# Centering lower-level interactions in multilevel models

Haeike Josephy Tom Loeys

International Meetings of the Psychometric Society 2017







### Longitudinal diary study on sexual behavior in Flanders

- ► Info on 66 heterosexual couples
  - ▶ Here, we only focus on men's data
- Daily measures during 3 weeks:
  - Daily morning reports on sexual and intimate behavior: amount of intimate acts (kissing, cuddling and caressing) measured on a 7-point scale
  - Daily evening reports on positive relationship feelings: average score of 9 items (happy, satisfied, understood, ...) measured on a 7-point scale

### Longitudinal diary study on sexual behavior in Flanders

- ► Info on 66 heterosexual couples
  - ► Here, we only focus on men's data
- Daily measures during 3 weeks:
  - Daily morning reports on sexual and intimate behavior: amount of intimate acts (kissing, cuddling and caressing) measured on a 7-point scale
  - ▶ Daily evening reports on positive relationship feelings: average score of 9 items (happy, satisfied, understood, ...) measured on a 7-point scale

Question: What is the contribution of intimacy to next-day positive relationship feelings?

#### In our example:

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- ► Yii: next day's positive relational feelings

Standard analysis by a multilevel model with random intercept  $b_i$ :

$$E(Y_{ij}|X_{ij},b_j) = \gamma_0 + \gamma X_{ij} + b_j \tag{1}$$

$$X \xrightarrow{\gamma} Y$$

#### In our example:

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- ► Y<sub>ii</sub>: next day's positive relational feelings

Standard analysis by a multilevel model with random intercept  $b_i$ :

$$E(Y_{ij}|X_{ij},b_j) = \gamma_0 + \gamma X_{ij} + b_j \tag{1}$$

Unfortunately, there may be upper level endogeneity!

### Standard multilevel modeling

#### In our example:

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- ► Y<sub>ii</sub>: next day's positive relational feelings

Standard analysis by a multilevel model with random intercept  $b_j$ :

$$E(Y_{ij}|X_{ij},b_j) = \gamma_0 + \gamma X_{ij} + b_j \tag{1}$$

(1) assumes that  $b_j$  and  $X_{ij}$  are independent  $\Rightarrow$  biased estimator for  $\gamma$  under upper-level endogeneity!

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- $\triangleright \gamma_W$  captures the within-subject effect
- $ightharpoonup \gamma_B$  captures the between-subject effect

### Centring of lower level effects

A solution to the upper-level endogeneity problem is to separate withinfrom between-effects:

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

As  $X_{ij} - \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_j$  in case of upper level endogeneity.

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- As  $X_{ij} \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_i$  in case of upper level endogeneity.
- ▶ The OLS-estimator for  $\gamma_W$  will converge to (in balanced designs):

$$\hat{\gamma}_{W} = \frac{\operatorname{cov}(Y_{ij}, X_{ij} - \overline{X}_{j})}{\operatorname{var}(X_{ij} - \overline{X}_{j})} \to \gamma$$
(3)

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- As  $X_{ij} \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_i$  in case of upper level endogeneity.
- ▶ The OLS-estimator for  $\gamma_W$  will converge to (in balanced designs):

$$\hat{\gamma}_{W} = \frac{\operatorname{cov}(Y_{ij}, X_{ij} - \overline{X}_{j})}{\operatorname{var}(X_{ij} - \overline{X}_{j})} \to \gamma$$
(3)

 $\Rightarrow$  No bias!

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- As  $X_{ij} \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_j$  in case of upper level endogeneity.
- ▶ The OLS-estimator for  $\gamma_B$  will converge to (in balanced designs):

$$\hat{\gamma}_{B} = \frac{\operatorname{cov}(\overline{Y}_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})} \to \gamma + \frac{\operatorname{cov}(b_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})}$$
(3)

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- As  $X_{ij} \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_i$  in case of upper level endogeneity.
- ▶ The OLS-estimator for  $\gamma_B$  will converge to (in balanced designs):

$$\hat{\gamma}_{B} = \frac{\operatorname{cov}(\overline{Y}_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})} \to \gamma + \frac{\operatorname{cov}(b_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})}$$
(3)

⇒ Bias under upper level endogeneity!

