

Sample Considerations for Detecting Person, Dyad, and Contextual Effects Using the Common Fate Model for Dyadic Analysis

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Outline

3 Parts

- The Common-Fate Model and the Between-Within CFM
- Simulation Design
- Results and Implications



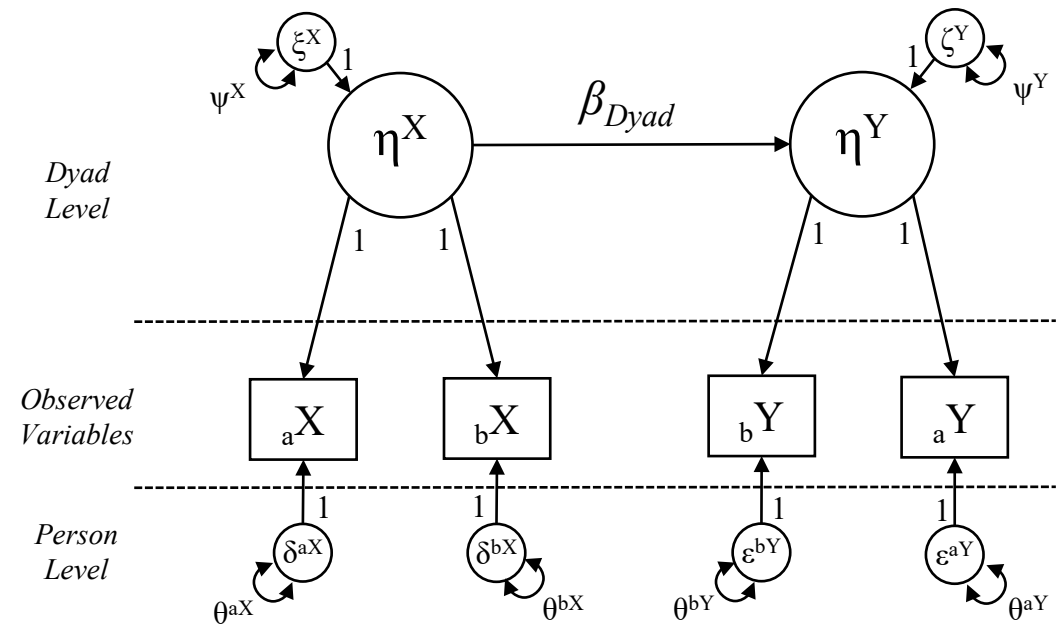
The Common-Fate Model and BW-CFM

Dyadic Analysis Models

- Several analytic approaches have been developed for dyadic data
- The Actor-Partner Interdependence Model (APIM; Kenny, 1996)
 - Most widely applied
 - Focuses on Person level relationships
 - Also accommodates Dyad-level predictors
- The Common-Fate Model (CFM; Kenny, 1996)
 - Increasing in popularity over the past decade
 - Focuses primarily on Dyad level relationships
 - Ledermann & Kenny (2011) expanded to incorporate Person-level associations
- Hybrid Actor-Partner Common-Fate Models (Wickham & Macia, 2019)

