A Comparison of Parceling Strategies in Structural Equation Modeling[1]

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Abstract

The congeneric strategy of aggregating items into parcels was developed and compared to other commonly used parceling strategies (random, item-to-construct balance). Results from a Monte Carlo simulation indicate that the congeneric strategy has less error in estimating the structural coefficient and is more efficient than the item-to-construct balance strategy.

Press paragraph

Within the field there is debate on the appropriateness of parceling, or placing items into groups after collecting data and then using these groups of items instead of individual items to test hypotheses. A new strategy of placing items into parcels was developed. A computer program generated the data used to compare the new strategy (congeneric) to other commonly used parceling strategies (random and item-to-construct balance). The congeneric strategy resulted in a closer approximation to the true estimate of the structural coefficient than the item-to-construct balance strategy. The limitations and practical implications of the simulation study are discussed.

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A Comparison of Parceling Strategies in Structural Equation Modeling

The practice of aggregating items into subsets and using the subsets of items as indicators in structural equation modeling is well known. When the subsets are determined post hoc, the procedure is called parceling. More frequently however, researchers have a prescribed set of items to place into subsets (e.g., subscales of a larger construct). When researchers have to place items post hoc into parcels, considerable debate exists in the literature on when and how this is appropriate (Bandalos & Finney, 2001; Little, Cunningham, Shahar, & Widaman, 2002). The purpose of this paper is to briefly review the issue of parceling items and to describe a simulation study that contrasts various parceling procedures. A new parceling procedure is developed and introduced into the methods literature.

Benefits of Using Parcels

In reviewing the merits of using parcels, Little et al. (2002) identified two broad categories: psychometric and model-level considerations. Psychometric considerations concern the item or indicator properties relative to the latent construct of interest. Items tend to be less reliable than aggregate indicators. Further, items drawn from a more diverse domain will be less efficient and therefore have lower communalities than will aggregate indicators (Little, Lindenberger, & Nesserlroade, 1999). This conclusion assumes that the aggregate indicators are not unduly influenced by nuisance factors in what Little et al. (2002) describe as “dirty measures.” As described above, the potential of shared systematic variance has lead many researchers to be less than optimistic about using aggregate indicators.

Items also have a greater likelihood of distributional violations compared to parcels. Aggregate indicators are more likely to be distributed normally. Items have fewer, larger, and less equal intervals between scale points than do parcels. An item measured on a 5-point scale has only five possible values, whereas an average (or sum) of three such items has 13 possible values. Therefore, parcels will resemble continuous variables more so than will items.

Using parcels has several benefits for evaluating structural equation models. Models based on parcels as compared to single items are more parsimonious in that there are fewer parameters to estimate. For instance, three latent constructs each measured with six items renders a covariance matrix to be analyzed with (18*(18 + 1))/2 = 171 entries. The same model with parceled data (e.g., three parcels each with two items) has (9*(9 + 1))/2 = 45 entries. Models based on parceled data also have fewer chances for residuals to be correlated or for dual loadings to emerge (Little et al., 2002). Other benefits exist (e.g., parceled data reaches convergence more efficiently and have smaller standard errors than item level data), but these are a matter of debate in the literature (cf. Little et al., 2002; Marsh, Hau, Balla, & Grayson, 1998; Nasser & Wisenbaker, 2003).

Dimensionality as a Source of Conflict

With few exceptions, most methodologists would agree that a set of items to be parceled should be unidimensional and relatively free from unwanted sources of shared variance (cf. Bagozzi & Edwards, 1998; Bandalos & Finney, 2001; Kishton & Widaman, 1994). A brief review of classical test theory will assist in illustrating this point. Any observed score for item i, can be conceptualized as having the following components:

$$X_i = T_i + S_i + e_i,$$

where X is the observed score, T is the true score for the latent variable, S is a source of systematic variance unrelated to the latent variable of interest, and e represents random measurement error. The goal of factor analysis is to partition the observed variance in a set of items into their common and unique sources of variance. The common source is that due to the latent variable, whereas the unique source is that due to systematic and error variance. When structural equation modeling is not used, the items are typically averaged to represent the latent variable. This assumes a unit weighting for each item and the observed score for the latent variable contains elements of the true score plus any systematic and unique error. This principle applies whether subsets of items or all items are averaged to represent the construct.