### Centring of lower level effects

A solution to the upper-level endogeneity problem is to separate withinfrom between-effects:

$$E(Y_{ij} \mid X_{ij}, u_j) = \gamma_0 + \gamma_W X_{ij}^c + \gamma_B \overline{X}_j + b_j$$
with  $\overline{X}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij}$  and  $X_{ij}^c = X_{ij} - \overline{X}_j$  (2)

- As  $X_{ij} \overline{X}_j$  removes all upper level effects, it no longer depends on  $b_i$  in case of upper level endogeneity.
- ▶ The OLS-estimator for  $\gamma_B$  will converge to (in balanced designs):

$$\hat{\gamma}_{B} = \frac{\operatorname{cov}(\overline{Y}_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})} \to \gamma + \frac{\operatorname{cov}(b_{j}, \overline{X}_{j})}{\operatorname{var}(\overline{X}_{j})}$$
(3)

⇒ Bias under upper level endogeneity!

(note that  $\overline{X}_j$  can also be excluded from (2), as  $\overline{X}_j \perp \!\!\! \perp X_{ij}^c$ )

# Revisited: Longitudinal study on sexual behavior in Flanders

New question: Does the effect of intimacy on next-day positive relationship feelings differ according to whether or not the participant has masturbated the previous day?

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- ► Y<sub>ij</sub>: next day's positive relational feelings
- $\triangleright$   $Z_{ij}$ : 1 when individual j has masturbated on day i, 0 if not

# Revisited: Longitudinal study on sexual behavior in Flanders

New question: Does the effect of intimacy on next-day positive relationship feelings differ according to whether or not the participant has masturbated the previous day?

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- Y<sub>ij</sub>: next day's positive relational feelings
- $ightharpoonup Z_{ij}$ : 1 when individual j has masturbated on day i, 0 if not

Adjusted multilevel model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij} + \gamma_2 Z_{ij} + \gamma_3 X_{ij} Z_{ij} + b_j$$
 (4)

⇒ Lower level interaction term!

# Revisited: Longitudinal study on sexual behavior in Flanders

New question: Does the effect of intimacy on next-day positive relationship feelings differ according to whether or not the participant has masturbated the previous day?

- $\triangleright$   $X_{ij}$ : daily measurement of intimacy of individual j at time i
- Y<sub>ij</sub>: next day's positive relational feelings
- $\triangleright$   $Z_{ij}$ : 1 when individual j has masturbated on day i, 0 if not

Adjusted multilevel model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij} + \gamma_2 Z_{ij} + \gamma_3 X_{ij} Z_{ij} + b_j$$
 (4)

- $\blacktriangleright$   $b_j$  may again be correlated with X, Y and/or Z in case of upper level endogeneity
- lacktriangle The 'naive' model may then again yield biased estimators for the  $\gamma$ 's  $_{5}$

There a two possible centring approaches:

► Product first, center next (P1C2):

$$X_{ij}*Z_{ij}$$

There a two possible centring approaches:

▶ Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

There a two possible centring approaches:

► Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

► Center first, take the product next (C1P2):

#### There a two possible centring approaches:

► Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

► Center first, take the product next (C1P2):

$$X_{ij}$$
  $Z_{ij}$ 

There a two possible centring approaches:

► Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

Center first, take the product next (C1P2):

$$X_{ij}$$
 $X_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 
 $Z_{ij}$ 

There a two possible centring approaches:

► Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

Center first, take the product next (C1P2):

$$\overline{X}_{j} \qquad X_{ij} \qquad Z_{ij} \qquad Z_{ij} \qquad Z_{ij} \qquad Z_{ij} = Z_{ij} - \overline{Z}_{j} \qquad Z_{ij}^{c} = Z_{ij} - \overline{Z}_{j}$$

There a two possible centring approaches:

► Product first, center next (P1C2):

$$\overline{XZ}_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} X_{ij} Z_{ij}$$
 
$$(XZ)_{ij}^{c} = X_{ij} Z_{ij} - \overline{XZ}_{j}$$

Center first, take the product next (C1P2):

$$\overline{X}_{j}$$
 $X_{ij}^{c} = X_{ij} - \overline{X}_{j}$ 
 $\overline{Z}_{j}$ 
 $Z_{ij}^{c} = Z_{ij} - \overline{Z}_{j}$ 
 $X_{ij}^{c} * \overline{Z}_{j}$ 
 $X_{ij}^{c} * \overline{Z}_{j}$ 

Question: which approach should we take? Do they differ in any way?

