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The Effects of Sample Size, Reliability, Number of Indicators Per Factor and Estimation Method on Fit Indices

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THE EFFECTS OF SAMPLE SIZE, RELIABILITY, NUMBER OF INDICATORS
PER FACTOR AND ESTIMATION METHOD ON FIT INDICES

BY

LIN DING

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
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Abstract

A simulation study was conducted to evaluate the effects of sample size (N), reliability/loading (L), Number of indicators per factor (p/m) and estimation method (E) on seven fit indices, including three frequently used fit indices: Chi-square (χ^2), Normed Fit Index (NFI) and Nonnormed of Fit Index (NNFI), and four recently proposed fit indices: Noncentrality d index, Centrality m index, Relative Noncentrality Index (RNI) and Comparative Fit Index (CFI). The performance of these indices were examined over four levels of N (50, 100, 200 and 500), three levels of L (0.50, 0.70 and 0.90), five levels of p/m (2, 3, 4, 5 and 6), and two levels of estimation method (GLS and ML). The results of this study indicated that: 1) All seven indices showed downward bias when sample sizes were small. However, RNI and CFI were relatively less affected by sample size than other indices. 2) Reliability/Loading did not have strong effects on these fit indices (except NFI) in general. 3) All seven fit indices showed downward bias when p/m ratio increased. This effect is much more severe on χ^2 , NFI, d and m than on NNFI, RNI and CFI. 4) All seven fit indices were found to be estimation method specific. The interaction effects of these influence factors were strong. The effect of p/m ratio on fit indices is related to the parsimony problem. The correctness of parsimony justification of these indices was also investigated and discussed.

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INTRODUCTION

Structural modeling attempts to explain the relationships among a set of observed variables in terms of a generally smaller number of latent unobserved variables. The relationships among the observed variables are characterized by the covariances among those variables (Long, 1983). In its general form, a structural model has two components: a measurement model which usually consists of one or more latent factors linking the observed variables to the unobserved variables, and a structural equation model depicting the relationship(s) among the latent variables.

The measurement model can be expressed as

$$[1] \quad \mathbf{y} = \Lambda_y \boldsymbol{\eta} + \boldsymbol{\epsilon}$$

where $\mathbf{y}$ is a $(p \times 1)$ vector of observed variables, $\boldsymbol{\eta}$ is a $(m \times 1)$ vector of common factors (exogenous and endogenous latent variables), and $\boldsymbol{\epsilon}$ $(p \times 1)$ is a vector of unique factors or errors in measurement. Λ_y is a $(p \times m)$ matrix of the loadings of the $\mathbf{y}$'s on the $\boldsymbol{\eta}$'s.

The structural equation model can be expressed as

$$[2] \quad \boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\zeta}$$

where $\mathbf{B}$ is a $(m \times m)$ matrix of coefficients relating the latent variables to one another, and $\boldsymbol{\zeta}$ is a $(m \times 1)$ vector of errors in equations or prediction error.

Most applications of structural modeling involves following four consecutive steps:

(1) Model specification. This refers to formulating the initial model prior to estimation by depicting the hypothesized relationships among the variables. This model

is formulated on the basis of one's theory or past research in the area (Bollen & Long, 1993).

(2) Identification. This refers to determining whether it is possible to find unique values for the parameters of the specified model. If a model can not be identified, the estimation results are meaningless (Bollen & Long, 1993).

(3) Estimation. The general objective in estimating the structural model is to find estimates of the parameters that reproduce the sample matrix of variances and covariances of the observed variables as closely as possible. There are several estimation methods available. Selection of estimation techniques is often determined by the distributional properties of the variables being analyzed (Long, 1983; Bollen & Long, 1993).

(4) Testing Fit. After the estimates are obtained, the researcher can test whether the model is consistent with the data. If so, the process can stop after this fourth step. More typically, the fit of the model could be improved through respecification. Diagnostic indicators are available to guide respecification. Once respecified, step 2 through 4 may be repeated.

Although all steps in applying structural modeling are important researching issues, testing fit has received the most attention. This is because assessing fit is an important issue both theoretically and empirically, and because despite years of work in this area, it remains one of the most controversial topics in structural modeling research. Many fit indices have been proposed, none of which has been generally accepted as the 'best index' by the majority of researchers (Bollen & Long, 1993)

The aim of this project is to empirically evaluate several alternative fit indices, some of which have not been studied as much, under a wide range of conditions using simulated data.

The Development of Fit Indices

In the early literature on structural modeling, the likelihood ratio chi-square statistic was widely used to evaluate fit. The rationale for this fit assessment is that: if the model was specified correctly and if the distributional assumptions for the data were satisfied, then analysts could use the test statistic which has an asymptotic χ^2 distribution to test the null hypothesis that the specified model leads to an exact reproduction of the population covariance matrix of the observed variables (Bollen & Long, 1993). As its rationale indicates, χ^2 is a badness-of-fit measure -- it gets larger as the fit worsens. This test has been criticized by numerous researchers (e.g., Gerbing & Anderson, 1993). First, it is a badness-of-fit test, i.e., it attempts to prove the null hypothesis. The value of the statistic can go to infinity, which indicates a poor degree of fit. Second, sample size has a strong effect on its value (e.g., Bentler & Bonett, 1980; Marsh, Balla & McDonald, 1988). Increasing sample size leads to increasing statistical power. Therefore, when sample size becomes increasingly large, even a correctly specified model could be rejected. This tendency can be proven by its formula $\chi^2 = (N-1)FF$, where FF is the fitting function obtained by a particular estimator and N is the sample size. FF is independent of sample size, so, two equally well fitting models can have the same FF value. However, the model with the larger sample will have a larger χ^2 . The bigger the

χ^2 value, the more likely it is statistically significant, and the more likely it is to be rejected. Third, the test is very sensitive to violations of the distribution assumptions (Harlow, 1985). With highly kurtotic data, the χ^2 will tend to be inflated, thus leading to a higher probability of incorrectly rejecting a correct model. Fourth, the performance of this test statistic in simulation studies, i.e. under ideal conditions, has shown that it can be very inaccurate (Zwick & Velicer, 1982, 1986; Velicer & Jackson, 1990).

Since the realization of these major problems with χ^2 as a fit index, researchers have developed alternate fit indices (e.g., Bentler & Bonett, 1980; Hoetler, 1983; James, Mulaik & Brett, 1982; Jorekog & Sorbom, 1981). In fact, a large number of indices have been developed. Selecting a good fit index is now a problem, because there are so many and none has yet proven to be superior to all others.

Gerbing and Anderson (1993) proposed three properties which the ideal fit index should have: (1) Indicate degree of fit along a continuum bounded by the values 0 and 1, where 0 reflects a complete lack of fit and 1 reflects perfect fit; (2) be independent of sample size (higher or lower values would not be obtained simply because the sample size is large or small); and (3) have known distributional characteristics to assist interpretation and allow the construction of a confidence interval.

Although a few indices have demonstrated one or more of these properties, no one index has convincingly been shown to satisfy all of these conditions acceptably. Further, not all researchers would even agree with all these criteria. However, results from studies which evaluate fit indices can: (1) guide the interpretation of the fit indices; (2) provide a basis for selecting a fit indices; and (3) provide an overview of the

performance of the index under different conditions.

Alternative Fit Indices

Different fit indices have been proposed based on different theoretical justifications. Most indices attempt to assess the degree to which the model accounts for the sample covariances. Marsh, Balla and McDonald (1988) classified fit indices into three types: (1) Stand-alone Indices, (2) Type I Incremental Fit Indices, and (3) Type II Incremental Fit Indices.

Stand-alone Indices. These indices are based on the results compared to just the target model. The target model is the a priori model posited by the researcher to fit the data. The χ^2 test and χ^2/df ratio are of this type of index.

Incremental Fit Indices. Bentler & Bonett(1980) proposed that model fit can be evaluated by the degree to which the model accounts for the sample covariances relative to a more restricted model. Typically this involves a series of nested models, i.e, a series of succeedingly more complex models, each including all of the parameters of the simpler model. The most basic model is usually a null model in which all the observed variables are assumed to be uncorrelated, and only "p" variables are estimated. This approach yields incremental fit indices. The two alternative forms of the incremental indices are:

$$[3] \quad \text{Type I indices} = |t - n| / \text{Max}(t, n)$$

$$[4] \quad \text{Type II indices} = |t - n| / |e - n|$$

where t is the value of a stand-alone index for the target model, n is the value for the

null model, and e is the expected value of the stand-alone index if the target model is true.

A Type I Fit Index involves only empirically derived values for the null and target models. The Normed Fit Index (NFI) (Bentler & Bonett, 1980) based on χ^2 values for the null and target models, belongs to this type. James et al (1982) have found that both Stand-alone and Type I Incremental Fit Indices can be improved by simply freeing more parameters regardless of the appropriateness of the model. Therefore, James et al. (1982) proposed a new class of indices that adjusts for the additional degrees of freedom (df) included in parsimonious models. A Parsimonious Fit Index invokes a penalty function for using additional parameters by multiplying a Stand-alone or a Type I Incremental Index by the ratio of the dfs for the target over the null models.

In addition to empirically derived values for the target and null models, a Type II Incremental Index requires the expected value for a true model (e.g. Nonnormed Fit Index (NNFI)). For example, when indices of this type are based on χ^2 , the expected value for a true model χ^2 is the df . This type of index, by definition, takes df into account, which is supposed to avoid the problem of not adjusting for the use of additional parameters. Therefore, theoretically, parsimony indices for this type would be unnecessary.

Besides the parsimony issue, the dependence of the fit index on sample size is another problem. The obtained value of most proposed indices have been showed to be noticeably biased downward for relatively small sample sizes (e.g. Marsh, Balla and McDonald, 1988). McDonald (1989), Steiger (1990), and Bentler (1990) proposed a

class of new indices based on the use of the noncentrality parameter from the noncentral χ^2 distribution. These new incremental indices are supposed to be sample size independent. While these new indices are promising, an empirical evaluation of their performance is needed.

A total of seven indices, including three Stand-Alone Indices, a Type I Incremental Fit Index, and three Type II Incremental Fit Indices were chosen for inclusion in this study. Some of these indices have been frequently reported in the application literature, but there is only limited evaluation information. The parsimony version of all these indices is also evaluated. Even though Type II Incremental Fit Indices have taken df into account as part of their formulation, deriving parsimonious indices based on them can be used as a comparison to see if these indices really do not need this adjustment.

The seven indices that are assessed in this study are described more fully below.

Definitions of Fit Indices

1. Chi-Square Index.

Let χ_n^2 be the Chi-square value for the null model with degrees of freedom df_n ; let χ_t^2 be the Chi-square value for the target model with degrees of freedom df_t , and:

$$[5] \quad df_n = p \times (p-1)/2$$

$$[6] \quad df_t = [p \times (p+1)/2] - t$$

where p is the number of observed variables and t is the number of free parameters in the model. The Chi-Square index to be evaluated is simply χ_t^2 .