Hall, Snell, and Singer-Foust (1999) demonstrated that small, modest sources of shared systematic variance had dramatic influences on parameter estimation in structural equation modeling. Bandalos (2002) demonstrated that shared sources of variance unrelated to the latent variable of interest influence parameter estimation as well as fit indices. If the unique sources of variance are shared across parcels, then the variance is not removed when estimating the latent variable. The shared variance across parcels is subsumed into latent variable variance. The subsumed variance defines the *distributed uniqueness strategy* for forming parcels (Hall et al., 1999). In contrast, Hall et al. (1999) recommended an *isolated uniqueness strategy* for the formulation of parcels by placing items that share unique variance into the same parcel. Any shared systematic variance can then be separated from the latent variable variance (i.e., it is represented in some but not all parcels).

A problem with the isolated uniqueness strategy of Hall et al. (1999) is in determining the presence of an unrelated latent variable (e.g., social desirability). Hagtvet and Nasser (2004) used a second-order factor analysis strategy to compare isolated versus distributed uniqueness strategies. The work by Bandalos (2002), Hall et al. (1999), and Hagtvet and Nasser (2004) assume the presence of a secondary nuisance factor and that its influence is not shared by every indicator as might be the case for a method factor.

Methods for Parceling Items

Both of the recent reviews of parceling research (Bandalos & Finney, 2001; Little et al., 2002) provide descriptions of methods for parceling items. The rationale for parceling data should be clear and explicit (Bandalos & Finney, 2001; Hall et al., 1999). Further, the reason for parceling should drive the choice of the procedure to use. For instance, if a researcher's goal is simply to improve the normality of indicators, then items should be placed together that will "cancel out" the skewness of other items. Some researchers advocate parceling based on item content (Comrey, 1970, as cited in Bandalos & Finney, 2001), although this is not without controversy.

Cattell (1974; Cattell & Bursdal, 1975) advocated a method he called *radial parceling*. The two-step procedure involved a factor analysis of the items, and then forming parcels based on congruence coefficients of the factor loadings. The procedure is labor intensive and has the potential to place items that reflect different factors into the same parcels (see Bandalos & Finney, 2001; Barrett & Kline, 1981). The radial parceling procedure is most useful in complex multifactor datasets (e.g., personality measures).

Kishton and Widaman (1994) describe a *random* procedure. Little (Little et al., 1999; Little et al., 2002) has argued that randomly assigning items to parcels may be better than using items themselves under certain circumstances. Since parceling strategy has an influence on the measurement of the latent variable, random assignment may not lead to the most accurate assessment of the latent variable.

Little et al. (2002) describe a method that may be useful for developing parcels that are nearly parallel as indicators of the latent variable. The *item-to-construct balance* approach involves alternately assigning items to parcels based on item factor loadings. For example, to form three parcels of two items each, one takes the three highest loading items and assigns them to the first three parcels, respectively. Then, one takes the three lowest loading items and assigns them in reverse order to the three parcels, respectively. The *item-to-construct balance* approach should be used if and only if parallel indicators are desired because the negative influence of measurement error is distributed equally among the parcels thereby making structural equation modeling ineffective at partialing out unique error variance. The result is a smoothed out analysis, but at the risk of distributing uniqueness across parcels.

Finally, one may create *congeneric* rather than parallel parcels. Rather than assume the presence of a nuisance factor, or the need to balance the indicators, one can create parcels that isolate the most similar items in terms of their relationship to the latent factor. The procedure, first articulated by Fletcher (2005), involves placing the items with the most similar standardized factor loadings into the same parcels. For example, if six items are to be parceled into three indicators, the highest two loading items will go into parcel 1, the next two highest will go into parcel 2, and the lowest two items will go into parcel 3.