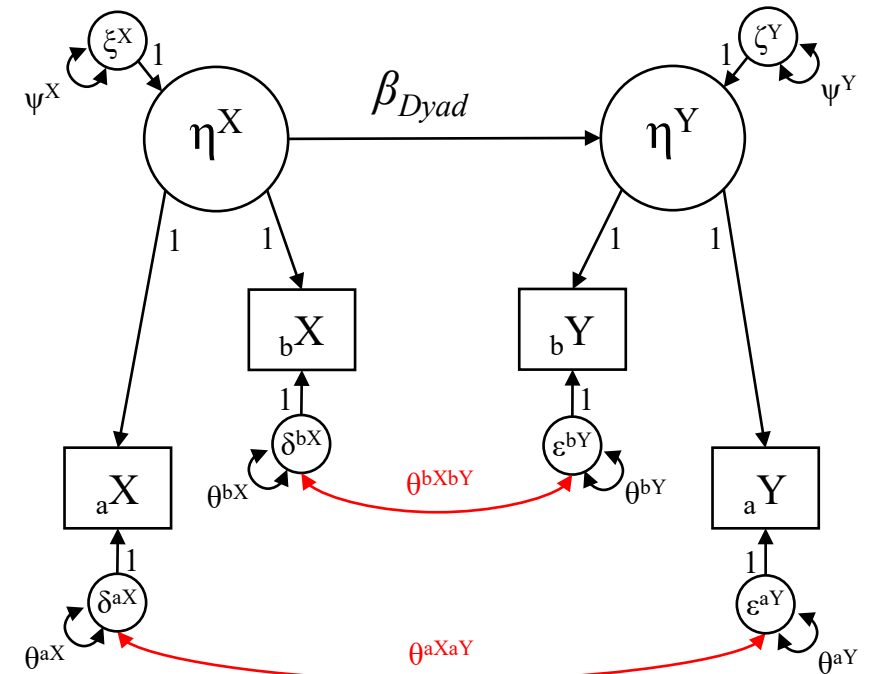
The Common-Fate Model

- 2 Variables (X, Y) \times 2 Persons (a, b):
 - Observed Variables ${}_aX, {}_bX, {}_aY, {}_bY$
- Latent Variables (η^X, η^Y) measured by Observed
 - Partitions variance into Dyad and Person level components
- β_{Dyad} describes regression of Dyad level outcome (η^Y) on predictor (η^X)
- $df = 3 \rightarrow$ Over-identifying constraints:
 - $cov({}_aX, {}_aY) = cov({}_aX, {}_bY) = cov({}_bX, {}_bY) = cov({}_bX, {}_aY)$



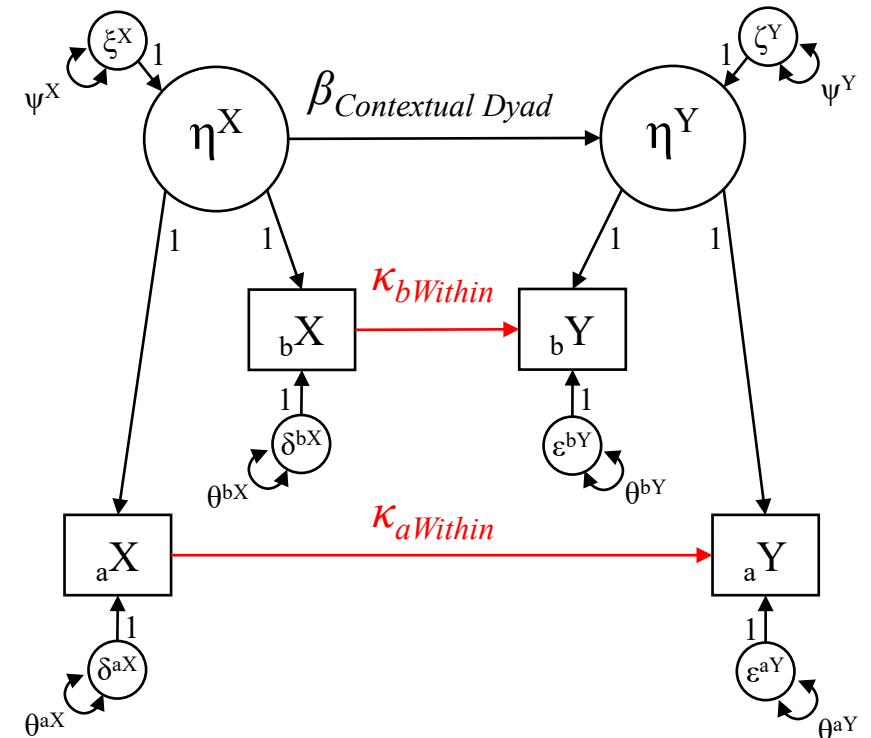
The Common-Fate Model

- Residual Person level relationships must be modeled when over-identifying constraints are untenable
 - Otherwise β_{Dyad} is biased
- Can incorporate covariance parameters to obtain unbiased estimate of β_{Dyad}
 - e.g., θ^{axay} , θ^{bxby}
- Unable to compare of magnitude of Dyad and Person level associations