2. Normed Fit Index (NFI).

Based on empirically derived Chi-square values for the target (χ_t^2) and null (χ_n^2) models described above, Bentler and Bonett (1980) proposed their Type I Incremental Fit Index as:

$$[7] \quad \text{NFI} = (\chi_n^2 - \chi_t^2) / \chi_n^2$$

This index assesses fit by comparing the target model with a more restricted null model in which all observed variables are assumed to be uncorrelated. The NFI can range from zero to one, with values closer to one preferred. This would correspond to having a smaller χ_t^2 value compared to the χ_n^2 value, also indicating better model fit.

3. Nonnormed Fit Index (NNFI).

Based on the Tucker-Lewis (1973) index (TLI), which was developed in factor analysis, Bentler and Bonett (1980) proposed their Type II Incremental Fit Index, the Nonnormed Fit Index (NNFI), which involves the χ^2/df ratio rather than just the simple χ^2 value. The index can be expressed as

$$[8] \quad \text{NNFI} = (\chi_n^2/\text{df}_n - \chi_t^2/\text{df}_t) / (\chi_n^2/\text{df}_n - 1).$$

Unlike NFI, NNFI can exceed the 0 and 1 range.

NFI and NNFI have been used in an absolute sense, where 1 indicates a perfect fit and 0 indicates a complete lack of fit (as bad as the null model). An index value of 0.9 or above has been conventionally regarded as indicating good to excellent fit for both fit indices.

4. Noncentrality d Index.

The noncentrality d is an index proposed by McDonald (1989) and others. Let δ be the noncentrality parameter from the noncentral χ^2 distribution. Then, d is a sample estimate of δ , where small values of d indicate good fit, and

$$[9] \quad d = \chi^2_t / (N-1) - df_t / N,$$

where N is sample size. The d index is not bounded by the 0 to 1 range of the NFI and NNFI, and can take on any value.

5. Centrality Index m

For ease of interpretation, McDonald (1989) defines the following index of centrality,

$$[10] \quad m = \exp (-1/2 d).$$

This index is bounded by 0 and 1, where 1 indicates perfect fit. However, sampling error can make m exceed 1. Both d and m are stand-alone indices.

6. Relative Noncentrality Index (RNI).

A Type II Incremental Fit index based on d alone, the relative noncentrality index (RNI), was defined by McDonald and Marsh (1990, p.250) as

$$[11] \quad \text{RNI} = 1 - d_t / d_n,$$

where d_t is the d value for the target model, and d_n is the d value for null model.

Although a value of 0 indicates a complete lack of fit, and 1 indicates a perfect fit, RNI, like NNFI, is not necessarily bounded by 0 and 1.

7. Comparative Fit Index (CFI).

For interpretational ease, Bentler's (1990, p.241) Comparative Fit Index is preferable. This index is defined as

$$[12] \quad CFI = 1 - d_t^*/d_n^*,$$

where $d_t^* = \max(d_t, 0)$ and $d_n^* = \max(d_n, d_t, 0)$. By definition, d_t^* and d_n^* are nonnegative.

Because $d_n^* > d_t^*$, CFI is normed, bounded between 0 and 1, with 1 indicating a perfect fit. When the value of RNI is between 0 and 1, $RNI = CFI$.

The last four indices were only recently proposed and have not been studied extensively.

For each of the seven indices, the corresponding parsimony indices (PI) can be derived as

$$[13] \quad PI_t = (df_t/df_n) I_t,$$

where I_t is any of the above fit indices, e.g.,

$$[14] \quad PNFI = (df_t/df_n) NFI.$$

Therefore a total of 14 indices will be evaluated in this study. They are summarized in Table 1.

Table 1

Summary of 14 Indices to be Evaluated

Index	Regular	Parsimonious
Chi-Square	χ^2	$P \times \chi^2$
Normed Fit Index	NFI	$P \times \text{NFI}$
Nonnormed Fit Index	NNFI	$P \times \text{NFI}$
Noncentrality Index	d	$P \times d$
Centrality Index	m	$P \times m$
Relative Noncentrality Index	RNI	$P \times \text{RNI}$
Comparative Fit Index	CFI	$P \times \text{CFI}$

Note. $P = (df_t / df_n)$; df_t = degrees of freedom in a target model;
 df_n = degrees of freedom in a null model.

Fit index and estimation

Let S be the sample covariance matrix and let Σ be the population covariance matrix. For a general structural model, Σ can be decomposed into four possible functions of the parameter matrices:

$$[15] \quad \Sigma = \frac{\Lambda_y (I-B)^{-1} (\Gamma \Phi \Gamma' + \Psi) (I-B)^{-1} \Lambda_y + \Theta_\epsilon \quad | \quad \Lambda_y (I-B)^{-1} \Gamma \Phi \Lambda_x'}{\Lambda_x \Phi \Gamma' (I-B)^{-1} \Lambda_y \quad | \quad \Lambda_x \Phi \Lambda_x' + \Theta_\delta},$$

where Λ_x is a loading matrix of exogenous observed variables on exogenous latent variables; Λ_y is a loading matrix of endogenous observed variables on endogenous variables; B is a matrix of coefficients relating the endogenous latent variables to one another; and Γ is a matrix of coefficients relating the exogenous latent variables to the endogenous variables. Φ is a matrix of correlations among latent exogenous variables. Ψ is a covariance or correlation matrix of the errors. Θ_δ is a matrix of unique factors for observed exogenous variables. Θ_ϵ is a matrix of unique factors for observed endogenous variables.

An estimate of Σ is Σ^* , where Σ^* is defined by the estimation of the corresponding parameters in the covariance matrix. The problem of estimation is to measure how close Σ^* is to S , and to find the values of parameters that produce the Σ^* that is as close as possible to S . A function that measures how close a given Σ^* is to the sample covariance matrix S is called a fitting function, $F(S, \Sigma^*)$.

Different estimation methods are available. Some make assumptions about the distributional properties of data (such as generalized least squares (GLS) and Maximum Likelihood (ML)), and some do not (such as unweighted least squares (ULS)). When the

data has a multivariate normal distribution, both GLS and ML have desirable asymptotic properties (Browne, 1974), which gives GLS and ML the advantage of having test statistics associated with them, while ULS does not.

Given the same data set, summaries of fit based on different estimation procedures should yield approximately the same results. However, a limited number of studies which investigated the effects of estimation method on fit indices (e.g., Tanaka, 1993; La Du & Tanaka, 1989) have shown that many fit indices vary as a function of estimation method. Therefore, fit indices must be evaluated under different estimation methods. Although GLS is widely available, ML has been predominantly used in both applications of structural modeling and simulation studies of fit indices. Since relatively little is known about the behavior of fit indices with GLS, both GLS and ML will be used in this study.

The GLS fitting function is

$$[16] \quad F_{GLS} = \text{tr}[(S - \Sigma^*)S^{-1}]^2;$$

The ML fitting function is

$$[17] \quad F_{ML} = \text{tr}(\Sigma^{*-1} S) + [\log |\Sigma^*| - \log |S|] - p,$$

where Σ^* is the estimated population covariance matrix, S is the sample covariance matrix, and p is the number of observed variables, including both independent and dependent variables.

In this study, normal data will be used. Results from both estimators will be compared, and the effects of estimation methods and their interaction effects with other factors such as sample size, loading size, and p/m ratio will be evaluated.

Potential Factors Influencing the Fit Indices

Sample size, loading size, p/m ratio (number of indicators (p) per factor (m)) and estimation method have been recognized as factors that may affect the fit indices.

Sample Size. When the multivariate normality assumption is met, the effect of sample size on the goodness of fit indices has been studied by a number of researchers (e.g. Anderson & Gerbing, 1984; Bearden, Sharma & Teel, 1982; Boomsma, 1982, 1985; Marsh et al., 1988; Mulaik et al., 1989). These studies have come to similar conclusions: 100 is the minimum recommended sample size for a model. Studies investigating the relation of sample size to component pattern or factor pattern recovery (e.g., Velicer, Peacock & Jackson, 1982; Velicer & Fava, 1993; Guadagnoli & Velicer, 1988) have found that a minimum sample size of 150 is usually sufficient to obtain accurate estimation.

Loading / Reliability. The effect of the size of the loading/reliability in structural modeling has only been studied by a few researchers (e.g., Boomsma 1982; Anderson & Gerbing, 1984). However, a great deal of research has been done in the field of Factor/Component Analysis (Velicer, 1974; Guadagnoli & Velicer, 1988; Velicer & Fava, 1987, 1993; Fava & Velicer, 1992a, 1992b, 1993). The FA/PCA studies conducted by Velicer and his colleagues have found that the size of a loading has a very strong effects on factor pattern recovery (Velicer & Fava, 1987) and the stability of a factor pattern (Guadagnoli & Velicer, 1988), with higher values preferred. Studies by

Boomsma (1982) and Anderson and Gerbing (1984), using a confirmatory factor model, did not find that loading/reliability had as strong an effect as sample size on the goodness of fit indices. Since there have not been many studies studying this in a structural modeling framework, it is of interest to determine the extent to which the findings from FA/PCA studies generalize to structural modeling, which is more complex than FA/PCA.

Ratio of Indicators to Factors (p/m). Findings evaluating the effect of p/m ratio (number of indicators per factor) are even more complex. The general conclusions are well established in the FA/PCA literature: The more indicators per factor, the better pattern recovery (Velicer & Fava, 1987, 1993). Also, the more stable the factor pattern, the less affected it will be by under-or over-extraction of factor/components (Fava & Velicer, 1992b, 1993). Findings from a very limited number of studies in the confirmatory factor analysis area are more complicated. Anderson and Gerbing (1984) used three levels of number indicators per factor (2,3,4) for their confirmatory factor model. They found that with more indicators per factor, the proportion of convergent and proper solutions increased. This replicates the factor analysis results of Velicer and Fava (1987, 1993). However, the value of the Goodness of Fit indices decreased (i.e. indicating a worse model fit with more indicators). The reason for this, as noted by Gerbing and Anderson (1993), is probably related to the issue of parsimony. However, such a result is troubling because more indicators should always be a positive situation. Clearly, more research about the effect of number of indicators per factor is needed.

