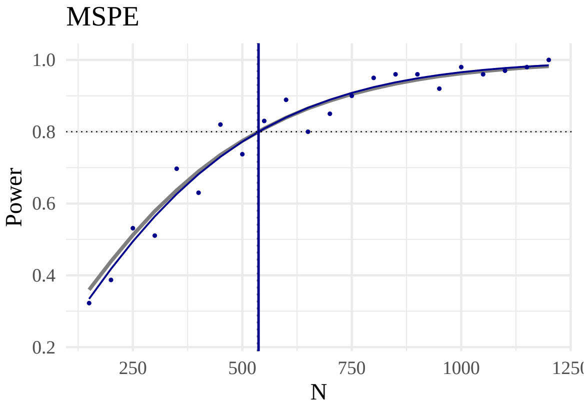

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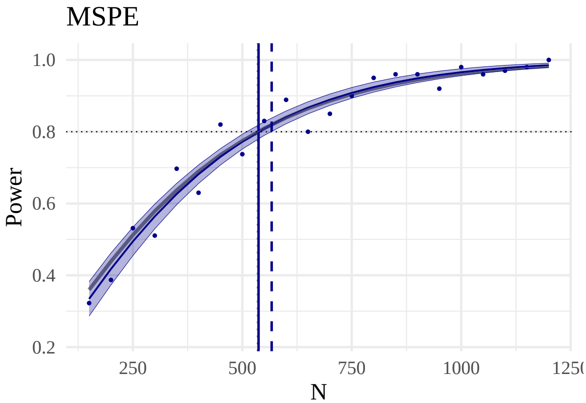
- Efficient due to modeling correlative structure of simulated data



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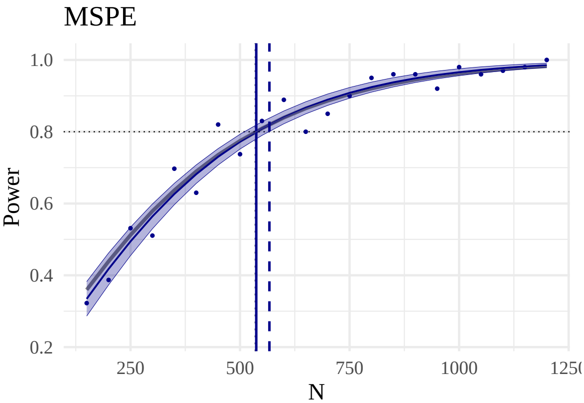

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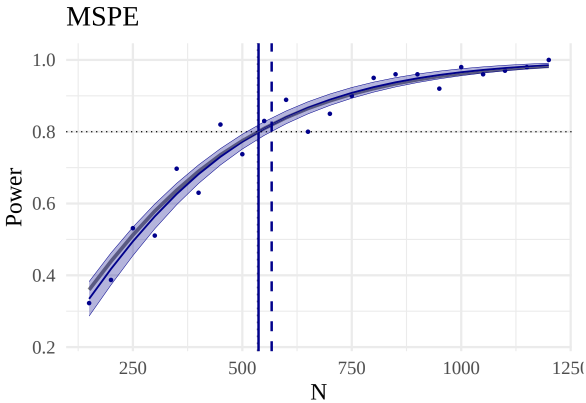

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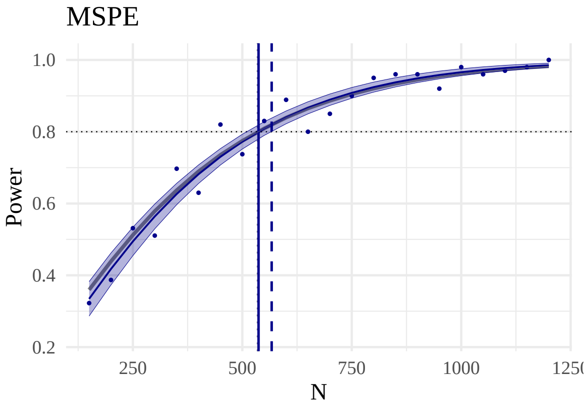

Simulation Studies Show:

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- MSPE outperformed other approaches