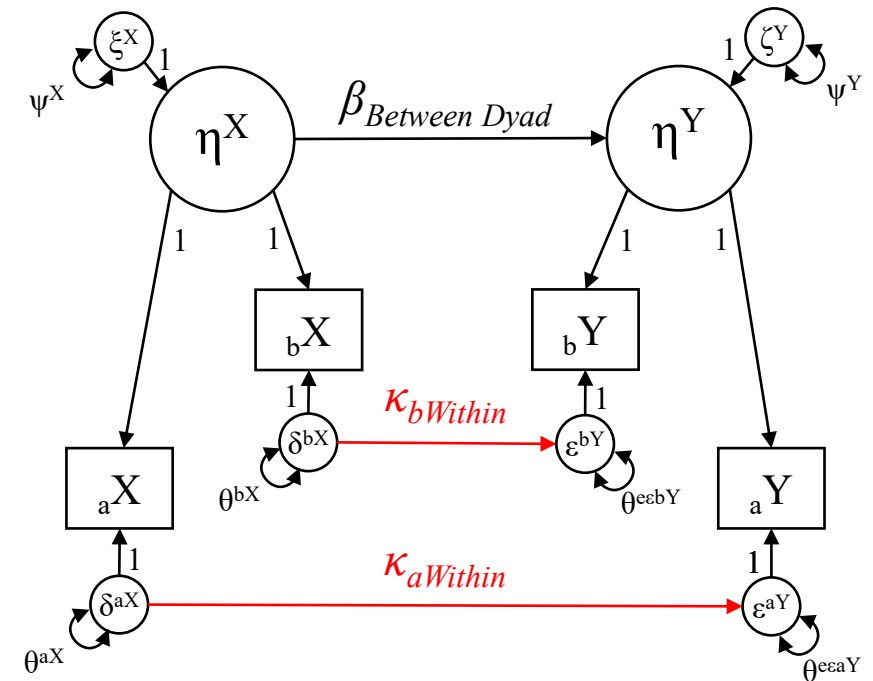
Contextual Effects Model

- Ledermann & Kenny (2011) described a variation on the CFM incorporating Person level relationships
 - Features regressions among observed Person level variables: aY on aX, bY on bX
- Under this parameterization:
 - $\beta_{Contextual\ Dyad}$ is the Contextual effect
 - $\beta_{Contextual\ Dyad} = \beta_{Between\ Dyad} - (.5 * K_{aWithin} + .5 * K_{bWithin})$
 - $K_{aWithin}$ and $K_{bWithin}$ are pure Within-Dyad effects



The Between-Within Common-Fate Model (BW-CFM)

- Wickham (2023) described the specification of a Between-Within Common-Fate Model (BW-CFM)
 - Features regressions among ‘explicit’ Person level residuals: ε^{aY} on δ^{aX} , ε^{bY} on δ^{bX}
- Under the BW-CFM parameterization:
 - $\beta_{Between\ Dyad}$ is the pure Between-Dyad effect
 - $K_{aWithin}$ and $K_{bWithin}$ are pure Within-Dyad effects
- Contextual effects can be obtained by specifying auxiliary parameters
 - e.g., $Y_{aContextual} = \beta_{Between\ Dyad} - K_{aWithin}$



The Present Study

- Dyadic data structure represents a special case of the standard multilevel design where $N_{\text{level 2}} = 2 * N_{\text{level 1}}$
- BW-CFM is specified as a 'wide' (single-level) SEM featuring regressions among latent variables
 - Documented sample size requirements for standard multilevel designs likely inadequate
- Present study reports results of Monte Carlo simulation to aid researchers in selection of sample size for studies utilizing the BW-CFM
 - Naturally, sample size and magnitude of X-Y relationships will be positively associated with power
 - Proportion of variance at Dyad (vs. Person) levels also related to power at each level

Simulation Design

BW-CFM Parameterization

- Deriving meaningful population parameter values requires elaboration regression and variance parameters at each level
- Assuming unit-variance for observed variables $_aX$ and $_bX$:
 - $\text{Var}(\eta^X) = \psi^X = \text{the Intra-Class Correlation} = r_{aXbX}$
- Furthermore: $R_{Dyad}^2 = \frac{\beta_{Between Dyad}^2 * \psi^X}{r_{aYbY}}$
 - Rearranging to obtain: $\beta_{Between Dyad} = \sqrt{\frac{\psi^X * R_{Dyad}^2}{r_{aXbX}}}$
- And, $\text{ResVar}(\eta^Y) = \psi^Y = r_{aYbY} - \beta_{Between Dyad}^2 * \psi^X$

BW-CFM Parameterization

- Because observed variables are set to z-scale
 - Variances of explicit residuals for Person level X variables, δ^{aX} and δ^{bX} are equal to $1 - r_{aXbX}$
- Furthermore: $R_{Person\ a}^2 = \frac{\kappa_{aWithin}^2 * \delta^{aX}}{1 - r_{aYbY}}$
- Rearranging to obtain: $\kappa_{aWithin} = \sqrt{\frac{R_{Person\ a}^2 * (1 - r_{aYbY})}{\delta^{aX}}}$
- And $ResVar(\epsilon^{aY}) = \theta^{\epsilon aY} = (1 - r_{aXbX}) - \kappa_{aWithin}^2 * \delta^{aX}$