Estimation Method. The effect of estimation method on fit indices has been largely overlooked in the literature of structural modeling (Tanaka, 1993). Most of the findings are based on Maximum Likelihood estimation exclusively. Although GLS has the same asymptotic property as ML when the normality assumption is met (Browne, 1984), a study conducted by La Du and Tanaka (1989) found that even supposedly estimation-method-free fit indices (such as NFI) were affected by choice of estimator. However, this study only considered sample size. Interaction effects involving estimation method with loading size and p/m ratio were not considered. Most of the comparisons between GLS and ML have focused on the problem of nonnormality (e.g. Huba & Harlow, 1983; Harlow, 1985; Muthen & Kaplan, 1985; Brown 1990). GLS and ML have been found to be robust and result in similar solutions for normal to moderately skewed data (Muthen & Kaplan, 1985; Huba & Harlow, 1983; Harlow, 1985). Unfortunately, all these conclusions are based on sample sizes of 400 or more. It seems that GLS has been assumed to perform identically to ML when the data is normally distributed. However, only limited empirical evidence exists to support this assumption.

Interaction Effects. Sample size, loading size, and p/m ratio may interact with each other. Fit indices may perform worse under the combinations of poor conditions (e.g. small sample size combined with low loadings). On the other hand, when sample size is sufficiently large (e.g., 400 or more) or the loadings are high (e.g., 0.8 or higher), the other factors may have little effect on indices. Interaction effects involving estimation method with these other factors have not been sufficiently evaluated.

Goals of This Study

This project will expand previous studies of fit indices in the following ways:

(1) The most important feature of this study, compared to previous studies, is that a general form of a structural model will be used rather than a simple confirmatory factor analysis (CFA) model (as most previous simulation studies used). In a structural model, the population covariance matrix is based on Λ_x , Λ_y , Φ , Ψ , B , Γ , Θ_δ , and Θ_ϵ . This involves more, and different kinds of, parameters than in a confirmatory factor model. In a CFA model, the population covariance matrix is reduced to $\Lambda_x \Phi \Lambda_y + \Theta_\delta$. The addition of a structural equation model will introduce regression coefficients and prediction errors into the reproduction of the covariance matrix. This makes a structural model a more complex model than a CFA model. Most structural modeling applications are more interested in the structural relationships among the latent variables, rather than just the relationships between the latent and manifest variables. Therefore, in practice, a general structural model may be more relevant than a confirmatory factor model. Conclusions based on a structural model will have more generalizability.

(2) This study will simultaneously evaluate a large number of fit indices, whereas most other studies have chosen only a smaller set of similar types of fit indices to evaluate. LISREL's (Joreskog & Sorbom, 1981) fit indices such as GFI, AGFI and RMR have received extensive evaluation. For other indices there is almost no empirical evaluations available. This study tries to evaluate all three types of fit indices, choosing representative set of fit indices for each type. Among them, χ^2 has been studied by many researchers. It is included here as a comparison to other fit indices. NFI and NNFI been

evaluated empirically. NFI has been found to substantially underestimate fit under conditions of small sample size. NNFI has been found to perform better with small sample sizes on average, but has demonstrated large sample variation (Mulaik et al, 1989; Marsh et al., 1988). NFI has been found to be estimation specific (La Du & Tanaka, 1989). However, none of these indices has been evaluated for effects of p/m ratio, and NNFI has not been evaluated for estimation method effect. The recently proposed indices, d , m , RNI and CFI, are supposed to be sample size independent. However, they have not been evaluated under a wide range of conditions. The results of this study will provide useful information regarding the performance of these fit indices.

(3). The impact of parsimonious corrections on different fit indices will be evaluated. The effect of p/m ratio should be related to the problem of parsimony. The df_i/df_n ratio for each p/m ratio (2,3,4,5,6) in this study are 0.46, 0.69, 0.79, 0.83, and 0.86, respectively. As we can see, the larger the p/m ratio, the more parsimonious the model. Since James et al. (1982) introduced parsimonious indices into the literature, little research has been done to address such issues as: (a) What is the optimal value (upper bound) of a parsimony index under perfect conditions? Because the df_i/df_n ratio will always be less than 1 (unless the true model actually is the null model), even when the model has a perfect fit value for some index, e.g. when $NFI=1$, the value for its corresponding PNFI will generally be less than 1. This feature of the parsimony index makes it very difficult to interpret. In this study, models will be correctly specified and the obtained value of the parsimony index under these conditions should be the optimal value. This will provide valuable information for researchers who use these indices. (b)

Is the adjustment provided by a parsimony index accurate? The purpose of a parsimonious fit index is to adjust stand-alone and type I indices. However, little research has been done to determine if this adjustment is correct, i.e. neither an under-or over-adjustment. This study will address this issue.

(4) All these indices will be evaluated for both GLS and ML solutions. Issues regarding to the effect of estimation methods and its interaction effect with other factors such as sample size, loading, and p/m ratio on fit indices will be addressed. This will expand the La Du and Tanaka (1989) study.

METHOD

Hypothesized Models

A three-construct model (the first two serve as uncorrelated independent factors and the third as a dependent factor) was hypothesized as the population structure underlying the simulations. Five levels of the number of indicators and three levels of indicator reliability were combined for a total of fifteen initial population or true variance-covariance matrices to be generated. The population or true values for the variances of the two independent constructs were set at 1.00. The regression coefficients and prediction error for the dependent construct were set at 0.50 for all the models.

An example of this model with 2 indicators per factor is illustrated in Figure 1.

Figure 1. Estimated Model with p/m=2 and Free Loadings=0.50

Note: 1. Observed variables are represented by Vs, unique variance or error immeasurement are represented by Es, Latent Variables are Fs.

2. Values inside parentheses are population values. They served as starting value in the model estimation.

3. * indicates free parameters . Fixed values are those not inside parentheses and without * sign.

Study Design

The design is a $4 \times 3 \times 5 \times 2$ (4 levels of sample size, 3 levels of loadings, 5 levels of the number of indicators per factor, 2 levels of estimation method) factorial design with repeated measures over the last factor (estimation methods).

For most multivariate studies, a sample size of 80 is considered to be fairly low and may produce unreliable results. Sample sizes over 200 are thought to produce stable results (Boomsma, 1982; Velicer et al. 1982; Guadagnoli & Velicer, 1988). However, in structural modeling applications, researchers have used sample sizes as small as 50. In order to cover a wide range of sample sizes found in structural modeling applications, four levels of sample sizes were chosen: 50, 100, 200, and 500. This range has been suggested by the literature (Anderson & Gerbing, 1984) to reflect a sample size ranging from very poor (50), fair (100), good (200) to excellent (500).

Low to high loadings (the square root of indicator reliabilities) are represented by uniform loadings of 0.50, 0.70, and 0.90. In a measurement model, a loading of 0.40 is commonly used as cut off point for selecting a item. When loadings exceed 0.80, indicators are considered to be very solid (Velicer et al.,1982). In this study, we choose 0.50 as the lower bound instead of 0.40 based on reliability considerations. For a loading of 0.5, only 25 percent of this indicator's variance is explained by the factor it belongs to. This is already a very low value.

The lowest bound of p/m ratio for a latent factor is 2 indicators per factor. Previous research in factor analysis (e.g. Guadagnoli & Velicer, 1988; Velicer & Fava, 1987, 1993) suggests that the variable to factor ratio is crucial to factor stability and

pattern recovery. The ratio $p/m = 3$ is the lowest acceptable bound, based on the Anderson and Rubin (1956) identification conditions. In the structural modeling applications, $p/m = 6$ or more is rare. Most applications fall within the range of 2-5. In order to evaluate the effect of p/m ratio thoroughly, we included 2 as our lower bound, and 6 as our upper bound. This range covers almost all possible structural modeling applications.

The design of this study is illustrated in Figure 2.

Sample generation

The combination of three levels of loadings and five levels of p/m ratio results in a total of fifteen population variance-covariance matrices. An example of a population variance-covariance is given in Table 2. EQS is a structural modeling program developed by Bentler (1989). The PC version (Bentler & Wu, 1990) has a built-in simulation procedure. This procedure was used to generate sample covariance matrices.

With four sample sizes for each initial population model, a total of 60 sets of sample variance-covariance matrices were generated with 100 replications in each set. Multivariate normal distributions were assumed. All models were perfectly specified.

Each sample was estimated using EQS. Both GLS and ML solutions were produced. χ_n^2 , χ_t^2 , NFI and NNFI are part of the regular output of EQS. In addition, the d , m , RNI, and CFI indices and all PI_t s were calculated.

Figure 2. Study Design

Sample Size	Loading Size	p/m ratio	Estimation Method	
			GLS	ML
N=50	.50	2		
		3		
		4		
		5		
		6		
	.70	2		
		3		
		4		
		5		
N=100	.50	2		
		3		
		4		
		5		
		6		
	.70	2		
		3		
		4		
		5		
N=200	.50	2		
		3		
		4		
		5		
		6		
	.70	2		
		3		
		4		
		5		
N=500	.50	2		
		3		
		4		
		5		
		6		
	.70	2		
		3		
		4		
		5		

Table 2

Example of Population Variance-Covariance Matrix
($p/m=2$, Free Loadings = 0.5)

1.0						
0.25	1.0					
0.0	0.0	1.0				
0.0	0.0	0.25	1.0			
0.25	0.25	0.25	0.25	1.75		
0.125	0.125	0.125	0.125	0.5	1.0	

Data Analyses

(1) Nonconvergence and Boundary cases

Frequency of nonconvergence and boundary cases are reported. If a sample did not converge with either GLS or ML or both, this sample was excluded from any further analysis.

(2) Summary Statistics

For χ^2 , the percentage of significant χ^2 values with $p < .05$ (i.e. those rejecting the null hypothesis) is reported as a summary statistic for each condition. For the other indices, the means and standard deviations for the indices are reported as summary statistics.

(3) Effects

A series of four-way Analyses of Variance were conducted to assess the following main effects and interaction effects on each of the fourteen fit indices (seven indices, both corrected and uncorrected for parsimony): (1) Main Effects: Sample Size (N), Loading size (L), Number of indicators per factor (k), i.e. p/m, Estimation Method (E); (2) Interaction Effects: $N \times L$, $N \times k$, $N \times E$, $L \times k$, $L \times E$, $k \times E$ and the higher order interactions. The critical value was set at $\alpha = 0.01$ for all ANOVA tests. Because of the extreme power of this study, only results with $\eta^2 \geq 0.05$ will be interpreted.

RESULTS

1. Non-convergence and boundary cases

Non-convergence. The frequency of nonconvergence occurring among 100 replicates is summarized in Table 3. The large number of non-convergent cases happened under the conditions of $N=50$, $L=.5$, the low sample size, low loading condition. This is consistent with results reported in a factor analysis context (e.g., Velicer & Fava, 1987, 1993). The frequency of non-convergence ranged from 7 to 63 across five p/m ratio models for the GLS solution and 3 to 73 for the ML solution. However, once the sample size reached 100 or the loading size reached .70, non-convergent cases were rare. GLS produces slightly more nonconvergent cases than ML does, in general. Non-convergent cases were deleted before performing any further analysis.