### The P1C2-approach

► P1C2 model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 (XZ)_{ij}^c + b_j$$
 (5)  
with  $(XZ)_{ij}^c = X_{ij} Z_{ij} - \overline{XZ}_j$  (and  $\overline{XZ}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij} Z_{ij}$ )  
 $\Rightarrow \hat{\gamma}_1, \hat{\gamma}_2$  and  $\hat{\gamma}_3$  are unbiased estimators for  $\gamma_1, \gamma_2$  and  $\gamma_3$ 

#### ▶ P1C2 model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 (XZ)_{ij}^c + b_j$$
 (5)  
with  $(XZ)_{ij}^c = X_{ij} Z_{ij} - \overline{XZ}_j$  (and  $\overline{XZ}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij} Z_{ij}$ )  
 $\Rightarrow \hat{\gamma}_1, \hat{\gamma}_2$  and  $\hat{\gamma}_3$  are unbiased estimators for  $\gamma_1, \gamma_2$  and  $\gamma_3$ 

► P1C2+ model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 (XZ)_{ij}^c + \gamma_4 \overline{X}_i + \gamma_5 \overline{Z}_i + \gamma_6 \overline{XZ}_i + b_i$$

 $\Rightarrow$  in balanced designs, the estimated within-effects  $\hat{\gamma}_1$ ,  $\hat{\gamma}_2$  and  $\hat{\gamma}_3$  are identical in both models

## The C1P2-approach

► C1P2 model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + b_j$$
 (6)

### The C1P2-approach

► C1P2 model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ii}^c + \gamma_2 Z_{ii}^c + \gamma_3 X_{ii}^c Z_{ii}^c + b_j$$
 (6)

► C1P2+ model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + \gamma_4 \overline{X}_j + \gamma_5 \overline{Z}_j + \gamma_6 \overline{X}_j \overline{Z}_j + b_j$$

### The C1P2-approach

► C1P2 model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + b_j$$
 (6)

► C1P2+ model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + \gamma_4 \overline{X}_j + \gamma_5 \overline{Z}_j + \gamma_6 \overline{X}_j \overline{Z}_j + b_j$$

► C1P2++ model:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + \gamma_4 \overline{X}_j + \gamma_5 \overline{Z}_j + \gamma_6 \overline{X}_j \overline{Z}_j + \gamma_7 \overline{X}_j Z_{ij}^c + \gamma_8 \overline{Z}_j X_{ij}^c + b_j$$

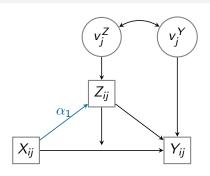
#### Example - Results

	Intimacy = X		Masturbation	n = Z	Interaction = XZ			
	Estimate	<i>p</i> -value	Estimate	p-value	Estimate	<i>p</i> -value		
P1C2	0.079 (0.015)	< .001	-0.151 (0.079)	.057	0.075 (0.039)	.054		
P1C2+	0.079 (0.015)	< .001	-0.150 (0.079)	.059	0.075 (0.039)	.054		
C1P2	0.080 (0.015)	< .001	-0.163 (0.080)	.042	0.102 (0.050)	.042		
C1P2+	0.080 (0.015)	< .001	-0.160 (0.080)	.045	0.098 (0.045)	.049		
C1P2++	0.080 (0.015)	< .001	-0.167 (0.080)	.037	0.096 (0.050)	.056		

- ► Different approaches lead to different estimates
- ▶ Different approaches lead to different conclusions (at the 5% significance level)!

Results

### Simulation Study - Settings



Simulation	$\alpha_1$	Distribution of $X$
Sim 1	0.0	N(0,1)
Sim 2	0.0	B(1, 0.5) - 0.5
Sim 3	-0.2	B(1,0.5)-0.5
Sim 4	-1.5	B(1,0.5)-0.5

#### Simulation study - Results

- ▶ X and Z are grand-mean centred to facilitate interpretation
- ► Focus on within-effects only

- ▶ X and Z are grand-mean centred to facilitate interpretation
- ► Focus on within-effects only
- ▶ P1C2 = P1C2+ and C1P2 = C1P2+

- X and Z are grand-mean centred to facilitate interpretation
- Focus on within-effects only
- ▶ P1C2 = P1C2+ and C1P2 = C1P2+
- Bias for interaction effect in C1P2=C1P2+ when Z is a mediator:

$$E(\hat{\gamma}_3) = \gamma_3 \frac{\operatorname{cov}[X_{ij}Z_{ij}, X_{ij}^c Z_{ij}^c]}{\operatorname{var}[X_{ij}^c Z_{ij}^c]}$$
(7)

- X and Z are grand-mean centred to facilitate interpretation
- Focus on within-effects only
- ▶ P1C2 = P1C2+ and C1P2 = C1P2+
- Bias for interaction effect in C1P2=C1P2+ when Z is a mediator:

$$E(\hat{\gamma}_3) = \gamma_3 \frac{\operatorname{cov}[X_{ij}Z_{ij}, X_{ij}^c Z_{ij}^c]}{\operatorname{var}[X_{ij}^c Z_{ij}^c]}$$
(7)