Simulation Design

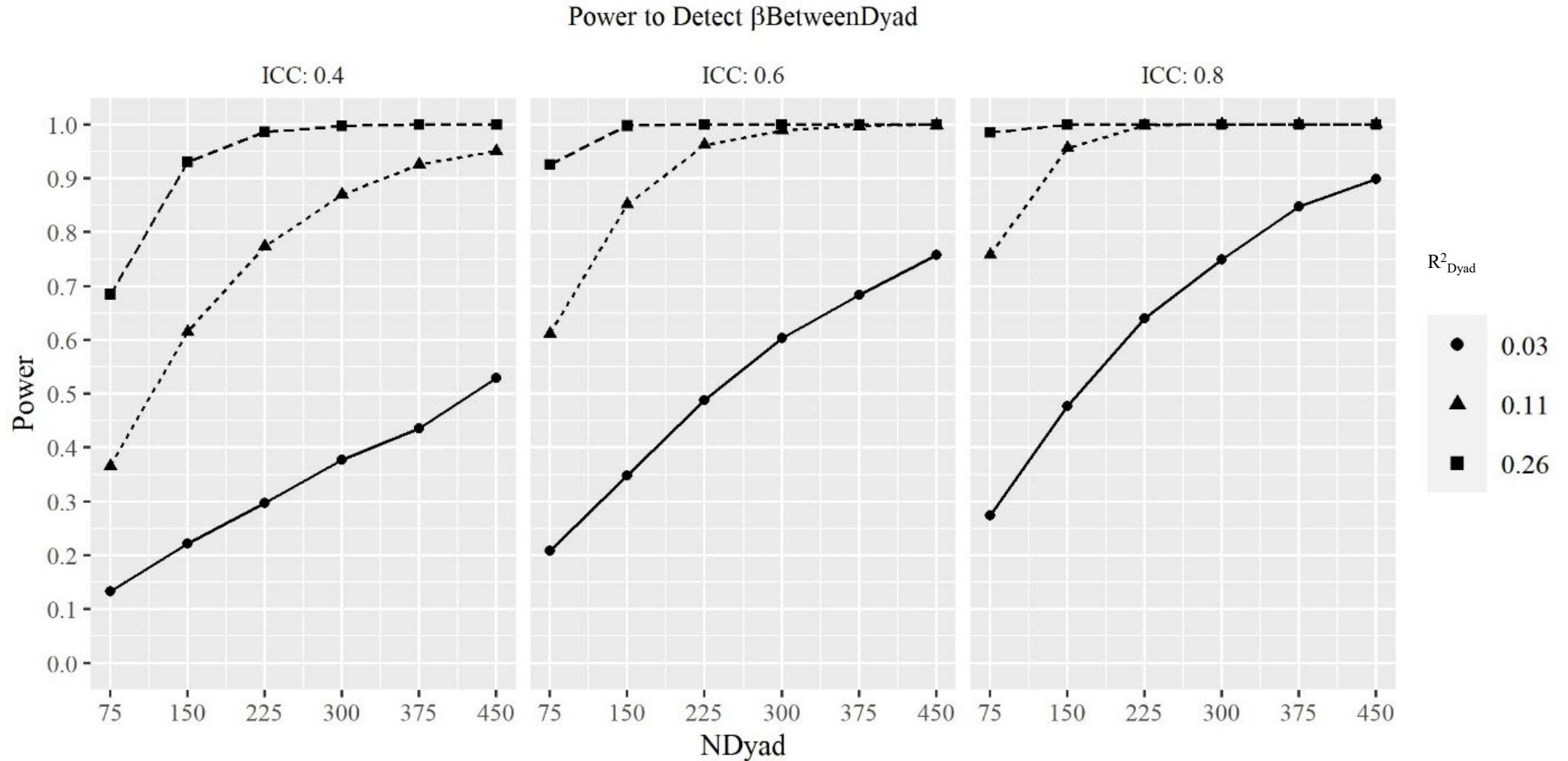
- An internal Monte Carlo conducted using *Mplus* 8.9
- Formulae described in previous slides used to derive population values
- Design:
 - 6 N_{Dyad} [75|150|225|300|375|450] ×
 - 3 ICC [.40|.60|.80] × → $r_{aXbX} = r_{aYbY}$
 - 3 R^2_{Dyad} [.03|.11|.26] × → Small, Medium, Large
 - 2 $R^2_{\text{Person a}}$ [.03|.11] × 2 $R^2_{\text{Person b}}$ [.11|.26]
- 216 cells @1000 reps per cell → All reps converged
- .out files extracted and compiled using *R/MplusAutomation* (Halquist & Wiley, 2018)
- Visualizations using *R/ggplot2* (Wickham, 2016)

Results

Results Summary: Dyad Level Power

- When ICC = 0.4:
 - $N_{\text{Dyad}} > 450$ to detect small effects
 - $N_{\text{Dyad}} \geq 150$ to detect medium effects
 - $N_{\text{Dyad}} \geq 150$ to detect large effects
- When ICC = 0.6:
 - $N_{\text{Dyad}} \approx 450$ to detect small effects
 - $N_{\text{Dyad}} \geq 150$ to detect medium effects
 - $N_{\text{Dyad}} \geq 75$ to detect large effects
- When ICC = 0.8:
 - $N_{\text{Dyad}} \geq 300$ to detect small effects
 - $N_{\text{Dyad}} \geq 75$ to detect medium and large effects