Boundary cases. The frequency of boundary cases occurring among 100 replications is summarized in Table 4. A clear relationships between the occurrence of boundary cases and sample size, loading size, and the number of indicators per factor can be seen. The occurrence of boundary cases decreased 1) when N increased; 2) when L increased; and 3) when p/m increased. These findings are consistent with previous findings (Boomsma, 1982; Anderson & Gerbing, 1984; Gerbing & Anderson, 1987; Velicer & Fava, 1987, 1993).

While the trends for both GLS and ML are the same, there are more boundary cases from the GLS solutions than from the ML solutions. When p/m increases, there is a bigger drop in the number of boundary cases for the ML solutions than with GLS solutions.

Table 3

Frequency distribution of non-convergent cases among 100 replicates across all conditions

		GLS				ML			
	p/m	N=50	N=100	N=200	N=500	N=50	N=100	N=200	N=500
L = .50	2	7	3	0	0	3	1	0	0
	3	31	0	1	0	42	1	0	0
	4	10	1	0	0	5	0	0	0
	5	63	2	0	0	73	0	0	0
	6	22	3	0	0	1	0	0	0
L = .70	2	9	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	4	1	0	0	0	0	0	0	0
	5	2	0	0	0	0	0	0	0
	6	6	0	0	0	0	0	0	0
L = .90	2	0	0	0	0	1	0	0	0
	3	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0
	5	2	0	0	0	0	0	0	0
	6	5	0	0	0	0	0	0	0

Table 4

Frequency distribution of boundary cases
among 100 replicates across all conditions

		GLS				ML			
	p/m	N=50	N=100	N=200	N=500	N=50	N=100	N=200	N=500
L = .50	2	74	46	12	0	72	50	15	0
	3	84	14	1	0	80	8	2	0
	4	45	7	0	0	16	0	0	0
	5	83	8	0	0	79	1	0	0
	6	54	3	0	0	6	1	0	0
L = .70	2	54	19	0	0	55	17	1	0
	3	10	0	0	0	8	0	0	0
	4	6	0	0	0	0	0	0	0
	5	18	0	0	0	0	0	0	0
	6	20	0	0	0	0	0	0	0
L = .90	2	56	16	1	0	50	15	1	0
	3	0	0	0	0	0	0	0	0
	4	2	0	0	0	0	0	0	0
	5	4	0	0	0	0	0	0	0
	6	7	0	0	0	0	0	0	0

2. Fit Indices

Chi-square (χ^2)

The percentage of significant χ^2 values under each condition is summarized in Table 5. The α level chosen was .05.

Under GLS estimation, the null hypothesis is rarely rejected. The percentage of significant χ^2 values ranged from 0.0 to 6.0 with one exception. With 100 replications, the expected percentage rejected is 5.0. No distinctive patterns can be detected, i.e. none of the factors seems to have a strong influence on the outcome. The overall average percentage of significant χ^2 values was 2.58 for GLS, an underestimate.

The results from ML followed a very different pattern. Sample size had a strong effect on the χ^2 values. However, the findings were contrary to a common criticism in applications, i.e., χ^2 tends to be significant simply because the sample size is large. The result was in the other direction, .i.e., the test works better when sample size increases. For example, the percentage of significant χ^2 values dropped from 39.4 to 6.0 when sample size increased from 50 to 500 under the condition of $p/m = 6$, $L = 0.5$. The p/m ratio also had a very strong effect on χ^2 . This effect is strongly interactive with sample size. When p/m becomes large, the percentage of significant χ^2 values increased, under $N=100$ and $L=0.5$. The percentage of significant χ^2 values ranged from 3.0 to 21.0 when p/m increased from 2 to 6. However, this situation improved dramatically when sample size increased. When N reached 500, no p/m effect was detected. The Loading size seems to have little influence on χ^2 . Overall the average percentage of rejection was 11.48 with ML, an overestimate.

Table 5

Percentage of significant Chi-square (χ^2) values ($\alpha = 0.05$)
across all conditions

	p/m	GLS				ML			
		N=50	N=100	N=200	N=500	N=50	N=100	N=200	N=500
L = .50	2	3.2	0	5.0	6.0	10.3	3.0	6.0	6.0
	3	11.6	1.0	4.0	1.0	36.2	5.1	6.0	1.0
	4	0	2.0	0	2.0	20.0	8.0	3.0	3.0
	5	0	4.1	4.0	3.0	25.9	10.0	10.0	6.0
	6	0	1.0	2.0	5.0	39.4	21.0	12.0	6.0
L = .70	2	0	3.0	4.0	5.0	6.0	5.0	4.0	5.0
	3	1.0	0	4.0	0	8.0	4.0	6.0	2.0
	4	1.0	3.0	1.0	3.0	21.0	11.0	4.0	4.0
	5	1.0	4.0	4.0	4.0	31.0	11.0	10.0	6.0
	6	0	1.0	2.0	4.0	38.0	22.0	12.0	5.0
L = .90	2	3.0	6.0	2.0	6.0	8.1	6.0	3.0	5.0
	3	1.0	0	3.0	4.0	9.0	8.0	6.0	4.0
	4	2.0	3.0	3.0	4.0	22.0	9.0	6.0	3.0
	5	1.0	4.0	5.0	3.0	34.0	15.0	9.0	6.0
	6	0	1.0	1.0	3.0	39.0	24.0	13.0	7.0

Table 6

Percentage of significant Parsimoniously adjusted Chi-square ($P\chi^2$) values ($\alpha = 0.05$) across all conditions

	p/m	GLS				ML			
		N=50	N=100	N=200	N=500	N=50	N=100	N=200	N=500
L = .50	2	0	0	0	0	0	0	0	0
	3	0	0	0	0	25.9	0	0	0
	4	0	0	0	0	1.1	0	0	0
	5	0	0	1.0	0	0	1.0	1.0	0
	6	0	0	0	0	4.0	1.0	0	0
L = .70	2	0	0	0	0	0	0	0	0
	3	0	0	0	0	1.0	0	0	0
	4	0	0	0	0	1.0	0	0	0
	5	0	0	1.0	0	1.0	1.0	1.0	0
	6	0	0	0	0	6.0	2.0	0	0
L = .90	2	0	0	0	0	0	0	0	0
	3	0	0	0	0	1.0	0	0	0
	4	0	0	0	0	3.0	1.0	0	0
	5	0	0	0	0	1.0	1.0	1.0	0
	6	0	0	0	0	7.0	2.0	0	0

The overestimation effect was overcome by using James's Parsimony Index. The results of $P\chi^2$ is presented in Table 6. We can see that $P\chi^2$ is rarely significant across all conditions except in one cell. The average percentage for the GLS estimation was 0.03, and the average percentage for the ML was 1.07. Therefore, the parsimoniously corrected Chi-square test would be a very conservative test, badly underestimating the true α level. $P\chi^2$ will be discussed in more detail in the Discussion section.

Normed Fit Index (NFI)

The Means and Standard Deviations are reported in Table 7 for the NFI estimates. The results are also illustrated in Figure 3 (GLS results) and Figure 4 (ML results). The MANOVA results show that all the factors had a significant effect on NFI. This is summarized in Appendix A, Table A-1.

Magnitude of effects. The main effect of sample size is $F_{(3,5744)} = 1725$, η^2 is 0.11. The main effect of loading is $F_{(2,5744)} = 2869.01$, η^2 is 0.13. The main effect of estimation method is $F_{(1,5744)} = 14402.41$, η^2 is 0.21. The interaction between estimation and sample size is $F_{(3,24)} = 1377.08$, $\eta^2 = 0.08$. All the other main and interaction effects were also significant but did not reach required η^2 level.

Variability. The Standard Deviations ranged from 0.0001 to 0.0152 across all conditions for GLS solutions and from 0.0017 to 0.7687 for ML solutions. The variability of NFI decreased when N increased or L increased. The ratio of p/m does not appear to affect the variability very much.

Table 7

Means and standard deviations for the Normed Fit Index

		GLS			ML			
Sample Size	p/m ratio	Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases	
Loading = 0.50	50	2	0.9768	0.0092	93	0.7710	0.1075	97
		3	0.9546	0.0152	69	0.5488	0.7687	55
		4	0.9573	0.0063	90	0.5769	0.0837	95
		5	0.9530	0.0091	37	0.5128	0.0746	27
		6	0.9582	0.0057	78	0.4740	0.0635	99
	100	2	0.9870	0.0056	97	0.8681	0.0703	99
		3	0.9742	0.0059	100	0.7856	0.0608	99
		4	0.9643	0.0054	99	0.7233	0.0530	100
		5	0.9575	0.0058	98	0.6789	0.0572	100
		6	0.9528	0.0050	97	0.6448	0.0536	100
	200	2	0.9925	0.0038	100	0.9249	0.0387	100
		3	0.9848	0.0042	99	0.8764	0.0372	100
		4	0.9780	0.0034	100	0.8413	0.0281	100
		5	0.9715	0.0041	100	0.8057	0.0339	100
		6	0.9671	0.0037	100	0.7884	0.0307	100
	500	2	0.9971	0.0017	100	0.9712	0.0170	100
		3	0.9932	0.0018	100	0.9445	0.0153	100
		4	0.9899	0.0017	100	0.9284	0.0132	100
		5	0.9870	0.0020	100	0.9139	0.0144	100
		6	0.9841	0.0021	100	0.9022	0.0145	100
Loading = 0.70	50	2	0.9882	0.0053	100	0.8983	0.0523	100
		3	0.9812	0.0048	100	0.8280	0.0505	100
		4	0.9783	0.0046	99	0.7776	0.0497	100
		5	0.9780	0.0043	98	0.7309	0.0394	100
		6	0.9798	0.0041	94	0.7002	0.0438	100
	100	2	0.9927	0.0033	100	0.9473	0.0268	100
		3	0.9867	0.0034	100	0.9097	0.0265	100
		4	0.9821	0.0032	100	0.8786	0.0245	100
		5	0.9791	0.0035	100	0.8543	0.0269	100
		6	0.9774	0.0034	100	0.8322	0.0263	100
	200	2	0.9961	0.0021	100	0.9732	0.0155	100
		3	0.9921	0.0023	100	0.9531	0.0141	100
		4	0.9892	0.0019	100	0.9381	0.0106	100
		5	0.9861	0.0023	100	0.9225	0.0136	100
		6	0.9842	0.0022	100	0.9129	0.0128	100
	500	2	0.9984	0.0009	100	0.9896	0.0062	100
		3	0.9965	0.0009	100	0.9804	0.0053	100
		4	0.9950	0.0009	100	0.9744	0.0046	100
		5	0.9937	0.0010	100	0.9688	0.0051	100
		6	0.9924	0.0011	100	0.9639	0.0051	100
Loading = 0.90	50	2	0.9978	0.0013	100	0.9592	0.0218	99
		3	0.9970	0.0011	100	0.9328	0.0200	100
		4	0.9967	0.0010	100	0.9100	0.0199	100
		5	0.9968	0.0008	98	0.8868	0.0160	100
		6	0.9971	0.0008	95	0.8685	0.0183	100
	100	2	0.9988	0.0006	100	0.9823	0.0098	100
		3	0.9979	0.0006	100	0.9680	0.0091	100
		4	0.9973	0.0006	100	0.9555	0.0088	100
		5	0.9969	0.0007	100	0.9450	0.0098	100
		6	0.9967	0.0007	100	0.9341	0.0090	100
	200	2	0.9993	0.0003	100	0.9912	0.0043	100
		3	0.9988	0.0004	100	0.9840	0.0047	100
		4	0.9984	0.0003	100	0.9782	0.0036	100
		5	0.9979	0.0004	100	0.9722	0.0045	100
		6	0.9977	0.0004	100	0.9679	0.0045	100
	500	2	0.9997	0.0002	100	0.9963	0.0020	100
		3	0.9995	0.0002	100	0.9935	0.0018	100
		4	0.9993	0.0002	100	0.9913	0.0015	100
		5	0.9991	0.0001	100	0.9893	0.0017	100
		6	0.9989	0.0002	100	0.9873	0.0017	100