Several assumptions must be made for this procedure to be viable. First, the items must be unidimensional to ensure that the items will correlate reasonably well within each parcel. Second, reasonable care should be given that the items within a parcel are homogenous (Kishton & Widaman, 1994; Little et al., 2002). It should be noted that the standardized loading to be used for parceling the items are from a completely standardized solution of a confirmatory factor analysis.

The procedure is similar to Catell's radial parceling procedure as well as Hall et al.'s (1999) isolated uniqueness procedure. However, this method presumes neither a multi-factor set of items nor the presence of some nuisance factor. The items will be reasonably homogenous within each parcel, but congeneric across each parcel. The marker indicator should be the one that contains the highest loading items and therefore the least amount of unique variance. In preliminary simulations, this *congeneric method* to parceling items more closely approximates item level estimation of the latent factor, whereas the item-to-construct balance approach to parceling items more closely approximates a unit-weighting of the items. The congeneric indicator approach should 1) remove the ill effects of measurement error by isolating the best items for the measurement of the latent factors, and 2) combine information from multiple items to increase the likelihood of efficiently measuring the latent variable leading to less bias in the structural coefficient.

In sum, the present research investigates several strategies for forming item parcels. The strategies are the use of items (no parcels), directly measured variables (averaging all items into a single parcel), randomly assigning items to parcels, item-to-construct balance approach and the congeneric approach.

Method

Design

The primary focus of the study is to investigate the effects of parceling strategy on the structural coefficients in structural equation modeling. We will look at five parcel strategies: items (no parcels), directly observed (one parcel), random assignment, item-to-construct balance, and congeneric. Three effect sizes will be simulated corresponding to no effect ($\gamma = 0$; to assess Type I error rate), medium effect ($\gamma = .3$) and large effect ($\gamma = .5$). Finally, we will manipulate the reliability of the items: low ($\rho_{xx'} = .84$) and high ($\rho_{xx'} = .92$).

Simulation Description

The data for this Monte Carlo study were simulated using PRELIS 2.72 (Jöreskog & Sörbom, 1996b). The data were generated to reflect the model depicted in Figure 1 with each replication having 200 observations. There were 999 replications for each condition. The model was generated with nine ordinal (e.g., Likert type) items reflecting the latent variable X and three continuous indicators reflecting the latent variable Y. Parcels were created with PRELIS according to the parcel condition. The latent variables X and Y were linked by the structural coefficient γ. The parameters of the items were simulated such that the factor loadings matched Table 1 for either the low or high reliability conditions. The models were estimated for each condition by fixing the marker indicator (e.g., the first parcel/indicator) to one. While this will shift the returned gamma coefficient slightly, fixing the marker indicator to one is a common practice and is necessary in LISREL to provide a metric for the latent variables. Otherwise, LISREL standardizes the latent variables. To reduce concerns of item variability and to be able to create enough variance such that items will be differentially correlated with the latent factor, the item variances were simulated to have a variance = 1 for all items (see Table 1). The data were then estimated using LISREL 8.72 (Jöreskog & Sörbom, 1996a) for each of the 999 replications within each condition.

Analytic Strategy

The primary statistics of interest for examining the effects of parcel strategy for the 999 replications was (1) examine mean and standard deviation of the structural coefficient (γ), (2) examine the root mean square error, (3) efficiency of each parcel strategy relative to using items, and (4) the distribution of the standard errors via the standard error ratio.

The root mean square error is defined as:

$$\sqrt{\frac{\left(\hat{\theta}-\theta\right)^2}{R}}$$

where R is the number of replications (R=999), θ is the population (simulated) effect size (γ = 0, .3, .5), and $\hat{\theta}$ is the estimated value (sampled) value of the structural coefficient for each replication. The efficiency of each method is computed as the ratio of RMSE for that condition divided by the RMSE for the item condition (Mooney, 1997). The standard error ratio is computed as the average of the observed standard errors divided by the empirical standard error. The empirical standard error is the standard deviation of the estimated values for each condition. Values of SER above and below 1.0 reflect over and under estimation of the standard errors.