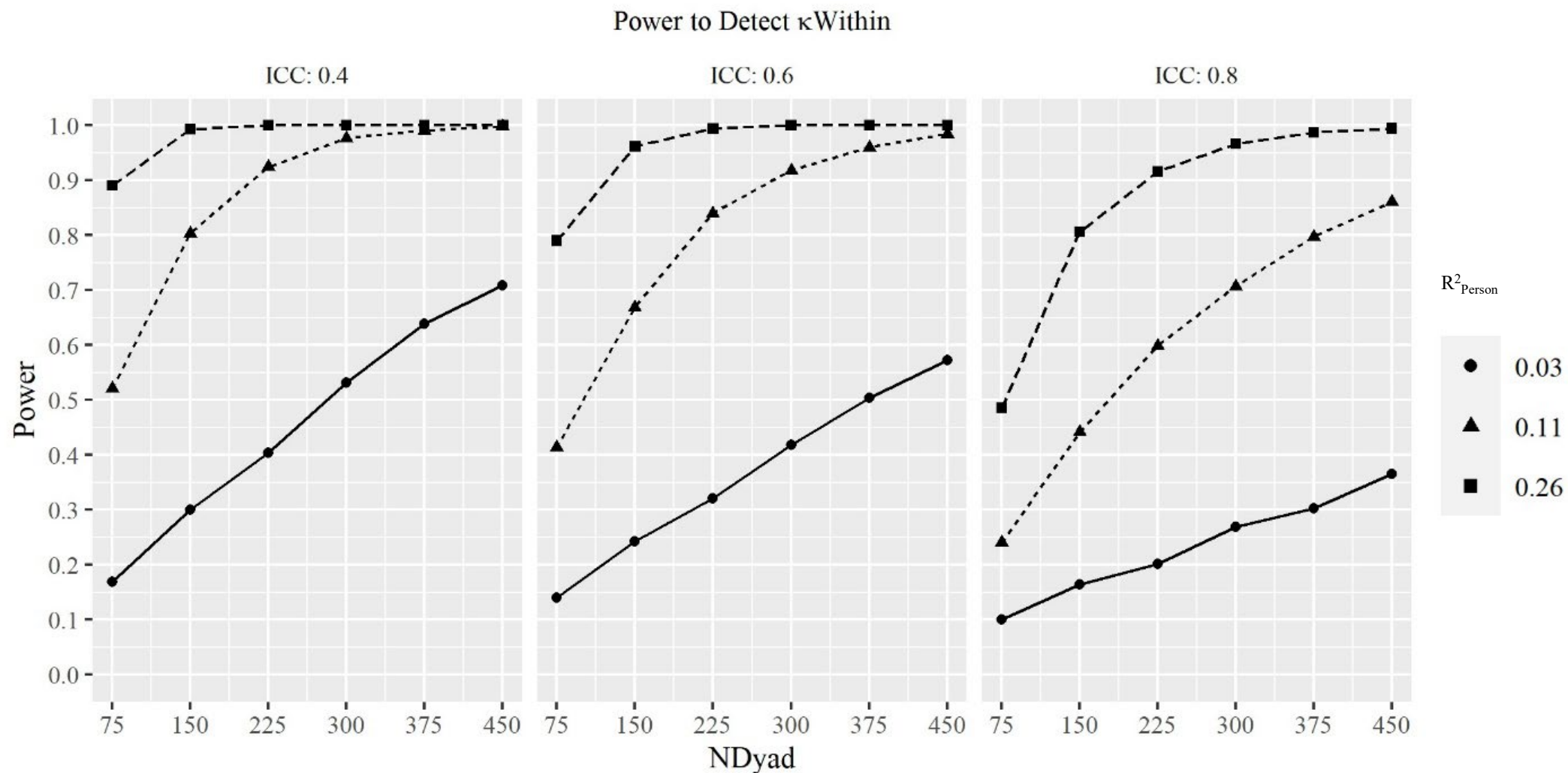
Results: Dyad Level Power



Results Summary: Person Level Power

- When ICC = 0.4:
 - $N_{\text{Dyad}} > 450$ to detect small effects
 - $N_{\text{Dyad}} \geq 225$ to detect medium effects
 - $N_{\text{Dyad}} \geq 75$ to detect large effects
- When ICC = 0.6:
 - $N_{\text{Dyad}} > 450$ to detect small effects
 - $N_{\text{Dyad}} \geq 225$ to detect medium effects
 - $N_{\text{Dyad}} \geq 75$ to detect large effects
- When ICC = 0.8:
 - $N_{\text{Dyad}} > 450$ to detect small effects
 - $N_{\text{Dyad}} \geq 375$ to detect medium effects
 - $N_{\text{Dyad}} \geq 150$ to detect large effects