Figure 3. Mean values of Normed Fit Index across all conditions under GLS estimation

Figure 4. Mean values of Normed Fit Index across all conditions under ML estimation

Pattern of performance. In general, NFI was estimation method specific, sample size dependent, and loading size dependent. The two estimators in this study generated quite different results. While NFI values from ML seem to be influenced by every factor, the NFI values from GLS were only slightly influenced by sample size and loading size. The GLS effects were too small to produce noticeable bias (All NFI values for GLS were above the acceptable value of 0.9 across all conditions). Issues regarding GLS estimation are discussed in the Discussion section.

Results from ML showed that sample size appears to have a strong effect on NFI. When $N=50$, the value of NFI is severely biased downward, especially when small sample size is combined with a low loading and a large p/m ratio. The loading size also has a strong effect on NFI. When loadings are low, the value of NFI is seriously biased downward. Only a very big sample size (at least 500) can compensate for a low loading of .5. The combined interaction effect of N and L is large. Although the effect of the p/m ratio on NFI is relatively small ($\eta^2 = 0.03$), the pattern of this effect is worth noting. With increased p/m , the value of NFI is decreased. When $L=0.5$, $N \leq 200$, all the values of NFI for $p/m=5$ or 6 are below 0.8. Under the worst condition ($N=50$, $L=0.5$), NFI ranged from 0.7710 to 0.474 for p/m of 2 to 6 accordingly. None of these is above the acceptable value of .90. This bias was decreased when N and L increased. However it did not totally disappeared even with $N=500$ and $L=0.9$. This bias may simply be due to the fact that there are relatively more free parameters in a small p/m model than in a large p/m model, compared to their corresponding number of variables. This issue is discussed in detail in the Discussion section.

Nonnormed Fit Index (NNFI)

The Means and Standard Deviations (SDs) are reported in Table 8 for the NNFI estimates. The results are also illustrated in Figure 5 (GLS results) and Figure 6 (ML results). The MANOVA results are summarized in Appendix A, Table A-2.

Magnitude of effects. Although all main effects and 9 out of 11 interaction effects were significant, none of the η^2 s exceeded 0.01. Therefore, these effects are not considered to be important.

Variability. The SDs ranged from 0.0002 to 0.0233 across all conditions for GLS and from 0.0019 to 0.7571 for ML. Like NFI, the variability decreased when: N increased or when L increased. Unlike NFI, when p/m increased, variability of NNFI decreased as well, however, the influence of p/m on variability was much smaller than that of N and L. Contrary to previous studies (e.g. Bentler & Bonett, 1980), this study did not find that NNFI had a larger variability than that of NFI, in general.

Pattern of performance. NNFI values from GLS solutions are almost perfect under any conditions. Solutions from ML suggest that when sample size is 50, the NNFI showed a downward bias. This bias is more severe with the increase of p/m. Note that NNFI is not completely independent of p/m. However, once sample sizes reach 100, values of NNFI for all conditions are above the acceptable value of 0.90. Both loading and p/m ratio have small effects on NNFI. However, they were interactive with small sample size when both factors are at the low levels. Once sample size reach 100, NNFI is almost independent of all three factors.

Table 8

Means and standard deviations for the Nonnormed Fit Index

	Sample Size	p/m ratio	GLS			ML		
			Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases
Loading = 0.50	50	2	1.0012	0.0231	93	0.9536	0.6587	97
		3	0.9968	0.0233	69	0.9800	0.7571	55
		4	1.0104	0.0131	90	0.9235	0.2775	95
		5	1.0074	0.0126	37	0.8740	0.1867	27
		6	1.0099	0.0074	78	0.8216	0.1352	99
	100	2	1.0030	0.0124	97	1.0151	0.2210	99
		3	1.0048	0.0102	100	1.0179	0.1409	99
		4	1.0034	0.0095	99	0.9763	0.1032	100
		5	1.0046	0.0091	98	0.9719	0.1034	100
		6	1.0032	0.0069	97	0.9445	0.0820	100
	200	2	1.0003	0.0086	100	1.0005	0.1082	100
		3	1.0014	0.0065	99	1.0049	0.0659	100
		4	1.0011	0.0048	100	0.9937	0.0408	100
		5	1.0009	0.0057	100	0.9886	0.0475	100
		6	1.0013	0.0049	100	0.9890	0.0425	100
	500	2	1.0005	0.0037	100	1.0052	0.0400	100
		3	1.0002	0.0026	100	1.0005	0.0228	100
		4	1.0001	0.0022	100	0.9988	0.0164	100
		5	1.0004	0.0025	100	0.9993	0.0184	100
		6	1.0003	0.0024	100	0.9991	0.0164	100
Loading = 0.70	50	2	1.0043	0.0130	100	0.9974	0.1517	100
		3	1.0047	0.0074	100	0.9752	0.0884	100
		4	1.0040	0.0066	99	0.9584	0.0824	100
		5	1.0041	0.0049	98	0.9370	0.0594	100
		6	1.0042	0.0034	94	0.9259	0.0567	100
	100	2	1.0016	0.0077	100	1.0030	0.0653	100
		3	1.0022	0.0051	100	1.0001	0.0431	100
		4	1.0014	0.0046	100	0.9889	0.0354	100
		5	1.0019	0.0044	100	0.9871	0.0344	100
		6	1.0013	0.0032	100	0.9784	0.0290	100
	200	2	1.0007	0.0045	100	1.0022	0.0341	100
		3	1.0006	0.0033	100	1.0003	0.0211	100
		4	1.0005	0.0023	100	0.9973	0.0136	100
		5	1.0003	0.0027	100	0.9955	0.0161	100
		6	1.0005	0.0023	100	0.9956	0.0148	100
	500	2	1.0004	0.0021	100	1.0022	0.0139	100
		3	1.0001	0.0013	100	0.9999	0.0076	100
		4	1.0001	0.0011	100	0.9995	0.0056	100
		5	1.0002	0.0012	100	0.9998	0.0062	100
		6	1.0001	0.0011	100	0.9997	0.0055	100
Loading = 0.90	50	2	1.0001	0.0023	100	0.9858	0.0494	99
		3	1.0006	0.0011	100	0.9894	0.0300	100
		4	1.0005	0.0010	100	0.9848	0.0281	100
		5	1.0006	0.0007	98	0.9771	0.0206	100
		6	1.0006	0.0005	95	0.9730	0.0204	100
	100	2	1.0003	0.0015	100	1.0008	0.0221	100
		3	1.0003	0.0007	100	0.9993	0.0137	100
		4	1.0002	0.0007	100	0.9962	0.0118	100
		5	1.0003	0.0006	100	0.9954	0.0115	100
		6	1.0002	0.0005	100	0.9922	0.0098	100
	200	2	1.0001	0.0007	100	1.0008	0.0095	100
		3	1.0001	0.0005	100	1.0000	0.0068	100
		4	1.0001	0.0004	100	0.9990	0.0045	100
		5	1.0000	0.0004	100	0.9982	0.0053	100
		6	1.0001	0.0003	100	0.9984	0.0051	100
	500	2	1.0000	0.0003	100	0.9999	0.0043	100
		3	1.0000	0.0002	100	1.0000	0.0025	100
		4	1.0000	0.0002	100	0.9999	0.0019	100
		5	1.0000	0.0002	100	0.9999	0.0020	100
		6	1.0000	0.0002	100	0.9999	0.0019	100

Figure 5. Mean values of Nonnormed Fit Index across all conditions under GLS estimation

Figure 6. Mean values of Nonnormed Fit Index across all conditions under ML estimation

Noncentrality d

The Means and Standard Deviations are reported in Table 9 for estimates of d . The results are also illustrated in Figure 7 (GLS results) and Figure 8 (ML results). The MANOVA results are summarized in Appendix A, Table A-3.

Magnitude of effect. The main effect of estimation method was $F_{(1,5747)} = 11409.29$, $\eta^2 = 0.11$. Among the interaction effects, estimation method by sample size was $F_{(3,24)} = 5143.07$, $\eta^2 = 0.14$. Estimation method by p/m was $F_{(4,24)} = 1937.84$, $\eta^2 = 0.07$. All other main effects and interaction effects (except the main effect of loading and its interaction effects with sample size) were also significant but did not reach the required η^2 level of .05 required for interpretation.

Variability. The SDs ranged from 0.0085 to 0.2704 for GLS across all conditions and from 0.0084 to 0.3667 for ML (except for the condition of $N=50$, $L=.5$ and $p/m=3$, where SD was exceptionally large ($SD=2.8779$)). The variability of d was strongly influenced by sample size and p/m ratio. The variability decreased when N increased and p/m decreased. Loading size had no influence on the variability of this index.

Pattern of Performance. Findings from this study suggest that d is very much estimation method specific. GLS and ML produce substantially different results for d . For GLS solutions, almost all the mean values across conditions are negative. d is not completely independent of sample size, particularly when N is less than 200 (see Figure 7). The d value decreased a great deal when p/m increased. However, since d is a parameter of noncentrality, it is determined approximately by $(\chi^2-df)/N$. Therefore, a

negative sign means that χ^2 is smaller than df . Theoretically, this simply represents sampling error under the condition where the alternative distribution does not differ from the null distribution. In this study, since all models are correctly specified, the difference between two distributions should only be due to random error, therefore the extreme and consistent pattern of departure in the negative direction is difficult to understand. This may have more to do with the estimator used than with the index itself (see below). When sample size reach 200, all values of d are close to 0, which is the true value for the correct specified model. Loading size had no effect on this index. Although the main effect of p/m is small, the interaction effect of p/m with estimation method is very strong.