Results

Table 2a and 2b show the means and standard deviations for the structural coefficient across each of the study conditions. The focus of the results is on the comparison of the balanced and congeneric parceling strategies. The balanced strategy grossly overestimates γ whereas the congeneric strategy more closely resembles that of the use of items as indicators. Further, there is much greater variablilty in the estimates of γ in the balanced strategy across conditions than in the congeneric strategy. Figure 2 displays these results graphically by contrasting the distribution of the estimated coefficients for each condition.

Table 3 shows the RMSE for all conditions. The balanced strategy has a much greater RMSE than the congeneric strategy. That is, the congeneric strategy has less error in estimating the population effect than does the balanced parcel strategy. With respect to comparing these strategies to the use of items, one can see that the congeneric strategy is marginally less efficient (16%; average efficiency ratio = 1.16) than the use of items, whereas the balanced strategy is much less efficient (81%; average efficiency ratio = 1.81) than the use of items (see Table 4).

If the standard errors are not estimated correctly, then the likelihood of Type I or Type II errors increases. Table 5 shows the standard error ratio for each condition. No appreciable pattern emerges with respect the estimation of the standard errors. However, Figure 3 shows significant differences in the distributions of the standard errors across conditions. The balanced strategy has the highest overall standard errors whereas the use of items has the lowest. Perhaps, the overestimation of the γ coefficient in the balanced strategy is off-set by the overestimation of the standard errors (i.e., no risk of statistical decision making error despite the lack of precision).

To assess the Type I error rates for each condition, we counted the number of occasions in which the *t*-value was above or below the critical value of the *t* distribution for the model (df = 198, $t_{\alpha/2}$ = +/- 1.972 for nominal α = .05). With the use of items and low reliability, 35/999 replications represented Type I errors (.035). For items and high reliability, the value was .033. Random parceling rendered .031 and .033 for low and high reliabilities respectively. The balanced parceling strategy rendered .038 and .033 for low and high reliabilities respectively. Finally, the congeneric parceling strategy rendered .035 and .035 for low and high reliabilities respectively. All values were well below the nominal α level of .05.

Discussion

Without a doubt, the use of item parcels in SEM is controversial. Statistical purists would argue that items should be used whenever possible. However, the use of parcels has a long history. Parcels have proved useful in many areas. However, how best to assign items to parcels has not always been clearly articulated. This simulation study compared various methods, namely the item-to-construct balanced approach (Little et al., 2002) and a newly articulated approach based on previous methods, the congeneric approach. In this simulation study, we generated items based on normal theory that closely resembled items commonly used in I/O psychology (e.g., Likert type items). We also scaled the latent variables according to the metric of the first or best loading item/parcel. The items were generated to have approximately the same variance ($\sigma^2 = 1.0$) and the parcels (random, balanced, congeneric) all had three items each averaged. The results demonstrated that the congeneric approach had less variability in estimation of the γ coefficient, and more closely approximated item level estimation than did the balanced approach. The balanced approach to constructing parcels resulted in overestimation of the structural coefficient and its standard errors tended to be correspondingly higher. Statistical decision-making errors are unlikely to result, and standardizing the effects may show little differences. However, since practitioners are often interested in the ‘raw’ metric effects and the practices presented here are consistent with ‘best practices’ in SEM, we think researchers will benefit from using the congeneric approach if parceling is used.

As with any Monte Carlo simulation, the results cannot be generalized beyond the factors simulated. We only simulated a single sample size (n = 200). We have no reason to believe that this would affect the present study. However, future research might investigate whether the standard errors are adversely affected by altering the sample sizes. That is, are the present results similar across all sample sizes? We only looked at two reliabilities and three effect sizes. These values were chosen to represent typical values in SEM research. Finally, when item are parallel, it is unlikely that any of these differences would emerge. Parcel strategy would make no difference in estimation. Of course, in practice, strictly parallel items are rare. Another limitation of this simulation is the potential for items to be misparceled. The parcel assignment is done based on population (simulated) values. To the extent that items were misparceled for some replications, we believe these results to be conservative. That is, item mis-parceling probably attenuated any differences between the item to construct balanced and the congeneric item parceling strategies.