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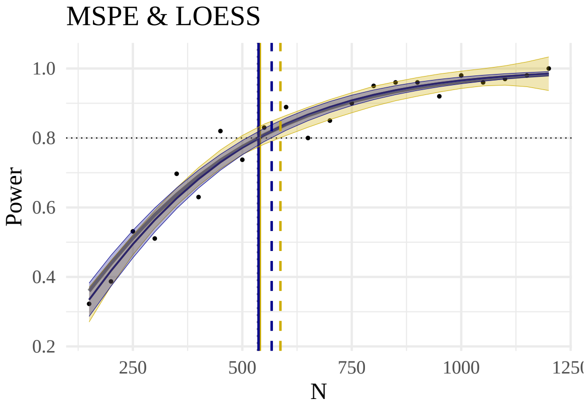

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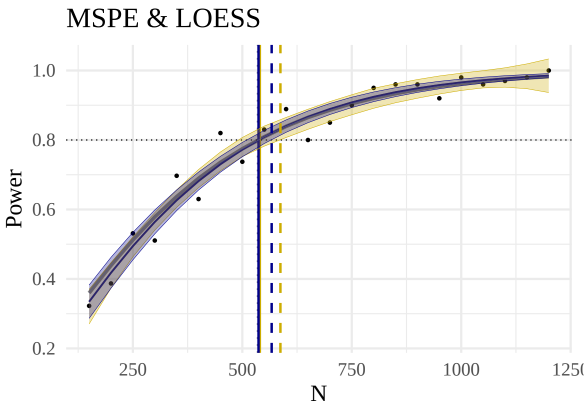

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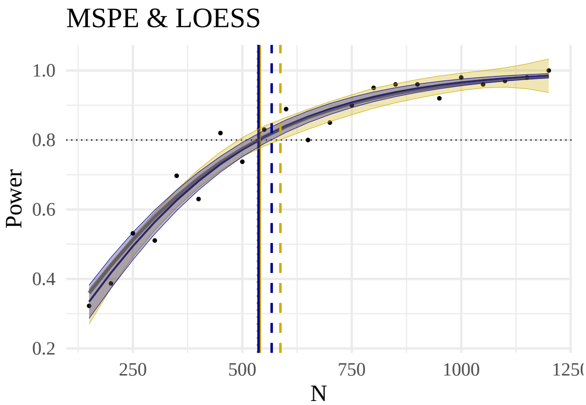
- Why? $\longrightarrow$ MSPE is the **MLE**
- Non-Parametric or Machine Learning Algorithms can show problems with extrapolation and intrapolation with few data points



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Open Problem: Why z-tests can be inferior to LRTs

Connection z-Test and LRT

- $z^2 =$ Wald-Test with df $= 1$
- Wald-Test with df $= 1$ is asymptotically equivalent to LRT with df $= 1$ (Buse, 1982; Engle, 1984)
- They differ in small samples

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- Time-scale dependence for discrete time parameters (CTSEM) (Driver, Oud, & Voelkle, 2017; Hecht & Zitzmann, 2021)
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Upsides of LRT

- Invariant to reparameterization (Gonzalez & Griffin, 2001)
- Known noncentral χ^2 asymptotics (Wald, 1943; Satorra & Saris, 1985)

CTSEM MSPE for LRT: Link via Noncentral χ^2

Classical result (Wald, 1943):

$$\text{Under } H_1: \quad \mathrm{LRT} \overset{a}{\sim} \chi^2_{\mathrm{df}}(\lambda), \qquad \text{Power} = \mathbb{P}\left(\chi^2_{\mathrm{df}}(\lambda) > c_\alpha\right), \; c_\alpha = \chi^2_{k,1-\alpha}.$$

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Satorra & Saris (1985):

$$\lambda(N) \propto N \quad \Rightarrow \quad \lambda(N) = \beta_0 + \beta_1 N, \quad \beta_1 > 0.$$

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MSPE Link for CTSEM LRT:

$$\boxed{\mathbb{P}(\mathcal{S} = 1 | N, \beta_0, \beta_1) = 1 - F_{\chi^2_{\mathrm{df}}\left(\lambda(\beta_0, \beta_1, N)\right)}\left(c_\alpha(\beta_0, \beta_1)\right)}$$

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Implications

- One/Two-parameter monotone link with β_1, $(\beta_0 = 0)$ or (β_0, β_1) or variations therof
- Inversion gives required N for target ρ
- β_0, β_1 can be estimated from *few* simulated N by MLE (binomial likelihood of significant/not).