▶ No bias for P1C2 = P1C2+ and C1P2++

#### Simulation study - Results

- X and Z are grand-mean centred to facilitate interpretation
- Focus on within-effects only
- ▶ P1C2 = P1C2+ and C1P2 = C1P2+
- Bias for interaction effect in C1P2=C1P2+ when Z is a mediator:

$$E(\hat{\gamma}_3) = \gamma_3 \frac{\operatorname{cov}[X_{ij}Z_{ij}, X_{ij}^c Z_{ij}^c]}{\operatorname{var}[X_{ij}^c Z_{ij}^c]}$$
(7)

- No bias for P1C2 = P1C2+ and C1P2++
- Precision of interaction effect estimator is about 30% smaller for P1C2 compared to C1P2++

#### Conclusions

- 1. P1C2 yields more precise estimators of the interaction effect compared to the C1P2-approaches
- 2. In contrast to C1P2, P1C2 is not affected by misspecification or omission of upper level effects (i.e. upper level endogeneity)

#### Conclusions

- 1. P1C2 yields more precise estimators of the interaction effect compared to the C1P2-approaches
- 2. In contrast to C1P2, P1C2 is not affected by misspecification or omission of upper level effects (i.e. upper level endogeneity)

Thank you!

### Possible complication when the predictors are NOT centred

► Again consider C1P2 or C1P2+:

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c + b_j$$

$$E(Y_{ij} \mid X_{ij}, Z_{ij}, u_j) = \gamma_0 + \gamma_1 X_{ij}^c + \gamma_2 Z_{ij}^c + \gamma_3 X_{ij}^c Z_{ij}^c$$

$$E(T_{ij} \mid \lambda_{ij}, \lambda_{ij}, u_j) = \gamma_0 + \gamma_1 \lambda_{ij} + \gamma_2 \lambda_{ij} + \gamma_3 \lambda_{ij} \lambda_{ij}$$

Bias in main effects for these approaches:

$$E[\hat{\gamma}_1] = \beta_1 + \beta_3 E(\overline{Z}_j)$$
  
$$E[\hat{\gamma}_2] = \beta_2 + \beta_3 E(\overline{X}_j)$$

# Results - Simulation Study

	stimator		Ŷı				Ŷ2				γ̂з		
		Estimate $(sd_E)$	se	Coverage	Power	Estimate $(sd_E)$	se	Coverage	Power	Estimate $(sd_E)$	se	Coverage	Power
E E	P1C2 C1P2	0.101 (0.031) 0.101 (0.032)	0.028 0.028	0.92 0.92	0.93 0.92	0.150 (0.027) 0.150 (0.027)	0.028 0.028	0.96 0.96	1.00 1.00	-0.101 (0.019) -0.101 (0.029)	0.020 0.029	0.95 0.95	1.00 0.94
S	C1P2++	0.101 (0.031)	0.028	0.93	0.93	0.150 (0.027)	0.028	0.96	1.00	-0.101 (0.029)	0.029	0.95	0.94
- 2	P1C2 C1P2	0.103 (0.056) 0.103 (0.056)	0.055	0.95 0.95	0.46	0.150 (0.027) 0.100 (0.027)	0.028	0.96 0.96	1.00	-0.101 (0.040) -0.099 (0.058)	0.039	0.95 0.95	0.72 0.41
Sim	C1P2++	0.103 (0.056)	0.056	0.95	0.46	0.150 (0.027)	0.028	0.96	1.00	-0.099 (0.058)	0.058	0.95	0.41
۳ E	P1C2 C1P2	0.103 (0.056) 0.103 (0.056)	0.055	0.95 0.95	0.46	0.150 (0.027) 0.150 (0.027)	0.028	0.96 0.96	1.00	-0.101 (0.040) -0.099 (0.058)	0.039	0.95 0.95	0.72 0.41
Si	C1P2++	0.103 (0.056)	0.055	0.95	0.46	0.150 (0.027)	0.028	0.96	1.00	-0.099 (0.058)	0.058	0.95	0.41
4	P1C2	0.103 (0.068)	0.069	0.95	0.33	0.150 (0.027)	0.028	0.96	1.00	-0.101 (0.040)	0.039	0.95	0.72
Sim	C1P2 C1P2++	0.103 (0.068) 0.103 (0.068)	0.069	0.95 0.96	0.33	0.150 (0.027) 0.150 (0.027)	0.028 0.028	0.96 0.96	1.00	-0.090 (0.055) -0.099 (0.055)	0.055	0.95 0.96	0.37
- 0	C1P2++	0.103 (0.068)	0.069	0.96	0.33	0.150 (0.027)	0.028	0.96	1.00	-0.099 (0.055)	0.056	0.96	