We believe the present study provides a number of implications for the researcher or SEM practitioner. First, if parcels are to be used, and if the items are not parallel, then the congeneric method will result in estimates of the population effect more efficiently than other methods (e.g., random assignment, balanced parcels). The congeneric strategy is less complex than other methods. One first conducts a CFA and then ranks the items according to their standardized factor loadings. The items are then assigned to parcels in rank order. The practice serves to assist in isolating the error variance such that it can be ‘extracted’ in the measurement of the latent variables.

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Table 1.

Measurement Properties of Population Values to be Simulated for X

	Λ_X (Factor Loading)		Θ_δ (Error Variance)		Parcel Assignment		
Item	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$	Congeneric	Balanced	Random
1	0.80	0.95	0.600^2	0.312^2	1	1	3
2	0.75	0.90	0.661^2	0.436^2	1	2	1
3	0.70	0.85	0.714^2	0.527^2	1	3	1
4	0.65	0.80	0.760^2	0.600^2	2	1	3
5	0.60	0.75	0.800^2	0.661^2	2	2	1
6	0.55	0.70	0.835^2	0.714^2	2	3	2
7	0.50	0.65	0.866^2	0.760^2	3	3	2
8	0.45	0.60	0.893^2	0.800^2	3	2	3
9	0.40	0.55	0.917^2	0.835^2	3	1	2

Note. ρ_{xx} is the composite reliability for the simulated items. Items were assigned to the random parcel condition by selecting random integers (1-9) without replacement until all items were assigned.

Table 2a.

Mean of Structural Coefficient (γ)

Parceling Method	No effect (γ = 0)		Medium (γ = .3)		Large (γ = .5)	
	ρ_{xx} = .84	ρ_{xx} = .92	ρ_{xx} = .84	ρ_{xx} = .92	ρ_{xx} = .84	ρ_{xx} = .92
Item	0.001	0.001	0.370	0.311	0.617	0.517
Direct	0.002	0.001	0.410	0.358	0.674	0.597
Random	0.002	0.001	0.436	0.356	0.725	0.592
Balanced	0.002	0.001	0.485	0.387	0.806	0.644
Congeneric	0.001	0.001	0.397	0.329	0.660	0.547

Note. Effect sizes: no effect = 0, medium effect = .3, and large effect = .5. ρ_{xx} is the composite reliability for the simulated items.

Table 2b.

Standard Deviation of Structural Coefficient (γ)

Parceling Method	No effect		Medium		Large	
	ρ_{xx} = .84	ρ_{xx} = .92	ρ_{xx} = .84	ρ_{xx} = .92	ρ_{xx} = .84	ρ_{xx} = .92
Item	0.093	0.075	0.092	0.072	0.091	0.068
Direct	0.104	0.088	0.101	0.084	0.095	0.078
Random	0.112	0.086	0.110	0.083	0.108	0.078
Balanced	0.127	0.095	0.125	0.092	0.123	0.084
Congeneric	0.100	0.079	0.100	0.077	0.099	0.072

Note. The standard deviation of γ is the empirical standard error. Effect sizes: no effect = 0, medium effect = .3, and large effect = .5. ρ_{xx} is the composite reliability for the simulated items.

Table 3.

Root Mean Square Error in Structural Coefficient (γ)

	No effect		Medium		Large	
Parceling Method	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$
Item	0.093	0.075	0.116	0.073	0.149	0.070
Direct	0.104	0.088	0.146	0.103	0.198	0.124
Random	0.112	0.086	0.175	0.100	0.249	0.121
Balanced	0.127	0.095	0.223	0.126	0.330	0.168
Congeneric	0.100	0.079	0.139	0.082	0.188	0.086

Note. Effect sizes: no effect = 0, medium effect = .3, and large effect = .5. ρ_{xx} is the composite reliability for the simulated items.