The performance of d from ML solutions was almost the reverse of the performance of d from GLS solutions (see Figure 8). Almost all the values were positive. When sample size was 50 and 100, the interaction effect of N and p/m was strong. With an increased p/m ratio, d increased, which represents a departure from the null distribution. This departure is quite large when p/m was 5 or 6. d goes to an extreme value under the condition of N=50, L=.5 and p/m=3. However, when sample size reached 200, these departures almost disappeared. The loading size appeared to have no effect on d with ML. Compared to the GLS solutions, we can see that the negative bias of d with GLS was reversed with ML. The latter makes sense, while the former does not. However, with a sample size of 200, the solutions were quite similar and they merged completely when N=500.

Table 9

Means and standard deviations for the Noncentrality Fit Index d

	Sample Size	p/m ratio	GLS			ML		
			Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases
Loading = 0.50	50	2	0.0057	0.0669	93	0.0352	0.0927	97
		3	0.0441	0.1839	69	0.8878	2.8779	58
		4	-0.1073	0.1858	90	0.1538	0.2498	95
		5	-0.1154	0.2768	37	0.2841	0.3023	27
		6	-0.3427	0.2616	78	0.5375	0.3638	99
	100	2	-0.0059	0.0268	97	-0.0008	0.0310	99
		3	-0.0223	0.0573	100	0.0009	0.0716	99
		4	-0.0223	0.0967	99	0.0394	0.1098	100
		5	-0.0530	0.1379	98	0.0613	0.1577	100
		6	-0.0470	0.1493	97	0.1451	0.1789	100
	200	2	0.0000	0.0187	100	0.0020	0.0207	100
		3	-0.0066	0.0339	99	-0.0005	0.0367	100
		4	-0.0067	0.0419	100	0.0096	0.0436	100
		5	-0.0072	0.0690	100	0.0212	0.0735	100
		6	-0.0164	0.0799	100	0.0296	0.0944	100
	500	2	-0.0015	0.0086	100	-0.0015	0.0086	100
		3	-0.0009	0.0135	100	0.0000	0.0132	100
		4	-0.0009	0.0174	100	0.0017	0.0175	100
		5	-0.0033	0.0271	100	0.0017	0.0289	100
		6	-0.0040	0.0343	100	0.0024	0.0349	100
Loading = 0.70	50	2	-0.0109	0.0592	100	0.0121	0.0797	100
		3	-0.0510	0.1187	100	0.0597	0.1602	100
		4	-0.0793	0.1950	99	0.1667	0.2550	100
		5	-0.1601	0.2329	98	0.3477	0.2865	100
		6	-0.3070	0.2594	94	0.5508	0.3667	100
	100	2	-0.0040	0.0339	100	0.0004	0.0371	100
		3	-0.0213	0.0561	100	0.0045	0.0713	100
		4	-0.0173	0.0984	100	0.0429	0.1109	100
		5	-0.0448	0.1415	100	0.0691	0.1571	100
		6	-0.0425	0.1474	100	0.1511	0.1778	100
	200	2	-0.0022	0.0174	100	-0.0009	0.0186	100
		3	-0.0045	0.0337	100	0.0003	0.0368	100
		4	-0.0067	0.0423	100	0.0102	0.0432	100
		5	-0.0050	0.0700	100	0.0232	0.0733	100
		6	-0.0142	0.0820	100	0.0316	0.0945	100
	500	2	-0.0016	0.0084	100	-0.0011	0.0086	100
		3	-0.0010	0.0130	100	0.0002	0.0135	100
		4	-0.0009	0.0184	100	0.0019	0.0179	100
		5	-0.0034	0.0271	100	0.0014	0.0290	100
		6	-0.0043	0.0341	100	0.0018	0.0347	100
Loading = 0.90	50	2	0.0040	0.0680	100	0.0281	0.0893	99
		3	-0.0462	0.1168	100	0.0687	0.1649	100
		4	-0.0666	0.2059	100	0.1725	0.2631	100
		5	-0.1558	0.2318	98	0.3570	0.2876	100
		6	-0.2877	0.2704	95	0.5581	0.3688	100
	100	2	-0.0043	0.0350	100	0.0005	0.0388	100
		3	-0.0208	0.0534	100	0.0069	0.0719	100
		4	-0.0165	0.1014	100	0.0424	0.1120	100
		5	-0.0458	0.1427	100	0.0702	0.1586	100
		6	-0.0464	0.1437	100	0.1559	0.1770	100
	200	2	-0.0019	0.0151	100	-0.0011	0.0168	100
		3	-0.0055	0.0333	100	0.0002	0.0372	100
		4	-0.0062	0.0437	100	0.0103	0.0427	100
		5	-0.0016	0.0696	100	0.0265	0.0721	100
		6	-0.0135	0.0828	100	0.0333	0.0946	100
	500	2	0.0003	0.0085	100	0.0004	0.0084	100
		3	-0.0007	0.0134	100	-0.0005	0.0135	100
		4	-0.0007	0.0182	100	0.0016	0.0176	100
		5	-0.0036	0.0266	100	0.0015	0.0274	100
		6	-0.0034	0.0351	100	0.0021	0.0356	100

Figure 7. Mean values of Noncentrality Index *d* across all conditions under GLS estimation

Figure 8. Mean values of Noncentrality Index d across all conditions under ML estimation

Centrality m

The Means and Standard Deviations are summarized in table 10 for estimates of m . The results are also illustrated in Figure 9 (GLS results) and Figure 10 (ML results). The MANOVA results for m is summarized on Appendix A, Table A-4.

Magnitude of effects. The main effect of estimation method is $F_{(1,5747)} = 1031.42$, $\eta^2 = 0.05$. The interaction effect between estimation method and sample size is $F_{(3,24)} = 495.72$, $\eta^2 = 0.07$. All other main and interaction effects were significant but their η^2 values were less than 0.05.

The centrality index m is the log transformation of d . This transformation narrowed the range of the value. Also note that a negative value of d will result in an m value that exceeds 1. A value of 0 for d is equal to an m value of 1, which reflects a perfect fit. Since the pattern of performance of this index is similar to that for noncentrality d , it is not necessary to describe the results in detail.

Table 10

Means and standard deviations for Centrality Fit Index m

		GLS			ML		
Sample Size	p/m ratio	Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases
50	2	0.9977	0.0332	93	0.9836	0.0448	97
	3	0.9819	0.0882	69	0.8374	0.2722	58
	4	1.0591	0.0962	90	0.9328	0.1129	95
	5	1.0705	0.1519	37	0.8767	0.1373	27
	6	1.1972	0.1536	78	0.7765	0.1378	99
100	2	1.0026	0.0133	97	1.0004	0.0154	99
	3	1.0120	0.0293	100	1.0003	0.0357	99
	4	1.0118	0.0489	99	0.9816	0.0534	100
	5	1.0299	0.0697	98	0.9730	0.0753	100
	6	1.0272	0.0758	97	0.9339	0.0827	100
200	2	0.9996	0.0101	100	0.9989	0.0107	100
	3	1.0034	0.0172	99	1.0004	0.0181	100
	4	1.0043	0.0210	100	0.9955	0.0215	100
	5	1.0040	0.0348	100	0.9898	0.0360	100
	6	1.0082	0.0409	100	0.9865	0.0471	100
500	2	0.9996	0.0035	100	0.9994	0.0037	100
	3	1.0003	0.0069	100	0.9999	0.0072	100
	4	1.0003	0.0096	100	0.9995	0.0090	100
	5	1.0020	0.0141	100	0.9992	0.0147	100
	6	1.0024	0.0176	100	0.9991	0.0176	100
50	2	1.0053	0.0290	100	0.9948	0.0386	100
	3	1.0269	0.0584	100	0.9733	0.0748	100
	4	1.0455	0.0999	99	0.9269	0.1141	100
	5	1.0897	0.1260	98	0.8487	0.1240	100
	6	1.1759	0.1513	94	0.7715	0.1397	100
100	2	1.0023	0.0170	100	1.0002	0.0191	100
	3	1.0109	0.0282	100	0.9986	0.0348	100
	4	1.0097	0.0497	100	0.9804	0.0541	100
	5	1.0252	0.0706	100	0.9688	0.0755	100
	6	1.0244	0.0756	100	0.9307	0.0824	100
200	2	1.0013	0.0090	100	1.0008	0.0094	100
	3	1.0025	0.0171	100	0.9998	0.0179	100
	4	1.0033	0.0216	100	0.9950	0.0208	100
	5	1.0028	0.0349	100	0.9895	0.0359	100
	6	1.0077	0.0418	100	0.9855	0.0465	100
500	2	1.0003	0.0039	100	1.0003	0.0039	100
	3	1.0003	0.0067	100	0.9997	0.0069	100
	4	1.0002	0.0095	100	0.9994	0.0093	100
	5	1.0020	0.0136	100	0.9989	0.0141	100
	6	1.0022	0.0177	100	0.9995	0.0178	100
50	2	0.9989	0.0341	100	0.9867	0.0432	99
	3	1.0253	0.0581	100	0.9697	0.0770	100
	4	1.0390	0.1036	100	0.9252	0.1177	100
	5	1.0881	0.1258	98	0.8455	0.1237	100
	6	1.1648	0.1543	95	0.7701	0.1411	100
100	2	1.0018	0.0182	100	1.0003	0.0195	100
	3	1.0102	0.0276	100	0.9971	0.0364	100
	4	1.0094	0.0508	100	0.9806	0.0545	100
	5	1.0258	0.0716	100	0.9683	0.0764	100
	6	1.0260	0.0737	100	0.9289	0.0821	100
200	2	1.0012	0.0081	100	1.0006	0.0085	100
	3	1.0029	0.0162	100	0.9995	0.0178	100
	4	1.0031	0.0222	100	0.9948	0.0219	100
	5	1.0014	0.0342	100	0.9874	0.0352	100
	6	1.0076	0.0419	100	0.9847	0.0470	100
500	2	0.9992	0.0037	100	0.9990	0.0039	100
	3	1.0004	0.0070	100	1.0000	0.0074	100
	4	1.0005	0.0097	100	0.9992	0.0096	100
	5	1.0016	0.0132	100	0.9997	0.0134	100
	6	1.0021	0.0181	100	0.9992	0.0172	100

Figure 9. Mean values of Centrality Index m across all conditions under GLS estimation

Figure 10. Mean values of Centrality Index m across all conditions under ML estimation

Relative Noncentrality Index (RNI)

The Means and Standard Deviations are reported in Table 11 for RNI estimates. The results are also illustrated in Figure 11 (GLS results) and Figure 12 (ML results). The MANOVA results are summarized in Appendix A, Table A-5.

Magnitude of effects. The only significant effect for RNI is the main effect of estimation method, $F_{(1,5747)} = 7.84, p < .01$. However, the $\eta^2 < 0.01$. RNI appears to be relatively independent of N, L and p/m.

