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The matching effect of intra-class correlation (ICC) on the estimation of contextual effect: A Bayesian approach of multilevel modeling

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Agenda

Introduction to this study

Contextual variables and contextual effects in MLM

Issues of ICCs in MLM

Estimation methods for MLM

A simulation pilot study

An empirical application

Conclusions and further study

Introduction

Organizations are multilevel in nature

Many topics in organization are related to hierarchical issues, such as

- **Leadership**
- **Teamwork/Group Dynamic**
- **Communication/Conflict**
- **Organizational effectiveness**
- **Organizational climate and culture**
- …

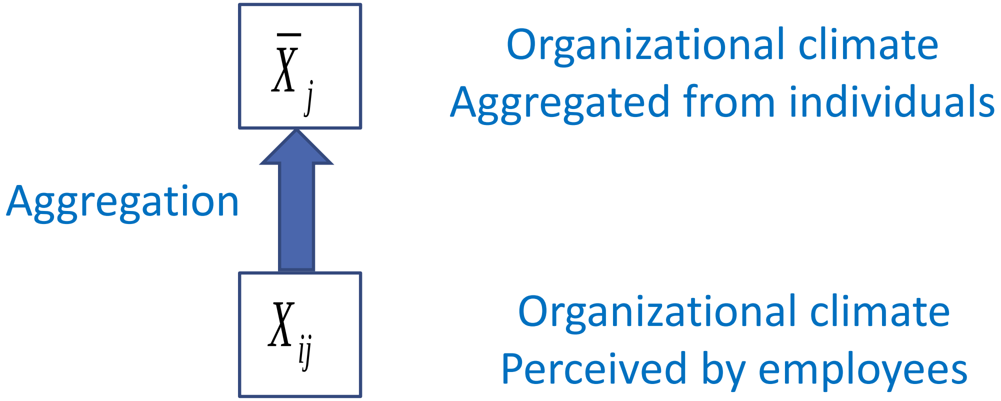
The organization researchers always concern about the **context** of organization with its influences on the organizational behaviors

Example also goes for the **big-fish-little-pond effect (BFLPE)** (Marsh, 2007) in education field that achievement at the individual student level has a positive effect on academic self-concept, but school- or classroom-average achievement has a negative effect on academic self-concept.

Contextual Variable

A group-level characteristic (such as the organizational climate) that is measured by an individual-level variable (such as the perceived climate) is treated as an level-2 explanatory variable.

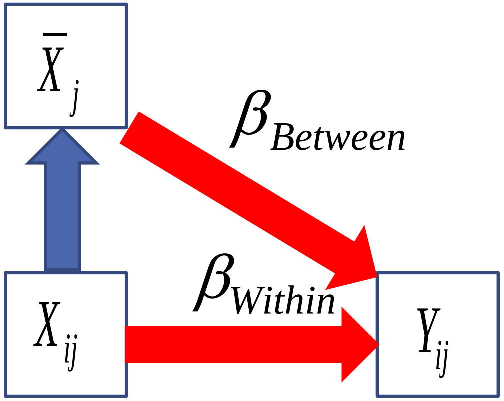
The cluster-mean of the individual-level variable ($\bar{X}_j$) is used as the proxy of the group-level characteristic to predict Y_{ij}.



Contextual Effect (CE)

CE is defined as the partial effect of the contextual variable ($\bar{X}_j$) on the outcome (Y_{ij}) after removing the impact of the explanatory variable at individual level (X_{ij}).

CE could be evaluated by the difference between regression coefficients for between-sluster and within-cluster in terms of the hierarchical linear model (HLM) framework (Raudenbush & Bryk, 1986; Raudenbush & Willms, 1995; Algina & Swaminathan, 2011)



$$\beta_{Contextual} = \beta_{Between} - \beta_{Within}$$

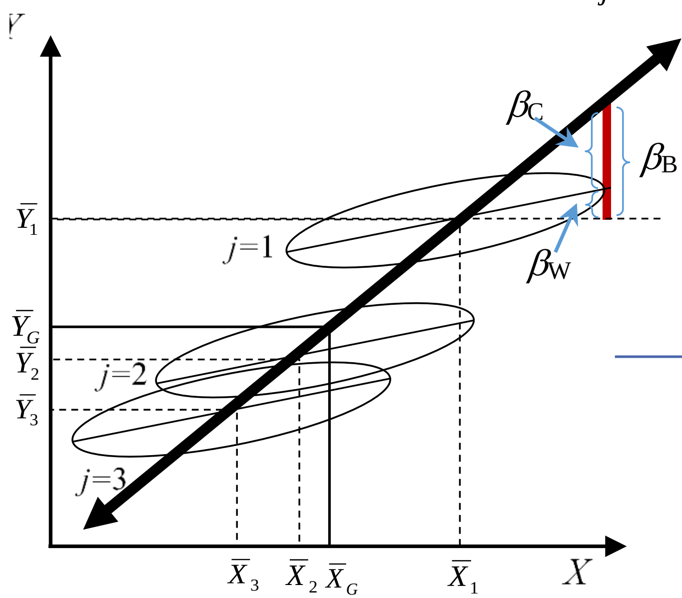
MLM notation

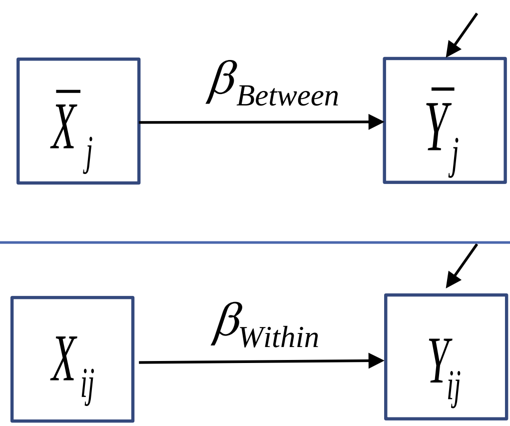
Level-1 (1) $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{X}_j) + [\varepsilon_{ij}]$

Level-2(Intercept) (2) $\beta_{0j} = \gamma_{00} + \gamma_{01}(\bar{X}_j - \bar{X}_G) + [u_j]$

Level-2(Slope) (3) $\beta_{1j} = \gamma_{10}$

Mixed (4) $Y_{ij} = (\gamma_{00} - \gamma_{01}\bar{X}_G) + \gamma_{10}X_{ij} + (\gamma_{01} - \gamma_{10})\bar{X}_j + [u_j + \varepsilon_{ij}]$