Results: Person Level Power

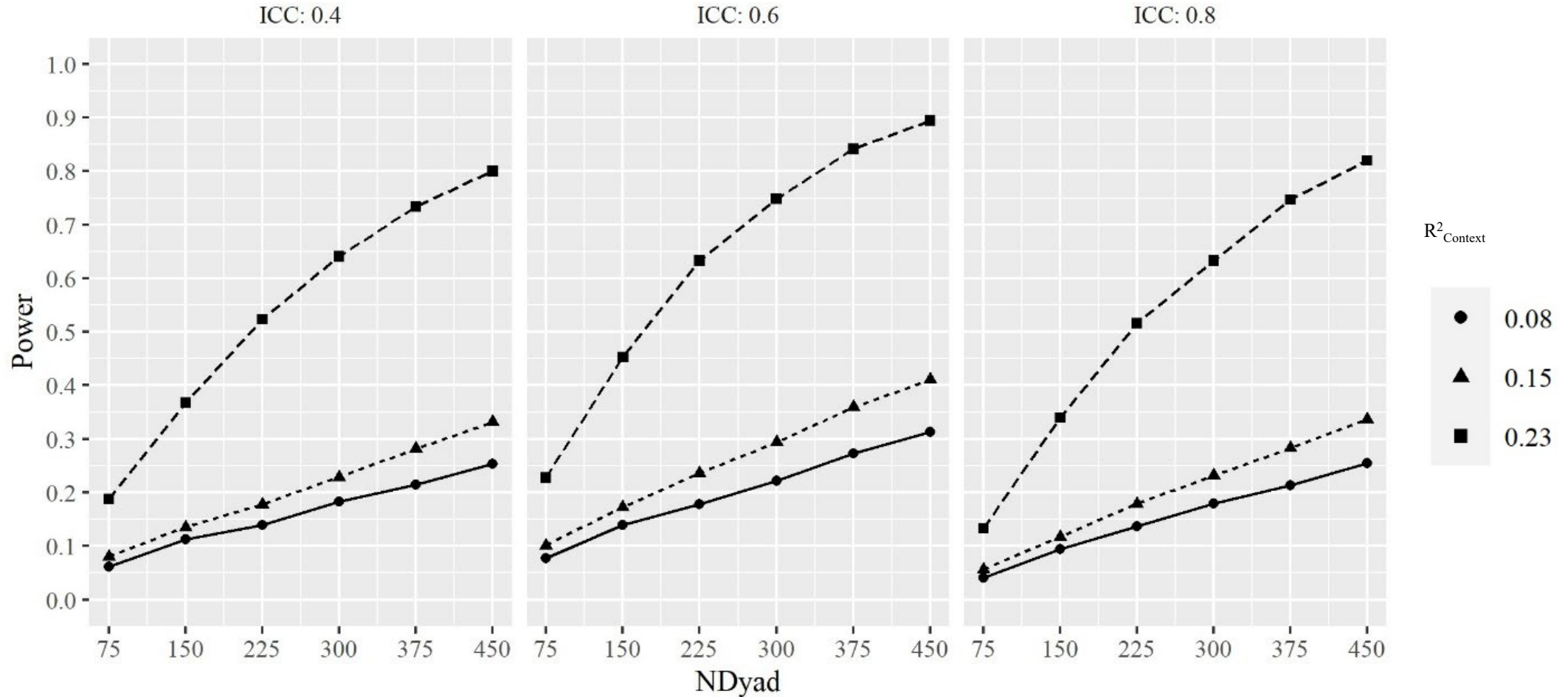


Results Summary: Contextual Power

- Contextual effect estimated as aux parameter using MODEL CONSTRAINT
 - i.e., $Y_{Contextual} = \beta_{Between\ Dyad} - K_{Within}$
- Power to detect Contextual effect was generally lower than power to detect $\beta_{Between\ Dyad}$ or K_{Within}
- Appears less sensitive to ICC
 - Some evidence that ICC = 0.6 was slightly better
 - ICC = 0.4 and 0.6 curves practically identical
- Observed Power reached (arbitrary) threshold of .80 only when $N_{Dyad} = 450$
- Detecting Contextual effects of smaller magnitude will be difficult unless sample size is very large!