Variability. The SDs from GLS are ranged from 0.0000 to 0.0169 across all conditions for GLS, and from 0.0000 to 0.5010 for ML (excluding the condition N=50, L=.5 and p/m=3, where SD = 3.3389). The variability of RNI is decreased when N increased, L increased, and p/m increased. Compared to NNFI and NFI, RNI had the smallest variability.

Pattern of Performance. Solutions from GLS appear almost perfect. However, RNI from ML showed some downward bias when sample size was 50. Once N reached 100, all factors examined here do not appear to have serious effects on RNI.

Table 11

Means and standard Deviations for the Relative Noncentrality Index

	Sample Size	p/m ratio	GLS			ML		
			Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases
Loading = 0.50	50	2	1.0002	0.0118	93	0.9021	0.5010	97
		3	0.9965	0.0169	69	1.1360	3.3389	58
		4	1.0070	0.0105	90	0.9241	0.2046	95
		5	1.0049	0.0104	37	0.8789	0.1508	27
		6	1.0076	0.0069	78	0.8295	0.1139	99
	100	2	1.0010	0.0064	97	1.0046	0.1027	99
		3	1.0031	0.0075	100	1.0093	0.0974	99
		4	1.0028	0.0074	99	0.9773	0.0809	100
		5	1.0037	0.0083	98	0.9717	0.0852	100
		6	1.0024	0.0067	97	0.9467	0.0711	100
	200	2	0.9996	0.0042	100	1.0002	0.0506	100
		3	1.0007	0.0052	99	1.0027	0.0458	100
		4	1.0004	0.0049	100	0.9941	0.0322	100
		5	1.0006	0.0055	100	0.9889	0.0399	100
		6	1.0011	0.0045	100	0.9889	0.0363	100
	500	2	0.9999	0.0010	100	1.0024	0.0192	100
		3	1.0000	0.0000	100	1.0005	0.0159	100
		4	1.0000	0.0000	100	0.9987	0.0132	100
		5	0.9999	0.0010	100	0.9995	0.0160	100
		6	1.0000	0.0000	100	0.9988	0.0139	100
Loading = 0.70	50	2	1.0019	0.0065	100	0.9960	0.0702	100
		3	1.0031	0.0060	100	0.9786	0.0609	100
		4	1.0028	0.0055	99	0.9625	0.0642	100
		5	1.0024	0.0046	98	0.9415	0.0492	100
		6	1.0022	0.0042	94	0.9288	0.0493	100
	100	2	0.9995	0.0039	100	1.0009	0.0308	100
		3	1.0012	0.0043	100	0.9995	0.0299	100
		4	1.0010	0.0041	100	0.9902	0.0283	100
		5	1.0010	0.0046	100	0.9880	0.0292	100
		6	1.0006	0.0028	100	0.9796	0.0253	100
	200	2	0.9998	0.0014	100	1.0014	0.0168	100
		3	1.0000	0.0014	100	0.9997	0.0148	100
		4	1.0000	0.0000	100	0.9973	0.0112	100
		5	1.0000	0.0014	100	0.9955	0.0142	100
		6	1.0003	0.0017	100	0.9956	0.0127	100
	500	2	1.0000	0.0000	100	1.0014	0.0075	100
		3	1.0000	0.0000	100	1.0002	0.0060	100
		4	1.0000	0.0000	100	0.9995	0.0054	100
		5	1.0000	0.0000	100	0.9997	0.0059	100
		6	1.0000	0.0000	100	1.0003	0.0058	100
Loading = 0.90	50	2	1.0000	0.0000	100	0.9923	0.0232	99
		3	1.0000	0.0000	100	0.9916	0.0210	100
		4	1.0000	0.0000	100	0.9864	0.0220	100
		5	1.0000	0.0000	98	0.9785	0.0174	100
		6	1.0000	0.0000	95	0.9745	0.0180	100
	100	2	1.0000	0.0000	100	1.0004	0.0108	100
		3	1.0000	0.0000	100	0.9997	0.0098	100
		4	1.0000	0.0000	100	0.9967	0.0097	100
		5	1.0000	0.0000	100	0.9957	0.0097	100
		6	1.0000	0.0000	100	0.9934	0.0093	100
	200	2	1.0000	0.0000	100	1.0004	0.0053	100
		3	1.0000	0.0000	100	0.9997	0.0056	100
		4	1.0000	0.0000	100	0.9991	0.0040	100
		5	1.0000	0.0000	100	0.9983	0.0055	100
		6	1.0000	0.0000	100	0.9990	0.0052	100
	500	2	1.0000	0.0000	100	0.9997	0.0017	100
		3	1.0000	0.0000	100	1.0000	0.0000	100
		4	1.0000	0.0000	100	1.0000	0.0000	100
		5	1.0000	0.0000	100	1.0000	0.0000	100
		6	1.0000	0.0000	100	1.0000	0.0000	100

Figure 11. Mean values of Relative Noncentrality Index across all conditions under GLS estimation

Figure 12. Mean values of Relative Noncentrality Index across all conditions under ML estimation

Comparative Fit Index (CFI)

The Means and Standard Deviations are reported in Table 12 for CFI estimates. The results are also illustrated in Figure 13 (GLS results) and Figure 14 (ML results). The MANOVA results are summarized in Appendix A, Table A-6.

Magnitude of effects. The main effect of sample size was $F_{(3,5746)} = 457.59$, $\eta^2=0.07$. The main effect of estimation method was $F_{(1,5746)}=1446.43$, $\eta^2 = 0.06$. The interaction effect between estimation method and sample size was $F_{(3,24)} = 484.58$, $\eta^2 = 0.07$. All other main effects and interaction effects were significant but did not reach the required η^2 level of .05.

Variability. The Standard Deviations ranged from 0.0000 to 0.0119 across all conditions for GLS solutions and from 0.0000 to 0.1463 for ML solutions (except for the condition of $N=50$, $L=.5$, $p/m=3$, which is 0.4067). SDs are decreased when N increased or L increased. The p/m ratio had only a small influence on CFI. CFI had the smallest variability compare to all other indices in this study.

Pattern of performance. The effects of sample size and loading size are bigger on CFI than that on RNI. However, CFI performs similar to RNI in general given the fact that $CFI=RNI$ when $RNI \leq 1$ (see Figure 13 and Figure 14). The magnitude of the bias of these two indices are very close.

Table 12

Means and standard Deviations for the Comparative Fit Index

	Sample Size	p/m ratio	GLS			ML		
			Mean	Standard Deviation	Number cases	Mean	Standard Deviation	Number cases
Loading = 0.50	50	2	0.9958	0.0077	93	0.8973	0.1463	96
		3	0.9914	0.0119	69	0.6798	0.4067	58
		4	0.9987	0.0034	90	0.8071	0.1285	95
		5	0.9986	0.0035	37	0.8574	0.1165	27
		6	1.0000	0.0000	78	0.8269	0.1089	99
	100	2	0.9986	0.0035	97	0.9661	0.0629	99
		3	0.9989	0.0031	100	0.9676	0.0524	99
		4	0.9988	0.0036	99	0.9545	0.0543	100
		5	0.9987	0.0037	98	0.9512	0.0593	100
		6	0.9990	0.0034	97	0.9376	0.0575	100
	200	2	0.9989	0.0031	100	0.9816	0.0346	100
		3	0.9990	0.0030	99	0.9833	0.0272	100
		4	0.9990	0.0030	100	0.9840	0.0215	100
		5	0.9989	0.0035	100	0.9777	0.0273	100
		6	0.9995	0.0022	100	0.9791	0.0230	100
	500	2	0.9999	0.0010	100	0.9937	0.0128	100
		3	1.0000	0.0000	100	0.9940	0.0086	100
		4	1.0000	0.0000	100	0.9942	0.0087	100
		5	0.9999	0.0010	100	0.9935	0.0095	100
		6	1.0000	0.0000	100	0.9940	0.0089	100
Loading = 0.70	50	2	0.9988	0.0033	100	0.9696	0.0439	100
		3	0.9994	0.0024	100	0.9646	0.0459	100
		4	0.9996	0.0020	99	0.9541	0.0540	100
		5	1.0000	0.0000	98	0.9378	0.0428	100
		6	1.0000	0.0000	94	0.9279	0.0476	100
	100	2	0.9990	0.0030	100	0.9884	0.0208	100
		3	0.9996	0.0020	100	0.9881	0.0189	100
		4	0.9996	0.0020	100	0.9831	0.0206	100
		5	0.9994	0.0024	100	0.9820	0.0221	100
		6	0.9999	0.0010	100	0.9770	0.0215	100
	200	2	0.9998	0.0014	100	0.9944	0.0116	100
		3	0.9999	0.0010	100	0.9941	0.0096	100
		4	1.0000	0.0000	100	0.9943	0.0079	100
		5	0.9999	0.0010	100	0.9919	0.0100	100
		6	1.0000	0.0000	100	0.9926	0.0084	100
	500	2	1.0000	0.0000	100	0.9982	0.0048	100
		3	1.0000	0.0000	100	0.9983	0.0038	100
		4	1.0000	0.0000	100	0.9983	0.0038	100
		5	1.0000	0.0000	100	0.9981	0.0039	100
		6	1.0000	0.0000	100	0.9985	0.0036	100
Loading = 0.90	50	2	1.0000	0.0000	100	0.9870	0.0183	99
		3	1.0000	0.0000	100	0.9875	0.0164	100
		4	1.0000	0.0000	100	0.9839	0.0190	100
		5	1.0000	0.0000	98	0.9775	0.0157	100
		6	1.0000	0.0000	95	0.9741	0.0172	100
	100	2	1.0000	0.0000	100	0.9963	0.0075	100
		3	1.0000	0.0000	100	0.9962	0.0063	100
		4	1.0000	0.0000	100	0.9945	0.0070	100
		5	1.0000	0.0000	100	0.9942	0.0079	100
		6	1.0000	0.0000	100	0.9924	0.0079	100
	200	2	1.0000	0.0000	100	0.9989	0.0035	100
		3	1.0000	0.0000	100	0.9983	0.0038	100
		4	1.0000	0.0000	100	0.9987	0.0034	100
		5	1.0000	0.0000	100	0.9975	0.0044	100
		6	1.0000	0.0000	100	0.9981	0.0039	100
	500	2	1.0000	0.0000	100	0.9997	0.0017	100
		3	1.0000	0.0000	100	1.0000	0.0000	100
		4	1.0000	0.0000	100	1.0000	0.0000	100
		5	1.0000	0.0000	100	1.0000	0.0000	100
		6	1.0000	0.0000	100	1.0000	0.0000	100

Figure 13. Mean values of Comparative Fit Index across all conditions under GLS estimation

Figure 14. Mean values of Comparative Fit Index across all conditions under ML estimation

Parsimonious indices

ALL the Means and Standard Deviations for parsimonious indices are reported in Appendix B. Table B-1 for PNFI, Table B-2 for PNNFI, Table B-3 for Pd , Table B-4 for Pm , Table B-5 for PRNI, Table B-6 for PCFI. Results for PNFI is also graphed as Appendix C, Figure C-1 (GLS results) and Figure C-2 (ML results). Since all the PIs have linear relationships with the original indices, the result are not presented here, related issues will be discussed in the Discussion section.