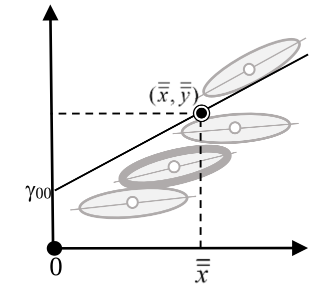
Level-2
Between Group
Cluster measures

Level-1
Within Group
Individual Measures

Centering issues in MLM

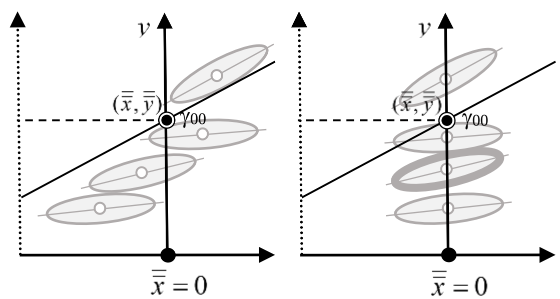
Two approaches for centering the predictors (Enders & Tofighi, 2007 ; Kreft & de Leeuw, 1998; Raudenbush & Bryk, 2002; Yang & Cai, 2014)

- **Centering at the Grand Mean; CGM**
  - (1) $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{X}_G) + [\varepsilon_{ij}]$
  - (2) $\beta_{0j} = \gamma_{00} + \gamma_{01}(\bar{X}_j - \bar{X}_G) + [u_j]$
  - (3) $\beta_{1j} = \gamma_{10}$
  - (4) $Y_{ij} = (\gamma_{00} - \gamma_{01}\bar{X}_G - \gamma_{10}\bar{X}_G) + \gamma_{10}X_{ij} + \gamma_{01}\bar{X}_j + [u_j + \varepsilon_{ij}]$
  - (5) $\beta_B = \gamma_{01} + \gamma_{10} = \beta_C + \beta_W$



(a) *NoC x*

- **Centering Within the Cluster; CWC**
  - (1) $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{X}_j) + [\varepsilon_{ij}]$
  - (2) $\beta_{0j} = \gamma_{00} + \gamma_{01}(\bar{X}_j - \bar{X}_G) + [u_j]$
  - (3) $\beta_{1j} = \gamma_{10}$
  - (4) $Y_{ij} = (\gamma_{00} - \gamma_{01}\bar{X}_G) + \gamma_{10}X_{ij} + (\gamma_{01} - \gamma_{10})\bar{X}_j + [u_j + \varepsilon_{ij}]$
  - (5) $\beta_C = \gamma_{01} - \gamma_{10}$



(b) CGM*x* (c) CWC*x*

Intra-Class Correlation (ICC)

ICC(1)

- The percent of the total variance in the outcome that is between groups (Bryk & Raudenbush, 1992).
- indicates the amount of variance that could potentially be explained by the Level-2 predictors (Hofmann, 1997)

ICC(2)

- The precision of a group-average score (Bryk & Raudenbush, 1992).
- determine the reliability of aggregated individual-level data in terms of sampling only a finite number of L1 units from each L2 unit. (Bliese, 2000; LeBreton & Senter, 2008)

$$ICC(1) = \rho = \frac{\tau_{00}}{\tau_{00} + \sigma_e^2}$$

$$ICC(2) = \frac{\tau_{00}}{\tau_{00} + \sigma_e^2 / n_j} = \frac{n_j \times ICC(1)}{1 + (n_j - 1) ICC(1)}$$

Sampling error

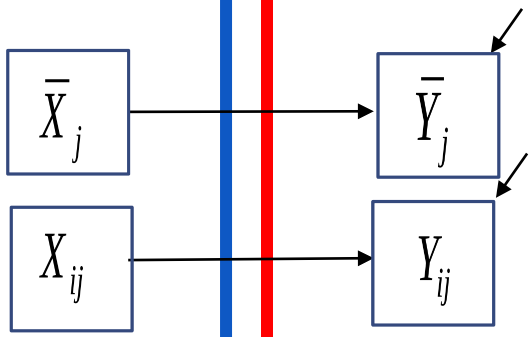
While looking at contextual effects We need both *ICCx* and *ICCy*

$\bar{Y}_j$ *group-average score of the outcome; Key of HLM*

$\bar{X}_j$ *group-average score of the predictor; Key of Context*

$$ICCx(1) = \frac{\tau_{00x}}{\tau_{00x} + \sigma_{ex}^2}$$

$$ICCx(2) = \frac{\tau_{00x}}{\tau_{00x} + \sigma_{ex}^2 / n_j}$$



$$ICCy(1) = \frac{\tau_{00y}}{\tau_{00y} + \sigma_{ey}^2}$$

$$ICCy(2) = \frac{\tau_{00y}}{\tau_{00y} + \sigma_{ey}^2 / n_j}$$

Research questions

If both the ICCx and ICCy can affect the estimation of contextual effects? And how?

1. In terms of the definition of ICC(1), the magnitudes of variances of $\bar{X}_j$ & $\bar{Y}_j$ are the focus
2. In terms of the definition of ICC(2), the sample size of level-1 and level-2 are the focus
3. For the cases of limited unit at level-1 and level-2, whether the Bayesian estimation is good alternative for traditional ML methods or not?

Methods of parameter estimation

Frequentist inferences

based on point estimates and hypothesis tests of significance for the measurement and latent variable parameters

- Full/Restriction information maximum likelihood estimation $L(\theta_1, \theta_2) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\theta_2}} \exp\left[-\frac{(x_i - \theta_1)^2}{2\theta_2} \right]$
- Generalized least squares procedures

Bayesian inferences

treat parameters as random or variable across a range of possible values. Parameters are estimated by a stimulation procedure for creating a confidence interval for a central value.

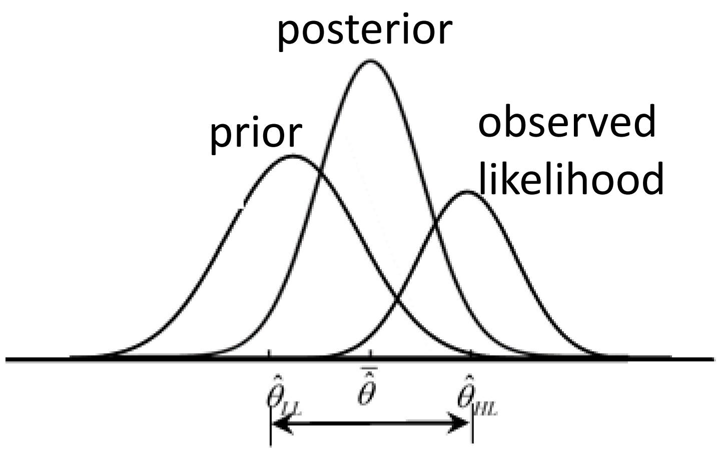
- requires the specification of prior distributions for the estimated parameters
- simulation techniques (Markov chain Monte Carlo, MCMC) could be used to implement Bayesian analysis in multilevel data (Dunson, 2000; Jedidi and Ansari, 2001)
- data from small-sample studies is less problematic