Table 4.

Efficiency of the Parceling Methods Relative to use of Items (Ratio of Root Mean Square Errors)

	No effect		Medium		Large	
Parceling Method	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$
Item	--	--	--	--	--	--
Direct	1.119	1.178	1.254	1.402	1.332	1.763
Random	1.199	1.159	1.505	1.369	1.679	1.712
Balanced	1.357	1.274	1.917	1.724	2.221	2.383
Congeneric	1.071	1.064	1.199	1.119	1.266	1.224

Note. Values above 1.0 indicate a more efficient parceling method. Values below 1.0 indicate a less efficient parceling method. Effect sizes: no effect = 0, medium effect = .3, and large effect = .5. ρ_{xx} is the composite reliability for the simulated items.

Table 5.

Standard Error Ratio of Structural Coefficient (γ)

	No effect		Medium		Large	
Parceling Method	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$	$\rho_{xx} = .84$	$\rho_{xx} = .92$
Item	1.059	.804	1.067	.827	1.075	.874
Direct	1.546	1.546	1.450	1.441	1.285	1.258
Random	1.037	1.043	1.047	1.050	1.052	1.055
Balanced	1.024	1.037	1.035	1.048	1.043	1.055
Congeneric	1.046	1.042	1.039	1.044	1.035	1.044

Note. Effect sizes: no effect = 0, medium effect = .3, and large effect = .5. ρ_{xx} is the composite reliability for the simulated items. Values above 1.0 reflect overestimation of the standard errors. Values below 1.0 reflect underestimation of the standard errors.

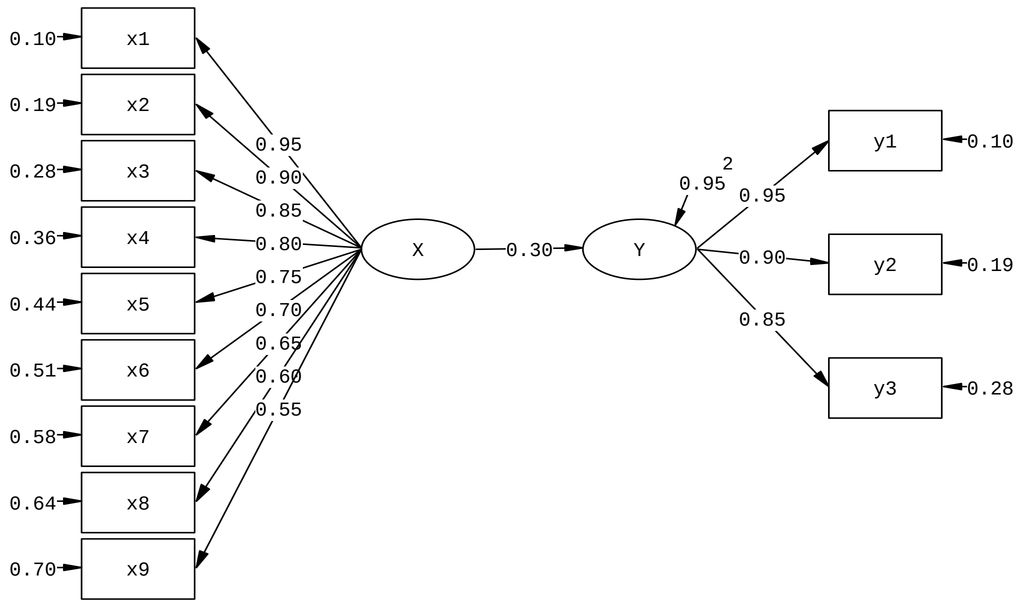

Figure 1. Original simulated model for medium effect size/high reliability.