Results: Contextual Power

Power to Detect $\gamma_{\text{Contextual}}$



BW-CFM: Pooled Within and Contextual Effects

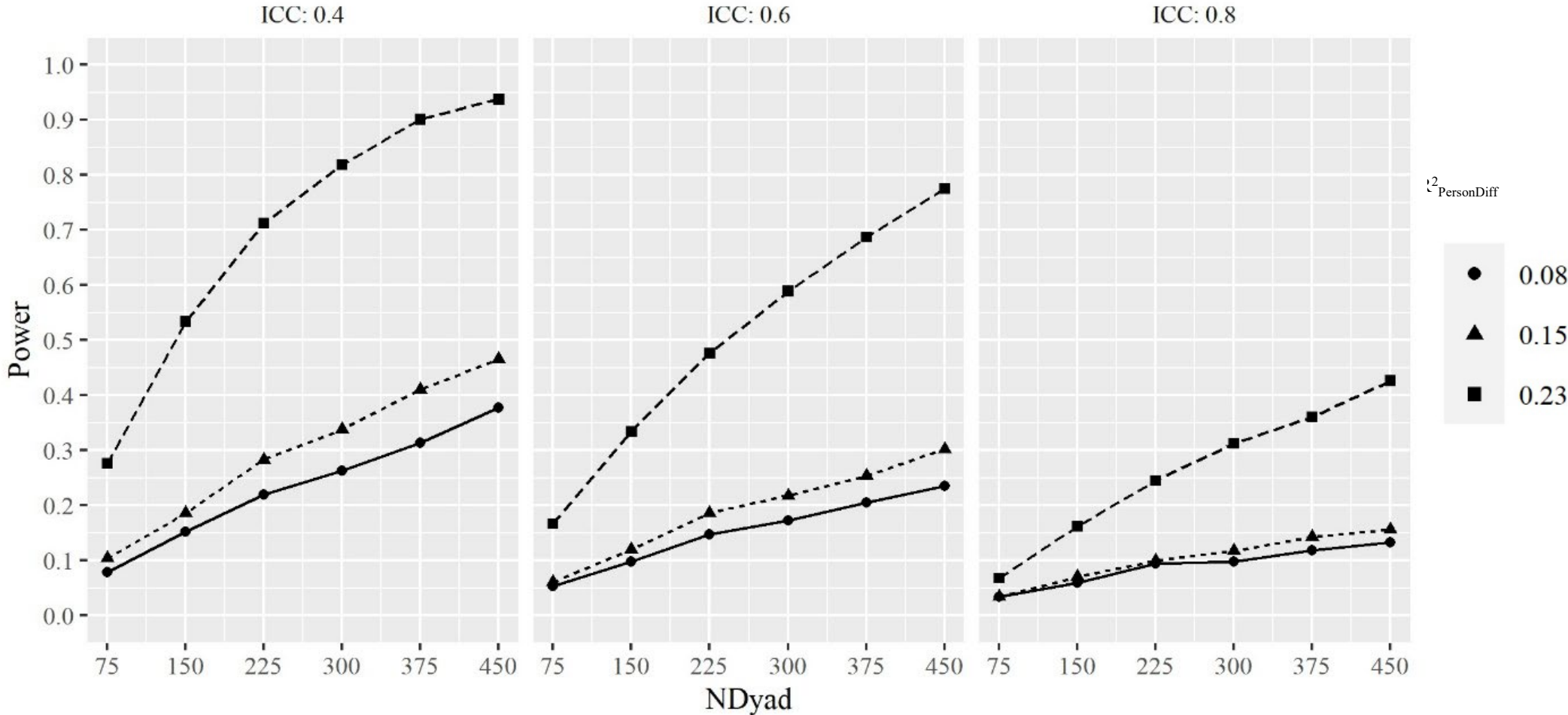
- $K_{aWithin}$ and $K_{bWithin}$ can be compared using model constraints (χ^2_{Diff} test) or auxiliary parameters:
 - $K_{WithinDiff} = K_{aWithin} - K_{bWithin}$
- When appropriate, a pooled Person level coefficient can be estimated as an aux parameter:
 - $K_{PooledWithin} = .5 * K_{aWithin} + .5 * K_{bWithin}$
- And the corresponding Pooled Contextual effect can also be estimated:
 - $Y_{PooledContextual} = \beta_{Between Dyad} - K_{PooledWithin}$

Results Summary: Within Difference Power

- $K_{WithinDiff} = K_{aWithin} - K_{bWithin}$ estimated using MODEL CONSTRAINT for cells where $R^2_{Person\ a} \neq R^2_{Person\ b}$
- Power to detect $K_{WithinDiff}$ highest when ICC = 0.4
- Large differences can still be detected when ICC = 0.6 and $N_{Dyad} \geq 450$
- In most cases it will be difficult to detect differences in magnitude of Person level coefficients