As the sample size increases, the posterior distribution will be driven less by the prior, and frequentist and Bayesian estimates will tend to agree closely

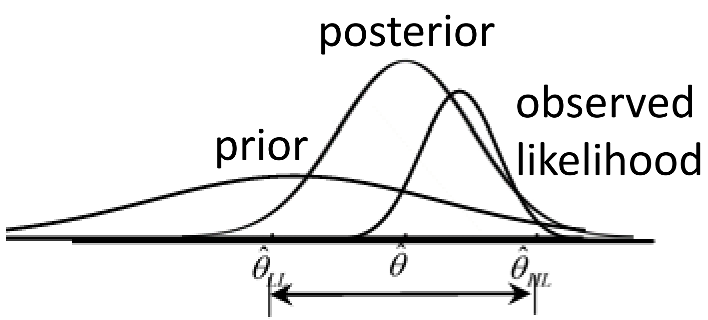
Probability density function in Bayesian estimation

Estimated parameter θ is defined as a random variable

$$P(\theta|z) \propto P(z|\theta)P(\theta)$$



credibility interval



credibility interval

MCMC methods

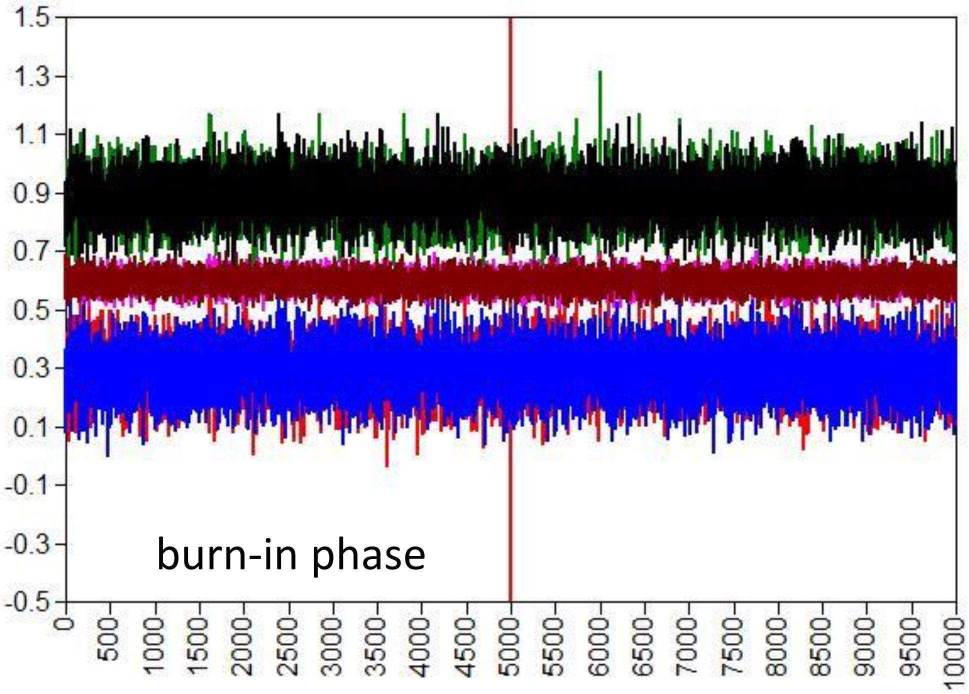
Gibbs Sampler
Metropolis-Hastings algorithm

$Z(1)$ is a draw from a target distribution $f(Z)$

$Z(1) \rightarrow Z(2) \rightarrow \ldots \rightarrow Z(t)$

Trace plots of can be very useful in assessing convergence whether the chain is mixing well

trace and autocorrelation plots



Simulation study

- The explanatory and outcome variables have a normal distribution
- Contextual effect (CE)=$\beta_W - \beta_B$=.75-.50=.25
- The ICCx and ICCy are set to [.1,.1], [.1,.5], [.5,.1], [.5,.5].
  - The variances of cluster means are set to .1111 or 1.0
  - The variances of level-1 variables are set to 1.0
  - ICC=.1111/(.1111+1)=.1; ICC=1/(1+1)=.5
- $N_{cluster}$: small(10), medium(30), large(100).
- N_j: small(10), medium(30), large(100).
- Prior distributions of random components: inverse Gamma IG(-1,0), IG(.001,.001), and uniform U(0,1000) (Muthén, 2010, Table25-29, pp.21-22）
- replications: 1000

Design based on

Hox, J. J., van de Schoot, R., & Matthijsse, S. (2012). How few countries will do? Comparative survey analysis from a Bayesian perspective. *Survey Research Methods*, *6(2)*, 87-93.

Muthén, B. (2010). Bayesian analysis in Mplus: A brief introduction. Retrieved from http://www.statmodel.com/download/IntroBayesVersion%203.pdf

Outputs of simulation

- Software: Mplus7.3
- average of the parameter estimates
- standard deviation of the parameter estimates
- average of the estimated standard errors
- mean square error for each parameter (M.S.E.)
  - the variance of the estimates across the replications plus the square of the bias.
- 95% coverage rate:
  - the proportion of the replications where the 95% Bayesian credibility interval covers the true value.

Design summary

Specification of parameters and true value

Parameter	True values ICC=.1	True values ICC=.5	ML	Bayes(1)	Bayes(2)	Bayes(3)
***Level*-1**						
α_W	0.00	0.00	-	N(0,10^{10})	N(0,10^{10})	N(0,10^{10})
β_W	0.50	0.50	-	N(0,10^{10})	N(0,10^{10})	N(0,10^{10})
$Var(y)$	1.00	1.00	-	IG(.001,.001)	IG(-1,0)	U(0,1000)
$Var(x)$	1.00	1.00	-	IG(.001,.001)	IG(-1,0)	U(0,1000)
***Level*-2**						
μ_X	0.00	0.00	-	IG(.001,.001)	IG(-1,0)	U(0,1000)
α_B	0.00	0.00		N(0,10^{10})	N(0,10^{10})	N(0,10^{10})
β_B	0.75	0.75	-	N(0,10^{10})	N(0,10^{10})	N(0,10^{10})
$Var(\bar{Y})$	.1111	1.00	-	IG(.001,.001)	IG(-1,0)	U(0,1000)
$Var(\bar{X})$	.1111	1.00	-	IG(.001,.001)	IG(-1,0)	U(0,1000)

Note. Contextual effect (CE)=$\beta_W - \beta_B$=.25. ICC specification: variance of $\bar{X}$ and $\bar{Y}$ set to .1111 and the variance of X and Y set to 1.0, ICC=.1111/(.1111+1)=.1; variance of $\bar{X}$ and $\bar{Y}$ set to 1.0 and the variance of X and Y set to 1.0, ICC=.1111/(.1111+1)=.1, ICC=1/(1+1)=.5 。 Baye(1): N refers to normal; IG refers to inverse Gamma; U refers to uniform.