Disclaimer: HPC Outage $\Longrightarrow$ Fewer Simulations (Preliminary Results Only!)

Figure. Cartoon server "overheating" to illustrate HPC downtime after a fire incident in Berlin Adlershof.

Server Issues after Fire

- HU high-performance cluster (HPC@HU) was offline $\approx$ 2 weeks.
- Emergency power (diesel) too costly to sustain normal operation.
- After restart: fragile system; only some nodes usable.

Figures created with ChatGPT 5

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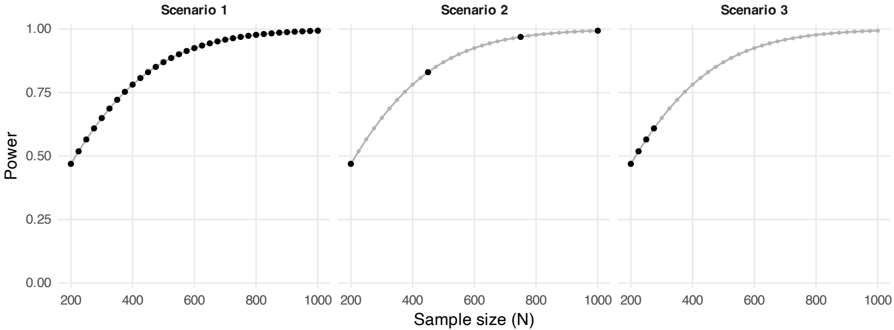
- $\Rightarrow$ Fewer simulations completed than planned.

Figures created with ChatGPT 5

CTSEM LRT Power: Three Scenarios of Inter-/Extrapolation



Why Inter and Extrapolation?

- Extra- and Interpolation necessary for automation of N-selection (Irmer et al., 2024b)

Model-Overview

- CTSEM with $n_T = 2$ fixed
- Distribution of $\Delta t \sim$ unif with mean of 1
- LRT for the two cross-lagged effects (H_0: no coupling, df $= 2$)

CTSEM LRT Power: Bias in $\hat{\rho}$

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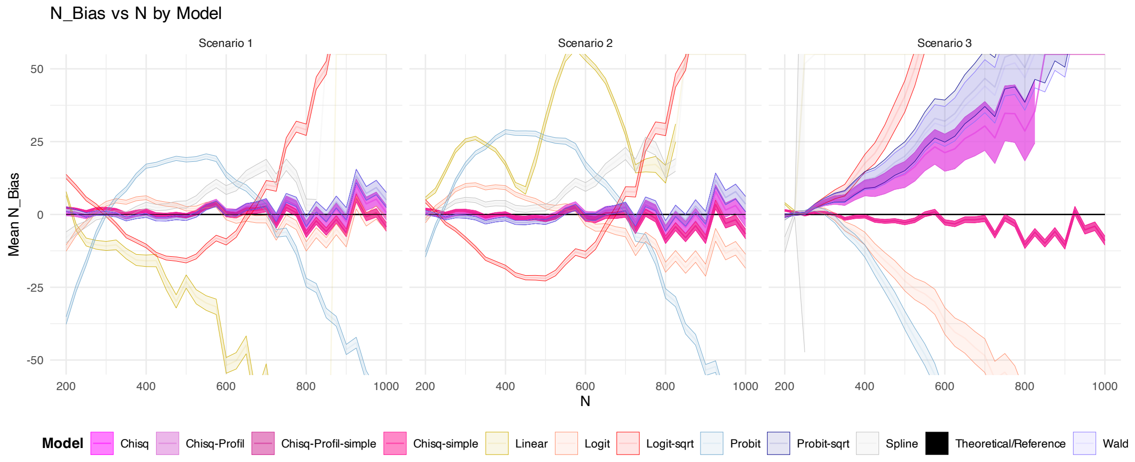

CTSEM LRT Power: Type I-error of $\hat{N}_\rho$ being smaller than N_ρ

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Take-Home Message

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Take-Home Message

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- MSPE for LRT works well, but might be numerically unstable (especially confidence interval)

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Thank you for you attention

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