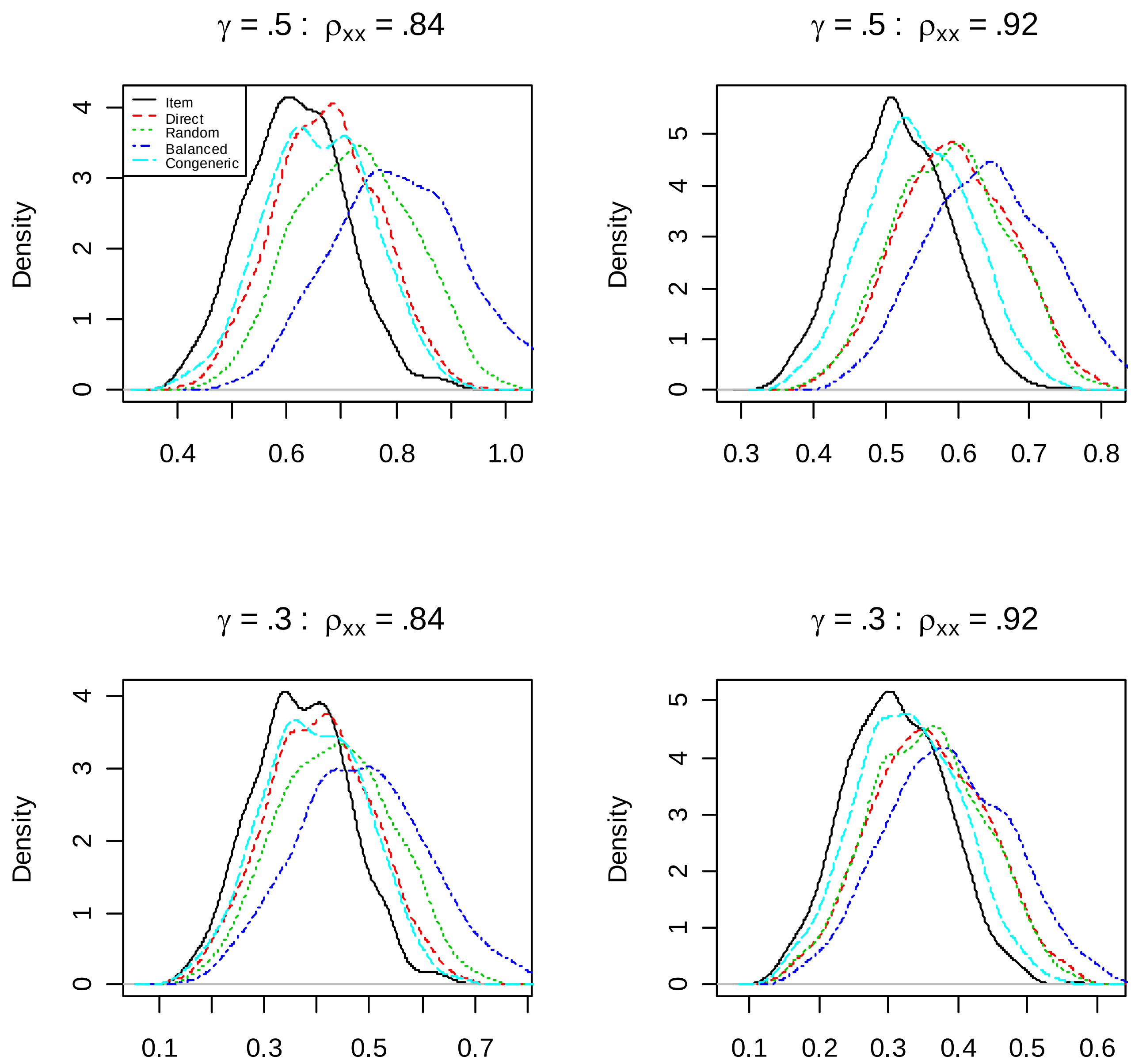

Figure 2. Distribution of Structural Coefficient (γ) for each condition for 999 replications.