An example of Mplus 7.3 syntax

```
TITLE:     BAYES ICCX=.5 ICCY=.1 IG(.001,.001) [30,30]
MONTECARLO:
    NAMES ARE Y X W;
    NOBS = 900; NREP = 1000; NCsizes = 1; CSIZES = 30 (30);
    !REPSAVE = 1; SAVE = M6ICC.1BAYESIG.001*.dat;
    WITHIN = X;
    BETWEEN= W;

MODEL POPULATION:
    %within%
    X*1;
    Y*1;
    Y on X*.5;

    %between%
    W*1;
    Y on W*.75;
    !X* 1;  !ICCX = 1/2 = 0.5
    Y* 0.11111;  !ICCY = 0.11111/1.11111 = 0.1

ANALYSIS:
    type = twolevel;
   !estimator = ml;
    estimator = bayes;
    fbiter = 100;
    process = 2;
```

```
MODEL:
    %within%
    Y on X *.5 (gamma10);
    X*1 (AX);
    Y*1 (AY);

    %between%
    Y on W *.75 (gamma01);
    W*1 (BW);
    !X*.11111 (BX);  !ICCX
    Y*.11111 (BY);  !ICCY

Model constraint:

    NEW(ICCY*.1);
    ICCY = BY/(AY+BY);

    new(CONTEXT*.25);
    CONTEXT=gamma01-gamma10;

Model priors:
    AX~IG(.001,.001);
    AY~IG(.001,.001);
    BW~IG(.001,.001);
    BY~IG(.001,.001);

PLOT: TYPE = PLOT2;
OUTPUT:!Tech8 TECH9;
       !STANDARDIZED;
```

Results of Monte Carlo Simulation

	True	Average				Standard deviation				MSE				95% cover rate			
ICCX=		.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50
ICCY=		.10	.10	.50	.50	.10	.10	.50	.50	.10	.10	.50	.50	.10	.10	.50	.50
A: [$N_{Cluster}$,N_j]=[10, 30], Cases=300																	
β_W	.50																
ML		.496	.496	.496	.496	.056	.056	.056	.056	.003	.003	.003	.003	.962	.962	.962	.962
Bayes(1)		.503	.503	.502	.502	.060	.060	.059	.060	.004	.004	.004	.004	.950	.950	.953	.953
Bayes(2)		.502	.502	.502	.502	.060	.060	.060	.060	.004	.004	.004	.004	.956	.956	.955	.955
Bayes(3)		.503	.503	.502	.502	.060	.060	.060	.060	.004	.004	.004	.004	.948	.950	.951	.955
β_B	.75																
ML		.750	.750	.755	.752	.436	.145	1.154	.385	.190	.021	1.331	.148	.903	.903	.896	.896
Bayes(1)		.738	.746	.714	.738	.434	.145	1.157	.386	.189	.021	1.338	.149	.918	.918	.939	.939
Bayes(2)		.738	.746	.714	.738	.435	.145	1.158	.386	.189	.021	1.341	.149	.972	.972	.974	.974
Bayes(3)		.737	.746	.714	.738	.435	.145	1.617	.387	.189	.021	1.350	.150	.963	.968	.972	.971
CE	.25																
ML		.254	.254	.259	.256	.439	.156	.155	.388	.193	.024	1.334	.151	.900	.916	.900	.906
Bayes(1)		.236	.244	.211	.235	.440	.158	.141	.392	.194	.025	1.347	.154	.916	.931	.940	.937
Bayes(2)		.236	.244	.211	.236	.440	.158	.162	.393	.194	.025	1.349	.154	.970	.970	.974	.972
Bayes(3)		.235	.243	.211	.235	.440	.158	.165	.394	.193	.025	1.358	.155	.962	.966	.971	.966
B: [$N_{Cluster}$,N_j]=[30, 30], Cases=900																	
β_W	.50																
ML		.500	.500	500	.500	.033	.033	.033	.033	.001	.001	.001	.001	.957	.957	.960	.960
Bayes(1)		.500	.500	.500	.500	.035	.035	.035	.035	.001	.001	.001	.001	.938	.947	.938	.943
Bayes(2)		.500	.500	.500	.500	.035	.035	.035	.035	.001	.001	.001	.001	.941	.941	.941	.941
Bayes(3)		.500	.500	.500	.500	.035	.035	.035	.035	.001	.001	.001	.001	.940	.941	.941	.940
β_B	.75																
ML		.735	.745	.719	.740	.218	.073	.590	.197	.048	.005	.349	.039	.927	.927	.923	.923
Bayes(1)		.747	.749	.750	.750	.217	.072	.583	.194	.047	.005	.340	.038	.948	.948	.962	.962
Bayes(2)		.747	.749	.749	.750	.217	.073	.585	.195	.047	.005	.342	.038	.960	.960	.965	.965
Bayes(3)		.747	.749	.749	.750	.217	.072	.584	.195	.047	.005	.341	.038	.963	.960	.967	.969
CE	.25																
ML		.236	.246	.220	.240	.220	.079	.591	.200	.049	.001	.350	.040	.926	.933	.921	.923
Bayes(1)		.247	.249	.250	.250	.218	.079	.583	.196	.048	.006	.340	.039	.945	.955	.958	.954
Bayes(2)		.247	.249	.249	.250	.219	.079	.585	.197	.048	.006	.341	.039	.961	.960	.965	.966
Bayes(3)		.247	.249	.249	.250	.218	.079	.585	.197	.048	.006	.341	.039	.968	.962	.966	.963

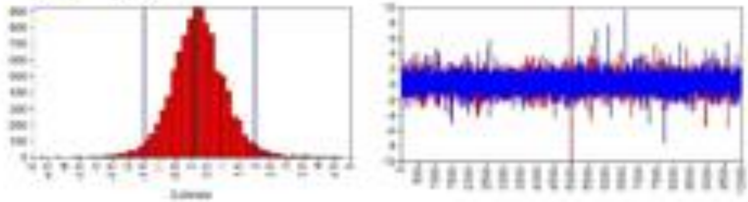
[continued]