Results: Within Difference Power

Power to Detect κ WithinDiff

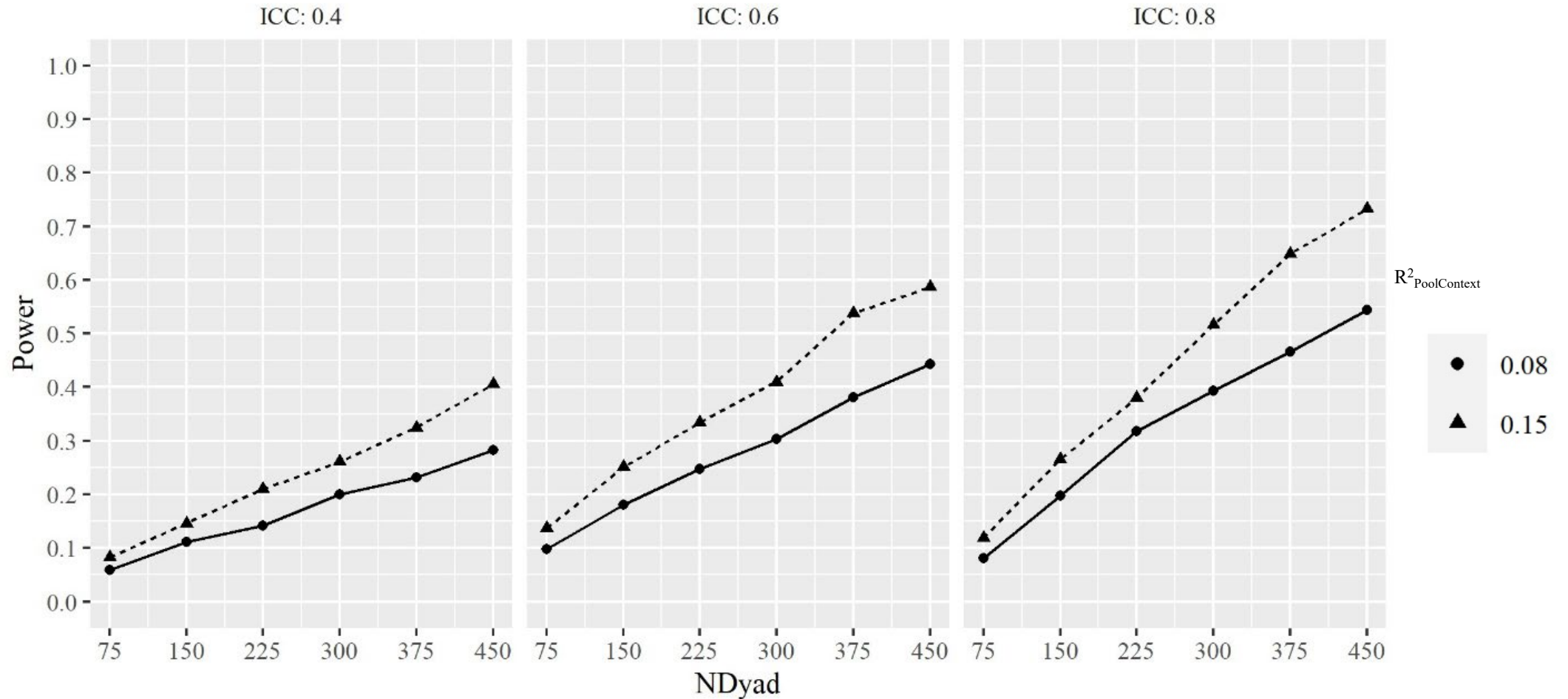


Results Summary: Pooled Contextual Power

- For cells where $R^2_{\text{Person a}} = R^2_{\text{Person b}} = 0.11$, $K_{\text{PooledWithin}}$ was specified as an aux parameter using MODEL CONSTRAINT
 - i.e., $K_{\text{PooledWithin}} = .5 * K_{a\text{Within}} + .5 * K_{b\text{Within}}$
- Because of partial offset of effect sizes across Person a and Person b, we obtain:
 - $R^2_{\text{Dyad}} - R^2_{\text{PersonPooled}} = .26 - .11 = .15$
 - $R^2_{\text{Dyad}} - R^2_{\text{PersonPooled}} = |.03 - .11| = .08$
- As expected, Power to detect this ‘pooled’ contextual effect was higher than the individual contextual effects
 - Positively related to ICC

Results: Pooled Contextual Power

Power to Detect $\gamma_{\text{PooledContextual}}$



Global Summary and Future Directions

- Whenever possible researchers should aim for $N_{\text{Dyad}} \geq 300$ to detect meaningful effect sizes using the BW-CFM
- Like many simulations, the present study assumed ‘tidy’ data (i.e., MVN)
- Future work should explore performance under more realistic conditions
- Work in progress:
 - These findings should be submitted for peer-review in the next few weeks
 - R function and SAS MACRO allowing user-specified design features currently in dev

Thank you!

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