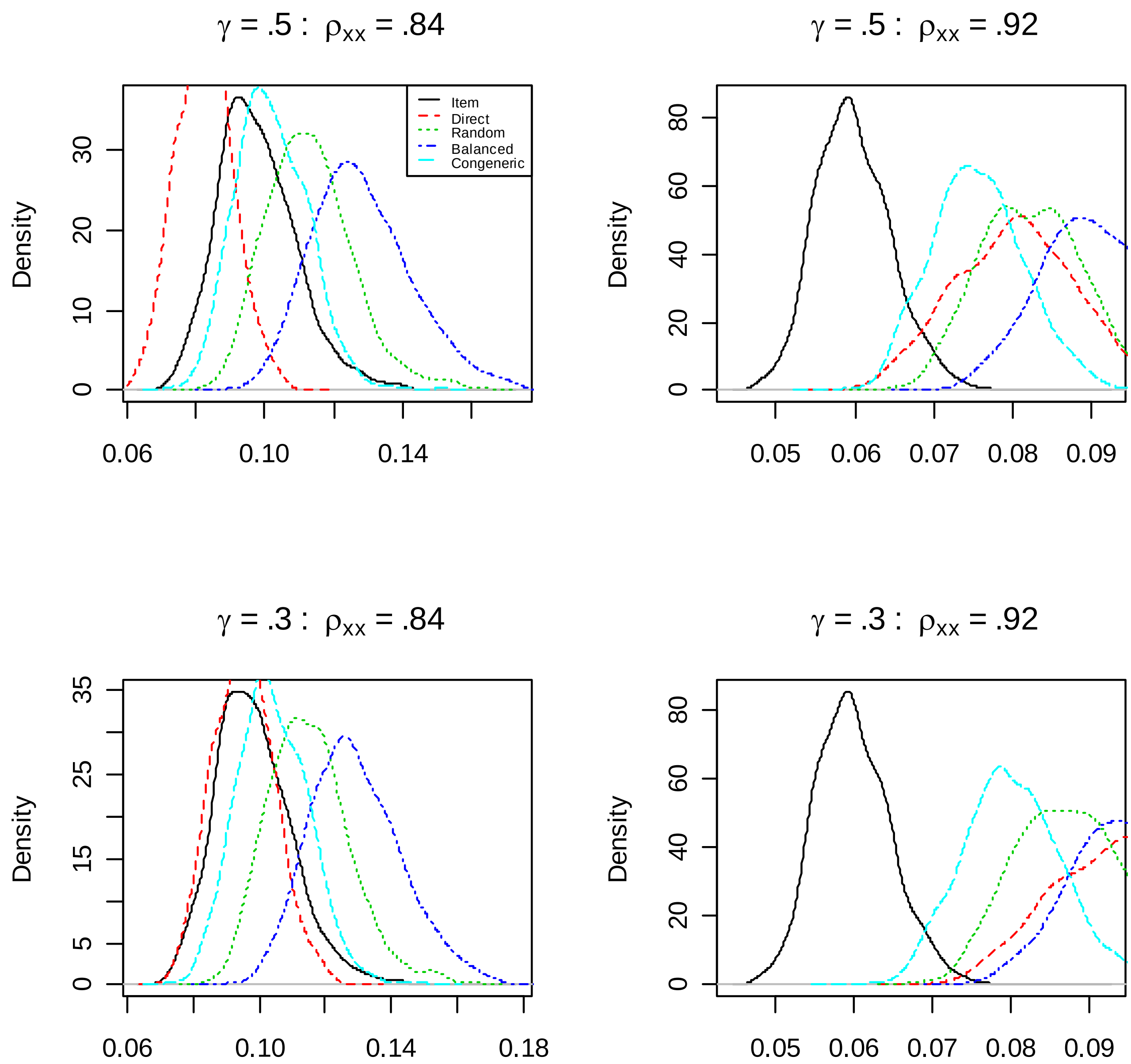

Figure 3. Distribution of Standard Errors for Structural Coefficient for each condition for 999 replications.