	True	Average				Standard deviation				MSE				95% cover rate			
ICCX=		.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50	.10	.50
ICCY=		.10	.10	.50	.50	.10	.10	.50	.50	.10	.10	.50	.50	.10	.10	.50	.50
C: [$N_{Cluster}$,N_j]=[100, 30], Cases=3000																	
β_W	**.50**																
ML		.500	.500	.500	.500	.018	.018	.018	.018	.0003	.0003	.0003	.0003	.957	.957	.956	.956
Bayes(1)		.500	.500	.500	.500	.019	.018	.019	.019	.0003	.0003	.0003	.0003	.946	.944	.944	.944
Bayes(2)		.500	.500	.500	.500	.019	.019	.019	.019	.0003	.0003	.0003	.0004	.945	.945	.945	.944
Bayes(3)		.500	.500	.500	.500	.019	.019	.019	.019	.0003	.0003	.0004	.0004	.944	.944	.946	.944
β_B	**.75**																
ML		.746	.749	.743	.748	.115	.038	.305	.102	.013	.002	.093	.010	.938	.938	.950	.950
Bayes(1)		.750	.750	.754	.752	.119	.040	.311	.106	.014	.002	.101	.011	.937	.939	.938	.938
Bayes(2)		.750	.750	.755	.752	.119	.039	.318	.106	.014	.002	.101	.011	.946	.942	.946	.942
Bayes(3)		.750	.750	.754	.752	.120	.040	.317	.106	.014	.002	.101	.011	.941	.947	.946	.942
CE	**.25**																
ML		.247	.249	.244	.248	.116	.042	.305	.103	.013	.002	.093	.011	.939	.939	.939	.950
Bayes(1)		.250	.250	.254	.251	.120	.043	.317	.107	.014	.002	.101	.011	.940	.946	.941	.942
Bayes(2)		.250	.250	.254	.251	.120	.043	.318	.107	.014	.002	.101	.011	.945	.950	.950	.944
Bayes(3)		.250	.250	.254	.251	.120	.043	.317	.106	.015	.002	.100	.011	.943	.951	.947	.943
D: [$N_{Cluster}$,N_j]=[100, 100], Cases=10000																	
β_W	**.50**																
ML		.500	.500	.500	.500	.010	.010	.010	.010	.0001	.0001	.0001	.0001	.963	.963	.963	.963
Bayes(1)		.500	.500	.500	.500	.010	.010	.010	.010	.0001	.0001	.0001	.0001	.952	.952	.951	.951
Bayes(2)		.500	.500	.500	.500	.010	.010	.010	.010	.0001	.0001	.0001	.0001	.954	.954	.953	.953
Bayes(3)		.500	.500	.500	.500	.010	.010	.010	.010	.0001	.0001	.0001	.0001	.957	.957	.953	.954
β_B	**.75**																
ML		.747	.749	.742	.747	.109	.036	.313	.105	.012	.001	.098	.011	.937	.937	.943	.943
Bayes(1)		.744	.748	.731	.744	.104	.035	.301	.100	.011	.001	.091	.010	.949	.949	.953	.953
Bayes(2)		.744	.748	.731	.744	.104	.035	.301	.100	.011	.001	.091	.010	.953	.953	.952	.952
Bayes(3)		.744	.748	.731	.744	.100	.035	.301	.100	.011	.001	.091	.010	.959	.953	.954	.959
CE	**.25**																
ML		.247	.249	.241	.247	.109	.038	.313	.105	.012	.001	.098	.011	.936	.944	.942	.941
Bayes(1)		.245	.248	.241	.244	.104	.036	.301	.100	.011	.001	.091	.010	.943	.955	.953	.954
Bayes(2)		.244	.248	.231	.244	.104	.036	.301	.100	.011	.001	.091	.010	.953	.954	.953	.953
Bayes(3)		.244	.248	.231	.244	.104	.035	.301	.100	.011	.001	.091	.010	.958	.960	.956	.955

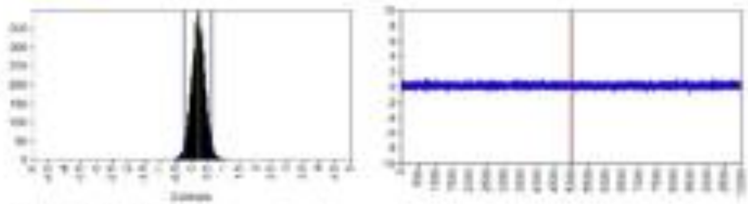
Note. CE: Contextual effect=β_W–β_B=.25. Bayes(1)(2)(3) refers to IG(.001,.001)、IG(-1,0)、U(0,1000).

(A) ICC=[.1,.1]

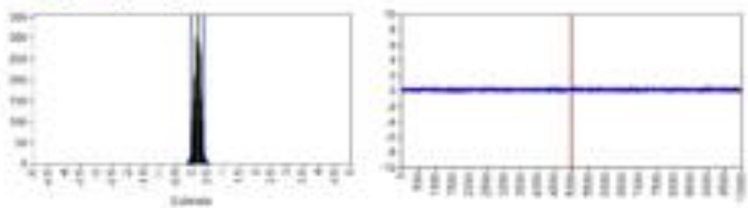
N=[10,30]



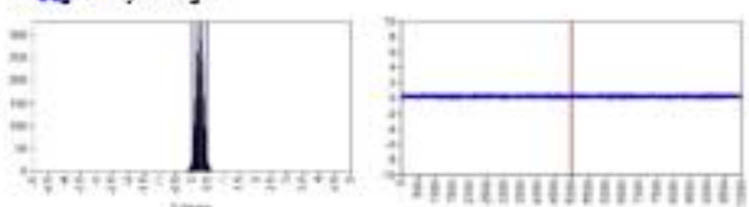
N=[30,30]



N=[100,30]

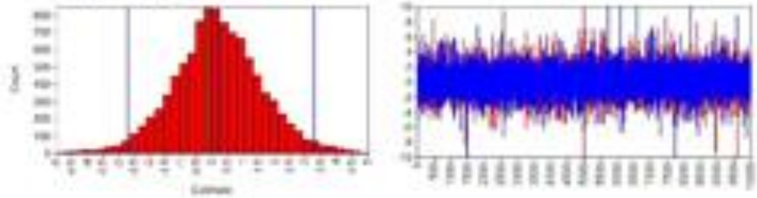


N=[100,100]

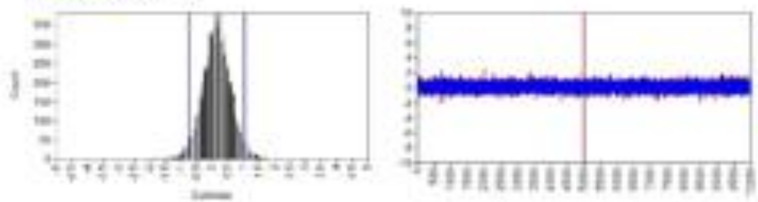


(C) ICC=[.1,.5]

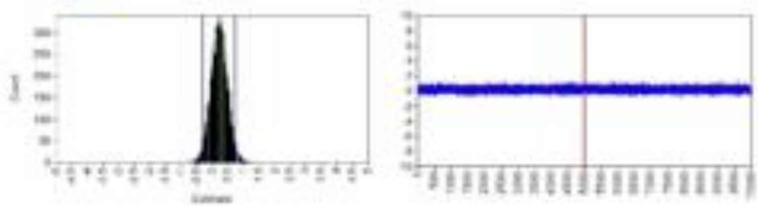
N=[10,30]



N=[30,30]



N=[100,30]



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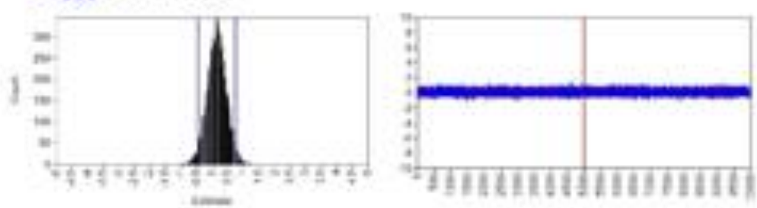
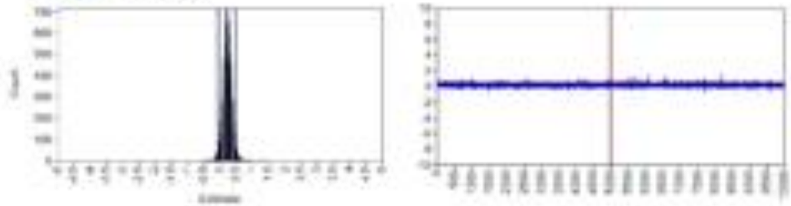
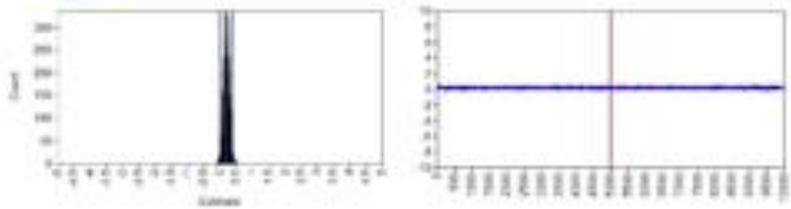


(B) ICC=[.5,.1]

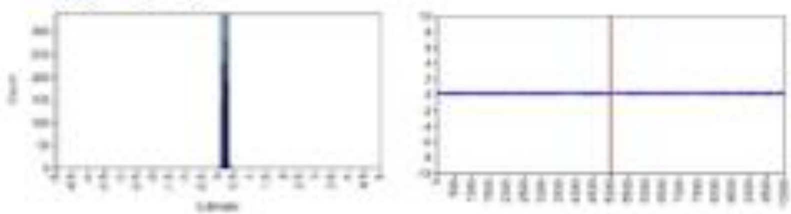
N=[10,30]



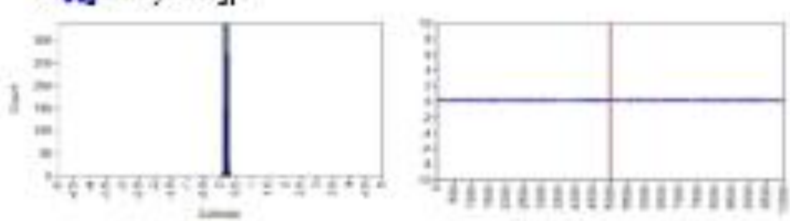
N=[30,30]



N=[100,30]

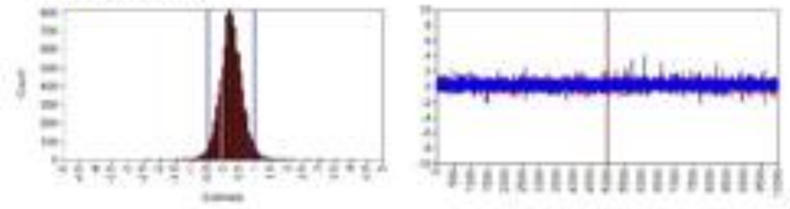


N=[100,100]

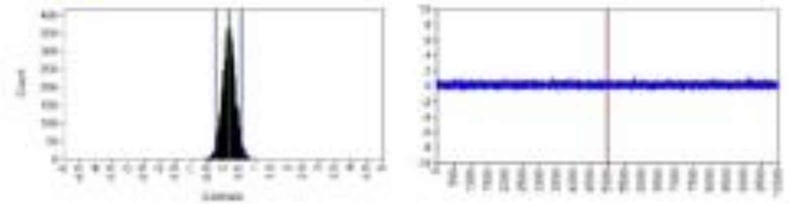


(D) ICC=[.5,.5]

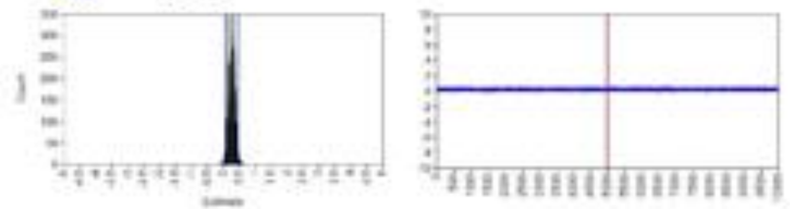
N=[10,30]



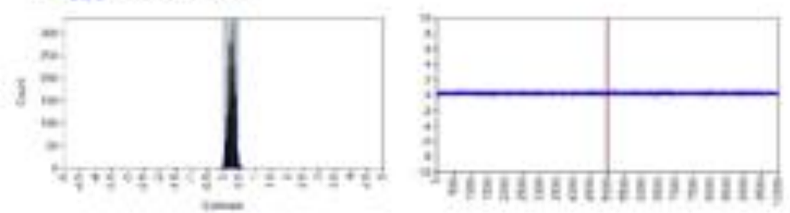
N=[30,30]



N=[100,30]



N=[100,100]



Results of simulation

The matching effects

- a higher ICCx combined with a lower ICCy [.5,.1] is more efficient
- a smaller ICCx combined with a higher ICCy [.1,.5] is worst efficient

The point estimation of the Bayesian estimation is similar to the maximum likelihood method. the Bayesian estimation shows the superiority of predicting the true value of the parameters, especially when the Ncluster is low,

the Bayesian method is a good alternative to the maximum likelihood method for estimating the contextual effects in the multilevel models while the number of cluster is small (ie. Less than 10).

Empirical Application

Data sources

Selected data from

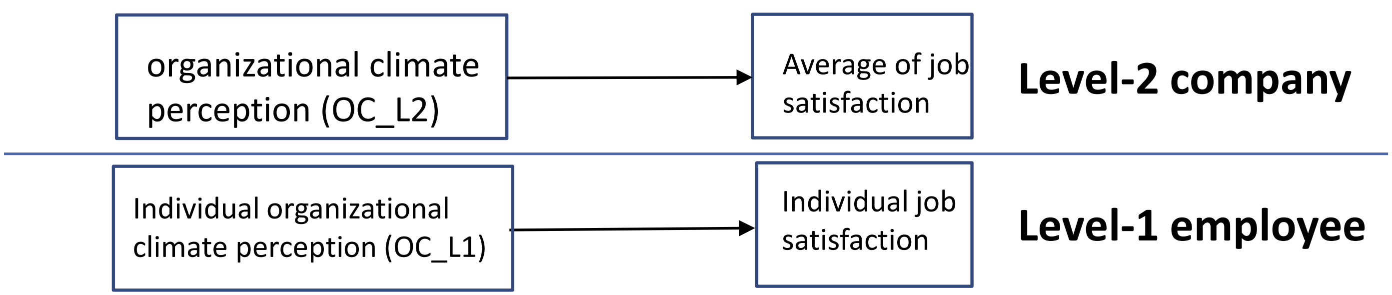
(1)Study of organizational culture and effectiveness (Chiou, Kao, and Liou, 2001)

(2)MOST project based a large-scale survey on the high-tech compnies at HsinChu Science Park in Taiwan

Sample

A total of 45 companies 1200 employees 741 male (61.8%) , 459 female (38.3%),

Average cluster size is 26.67 (Median 25, minimum 5, maximum 64



Data information

	F	Eta^2	Variance		ICC	r_{wgj}
			within	between		
X: perceived climate	9.28*	.257	.2822	.1230	.309	.876
Y: job satisfaction	8.27*	.235	.3604	.1175	.251	.867

Descriptive statistics and correlation coefficients

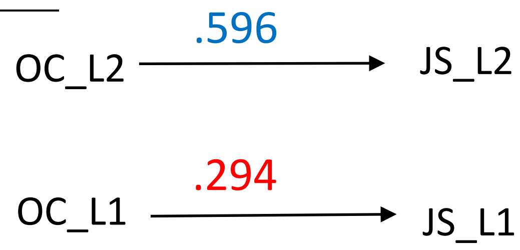
Variables	Descriptive statistics					Correlation	
	N	Mean	std	min	max	*1.*	*2.*
Company level							
1 OC $\bar{X}_i$	45	3.622	.627	2.535	4.267	1.00	
2 JS $\bar{Y}_i$	45	3.509	.683	2.514	4.125	.875**	1.00
Employee level							
1 OC X_{ij}	1200	3.649	.649	1.000	5.000	1.00	
2 JS Y_{ij}	1200	3.504	.755	1.000	5.000	.589**	1.00

* $p<.05$ ** $p<.01$

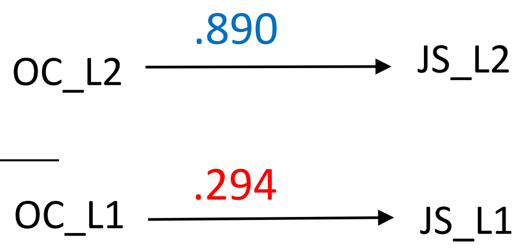
Summary of Results

		ML		Baysian	
		CGM	CWC	CGM	CWC
Fixed					
Intercept	γ_{00}	2.450(.260)	.292(.239)	2.447(.281)	.293(.259)
		[1.940,2.960]	[-.177,.760]	[1.900,3.005]	[-.213,.805]
OC_L1	γ_{10}	.596(.028)	.596(.028)	.595(.028)	.596(.029)
		[.541,.652]	[.541,.652]	[.540,.650]	[.540,.650]
OC_L2	γ_{01}	.294(.072)	.890(.066)	.296(.078)	.890(.072)
		[.153,.435]	[.761,1.019]	[.141,.446]	[.727,1.024]
Contextual	γ_{C}		.294(.072)		.295(.077)
			[.153,.435]		[.143,.445]
Random					
Within	σ^2	.261(.011)	.261(.011)	.262(.011)	.262(.011)
		[.240,.282]	[.240,.282]	[.241,.284]	[.241,.284]
Between	τ_0	.014(.011)	.014(.011)	.017(.008)	.017(.008)
		[.003,.025]	[.003,.025]	[.007,.037]	[.007,.036]
Model fit					
Level-1		.348(.025)	.270(.022)	.348(.025)	.270(.022)
R^2		[.298,.398]	[.226,.314]	[.297,.397]	[.226,.313]
Level-2		.473(.172)	.892(.048)	.445(.162)	.880(.056)
R^2		[.129,.817]	[.796,.988]	[.122,.734]	[.738,.953]

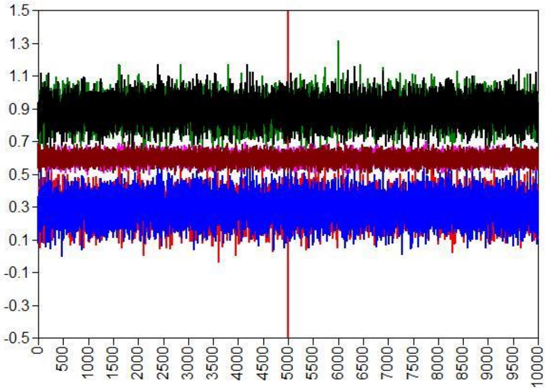
Grand-mean centering



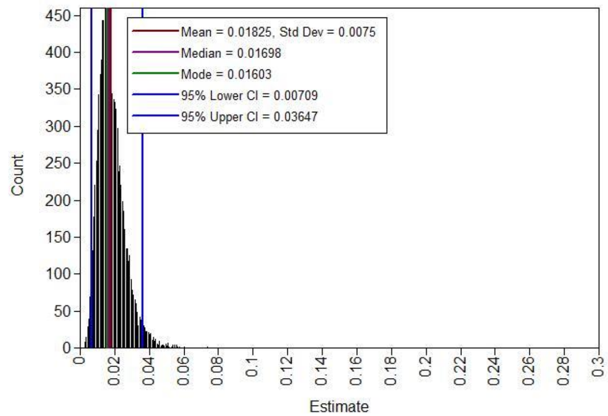
Group-mean centering



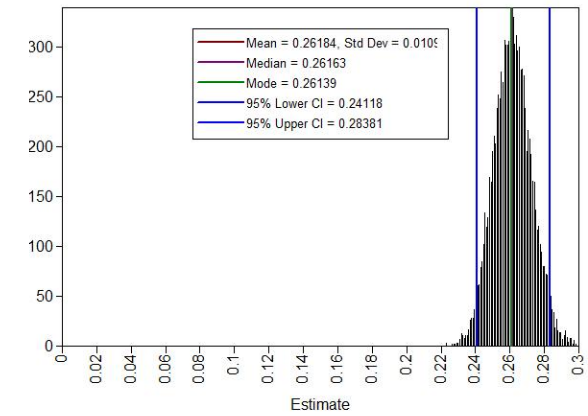
Bayesian results of empirical data



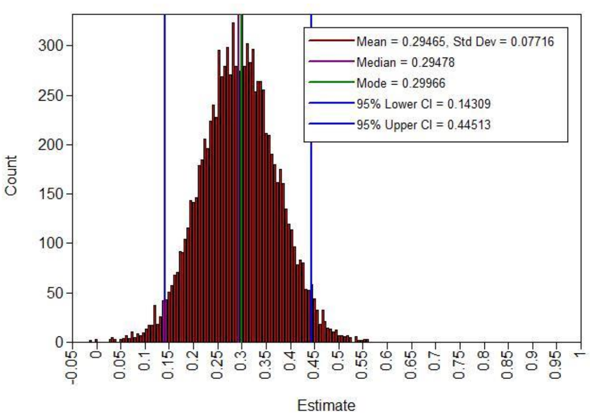
trace and autocorrelation plots for $\beta_{C}, \beta_{W}, \beta_{B}$



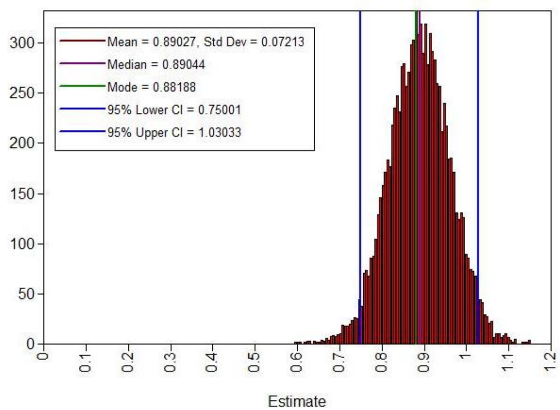
Estimates with .95BCI of τ_0 (between-cluster random effect)



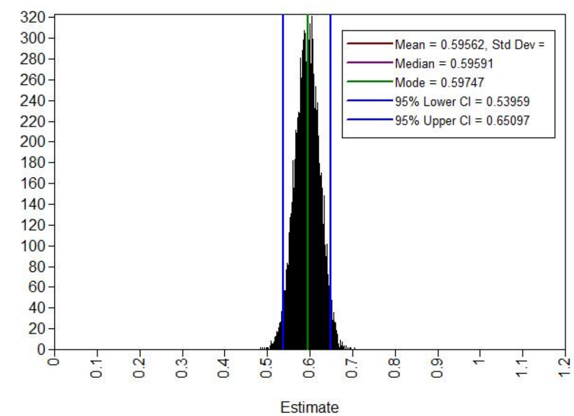
Estimates with .95BCI of σ^2 (within-cluster random effect)



Estimates with .95BCI of β_C



Estimates with .95BCI of β_B



Estimates with .95BCI of β_W

Some insights

1. We need to consider the clustering nature of the human data.
2. ICC play an important role in multilevel data analysis for both predictors and outcomes
3. Both ICCx and ICCy with matching pattern may have impact on the analysis
4. ICC(1) and ICC(2) reflect different psychometrical characters
5. The ICCs of latent variables are extensive with the ICCs concepts of manifest variables
6. Careful choice of estimation methods can provide the unbiased, consistent, and utilized estimates. Bayesian method is one of the alternatives.

Further works

Make a more comprehensive simulation about the effects of matching ICCx and ICCy on a full range of conditions

- Magnitude of ICCx and ICCy
- Differentiate the ICC2 from ICC1
- Different sample size of Level-1 and Level-2

The advantage of Bayesian inferences on the cases of small sample size

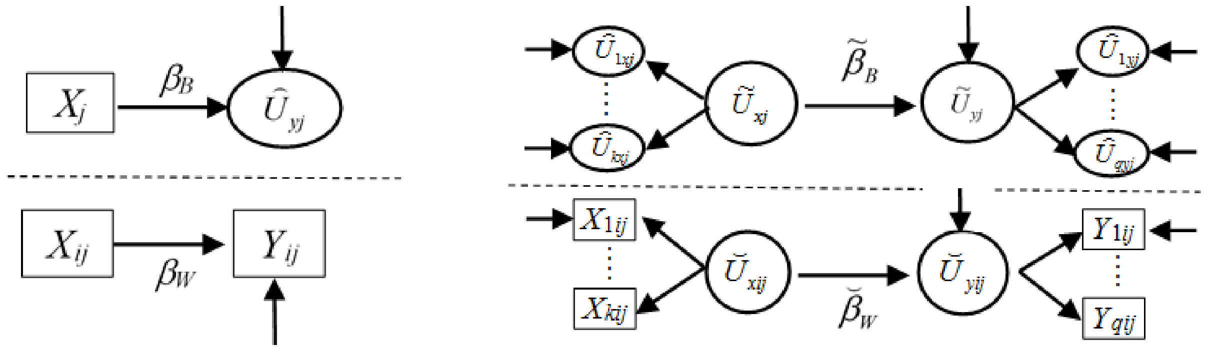
Integrating the sampling error with measurement error

- Appling the Latent variable modeling, i.e., the doubly latent multilevel models (ML-SEM) (Marsh, Lüdtke et al. 2009 , 2012; Lüdtke et al., 2008; 2011)
- Testing for the effects of indicator-number, magnitude of factor loading, on the estimation of contextual effects

While sampling errors meet measurement errors in the multilevel data,

What might be happened?

- *What's the influences of ICC(1), ICC(2)*
- *What's the matching effect of ICC(1)(2) on x and y*
- *What's the impact of the sample size*
- *What's the impact of the item number*
- *What's the estimation of the contextual effects*



Thanks for listening

For further information, please email hawjeng@ntnu.edu.tw