DISCUSSION

Findings and implications from this study

Major findings from this study are presented below for each of the factors examined in this study.

Sample dependency. All the seven fit indices were influenced by sample size. However, the biases were very small for d , m and three Type II incremental fit indices (NNFI, RNI, CFI) once a minimum sample size 100 is reached. There was no bias for these indices when N was 200 or larger. NFI produced severe bias when sample sizes were small. The influences of sample size are also reflected on the variability of the indices. The variabilities was decreased for all indices when sample size increased.

The influence of loading. NFI and CFI are the only two indices which were influenced by loading size. The downward bias under low loading conditions is big for

NFI. The effect of loading on CFI occurred only when sample size was 50. These findings are not in the agreement with findings from PCA/FA studies (e.g. Guadagnoli & Velicer, 1988). The fact that the effect of loading is not as strong may partially be due to the limitations of the study design. In this study all indicators have unique loadings and the lower bound of 0.5 is large compared to that of 0.0 for most PCA/FA studies. Therefore, the low loadings may not produce enough fusion to affect the structure pattern. However, since serious bias does occur in the case of NFI, we can conclude that other indices are less affected by loading size, if at all.

The effect of p/m ratio. Contrary to the findings from PCA/FA studies (e.g. Velicer, 1974; Velicer & Fava, 1987, 1993; Fava & Velicer, 1992a, 1992b), an increase of p/m had negative effects on some of the fit indices (such as NFI, d , m). The negative effects are reflected as either a bias of the fit index value or an increased SD when p/m becomes larger. The only benefit was found with the variability of NNFI and RNI, i.e. an increase of p/m resulted in decreased SDs. However, this effect was small compared to the effects produced by N and L . The negative effect of increased p/m has been related to the problem of parsimony (Gerbing & Anderson, 1993). We discuss this in more detail later. All three Type II Incremental Fit Indices (NNFI, RNI, CFI) did not show any serious bias when p/m increased if sample size was 100 or more. The fact that they had taken df into account did a good job of decreasing this bias.

Estimation Method Specific. An interesting phenomenon is that all indices estimated under GLS were much less affected by any factors in this study than those estimated with ML. Additionally, the variability was much smaller under GLS than under

ML. Even the NFI had very little bias under the worst conditions when GLS was used. Since our models are perfectly specified, we would expect the index to indicate a perfect fit. The less bias, the better an index is. However we can not conclude that all indices work better with the GLS estimator. Possibly the GLS estimator is generally insensitive, as La Du & Tanaka (1989) had detected in their study. If an estimator is not sensitive to sampling error such as these produced by small sample size or low loading, it is very possible that it is also not sensitive to misspecification of the model. We could not evaluate this hypothesis because misspecification conditions were not included in this study. This issue will be investigated more thoroughly in a future study which will focus on the problem of misspecification.

In conclusion, we found that the three Type II Fit Indices (NNFI, RNI, CFI) and the noncentrality d and centrality m were relatively independent of sample size as long as N is 200 or bigger. They are also independent of loading size and p/m ratio, once the requirement for sample size is met ($N \geq 200$). Among all these indices, CFI and RNI appear to be the two most appealing. CFI is normed, and it has the least variability. RNI had the least bias across all conditions, and its variability was small as well. However, it is important to remember that good fit indices should not only be relatively independent of factors studied here, they should also be sensitive to misspecification. Our conclusions therefore are limited by the study design.

The effect of p/m ratio and the parsimony problem.

We have talked about the negative effect of p/m on some fit indices and we have

related this effect to the problem of parsimony in fit indices (James et al., 1982). However, these two are not the same things. When we talk about p/m ratio, we are referring to a more parsimonious model or structure. PCA/FA studies (Velicer, 1974; Guadagnoli & Velicer, 1988; Fava & Velicer, 1992) have demonstrated that the larger the p/m ratio, the more stable a factor pattern and the more well identified the factors are. A large p/m ratio has produced positive effects with PCA/FA studies. Theoretically, this positive effect should exist with structural models as well. More indicators should result in better identified latent variables. A fit index should reflect this effect and produce a better fit when we hold the structure constant and have more indicators per factor. In other words, this is a question of whether a more parsimonious structural model should be rewarded. On the other hand, the parsimony problem with some fit indices, such as the NFI proposed by James et al. (1982), is actually referring to the fact that χ^2 and NFI (or stand-alone and Type I Fit Indices in general) can be improved simply by freeing more parameters. When we free a parameter in a particular model, we are not making the structure more stable or easier to be identified, we are just increasing the error allowance for that model. Although these two problems are different in nature, they are related by the fact that the bigger the p/m ratio, the larger the df_t/df_n ratio, and the more parameters being freed in a particular model. This confusion is hard to separate in practice. The investigation of the effects of the p/m ratio and the correctness of parsimony justification in this study leads to the following observations:

(1) In this study, all models were correctly specified and the downward bias when p/m increased which occurred for the NFI is obviously a problem for this index.

However, parsimonious adjusted index PNFI does not appear to be the solution for the problem (see Figure C-1 and Figure C-2 in appendix). The values of the PIs are largely determined by the df_i/df_n ratio in a particular model. The optimal values of PIs are equal to df_i/df_n ratios for indices with a upper bound value of 1, such as NFI, m , RNI, and CFI. For each particular df_i/df_n , the optimal value of PI is different. This made it very difficult to compare the fit across models. However, since NNFI, RNI and CFI are relatively unbiased against the gain of p/m , we could conclude that these fit indices overcome the problem caused by a df_i/df_n gain when p/m increases. However, these indices do not reward a more parsimonious model, that is, a higher p/m ratio does not improve the values of these fit indices.

(2) Although PIs with Incremental Fit Indices are difficult to interpret, $P\chi^2$ in this study did correct the negative effect of p/m . Since χ^2 is a badness-fit index, there is no requirement for a comparable optimal value across models. The findings from this study suggest that $P\chi^2$ may be a good solution to reduce the χ^2 statistic's tendency to reject the null hypothesis when there is indeed a good fit. However, until the behavior of $P\chi^2$ under misspecification conditions can be examined, no definitive conclusions can be drawn. It is possible that the reduction of χ^2 , i.e. the use of $P\chi^2$, also reduces the sensitivity of the χ^2 test to real misspecification. In addition, there are other serious problems with the χ^2 test, such as the inability to provide information with regard to the degree of fit and impact of nonnormality, which still can not be resolved.

(3) The parsimony problem (James et al., 1982) could not be adequately studied in this project because that problem is always related to misspecification. Given the same

number of variables, if a model which has more free parameters were correct, then the other(s) would be misspecified, or vice versa. Therefore, in order to study this problem, an appropriate focus would be to compare the effect produced by the gain or loss of df_i to the effect produced by misspecification in a series of nested models. We would expect that a good fit index should improve more by the closeness to the correct structure than by freeing a parameter in a wrong place.

Limitations of the study

A good fit index should have a value such as 1.0 when the specified model is correct. When the specified model is incorrect, the fit index should be sensitive to the degree of misspecification and a lower fit index value, which indicates the lack of fit should be obtained. The lack of fit should be affected more by misspecification than by simple sampling error (Gerbing & Anderson, 1993). Only if a fit index satisfies all these criteria, can an index be reliable and valuable. Because misspecification is a big issue, including misspecification would require a much larger simulation study. Since all models were accurately specified in this project, our conclusions about the performance of indices therefore were limited.

A fit index may perform excellently under the conditions of a correctly specified model and may be insensitive to misspecification. For example, when the model is misspecified, the fit index may still indicate good fit. If that occurs, the index can not be considered to be a good index. This study was not able to assess this aspect.

However, determining the performance of an index when the model is correctly

specified is an essential first step. An ideal index should perform well for accepting the correctly specified model and rejecting a misspecified model. Poor performance under either circumstance represents a basis for rejecting that fit index. Good performance under correct specification alone is not an adequate basis for recommending an index. Poor performance, however is an adequate basis for rejecting an index.

CONCLUSIONS

Findings from this study are summarized in Table 13.

1. Overall, all seven fit indices examined in this study were affected by sample size to some degree. When sample size increased, the performance of all fit indices improved. In general, a sample size of 200 or more can produce unbiased fit for three Type II Incremental fit indices (NNFI, RNI and CFI), and two Stand-alone fit indices (d and m).

2. The reliability/loading size had a strong effect only on NFI, had a small effect on NNFI and CFI, and had no effect on Chi-square, d , m and RNI. A loading size of 0.50 seems to be sufficient for fit indices studied here (except NFI) as long as the requirement for sample size (200) is met.

3. The number of indicators per factor (p/m ratio) had a negative effect on three stand-alone fit indices (χ^2 , d , m) and Type I Incremental fit index (NFI). In general, the larger the p/m ratio (especially when $p/m \geq 4$), the more biased the indices (d , m and

Table 13
Summary of results

INDEX	THE EFFECT OF SAMPLE SIZE	THE EFFECT OF LOADING	THE EFFECT OF p/m RATIO	THE EFFECT OF ESTIMATION METHOD	PARSIMONIOUS ADJUSTIFICATION	CONCLUSIONS
Chi Square	Either over or under estimation when N is small	No significant effect	negative effect	GLS produced underestimation ML produced overestimation	Overcorrected	Not recommended
NFI	Severe bias occurred when $N < 500$	Severe bias occurred when $L < .70$	negative effect	GLS produced less bias than ML in general	New problem ?	Not recommended when $N < 500$
NNFI	Small bias occurred when $N < 100$	No significant effect	No significant effect	GLS produced less bias than ML in general	Do not need	Need more Investigation under misspecification
d	Inaccurate when small N combines with large p/m	No significant effect	negative effect	Similar in size Opposite in direction	New problem ?	Need more Investigation under misspecification
m	Considerable bias when small N combines with large p/m	No significant effect	negative effect	GLS produced less bias than ML in general	New problem ?	Need more Investigation under misspecification
RNI	Small bias occurred when $N < 100$	No significant effect	No significant effect	Similar solutions	Do not need	Need more Investigation under misspecification
CFI	Small bias occurred when $N < 100$	Small bias occurred when $L < .70$	No significant effect	Similar solutions	Do not need	Need more Investigation under misspecification

NFI) were, or the less accurate the indices (e.g. χ^2) were. The p/m ratio had no significant effect on three Type II Incremental fit indices (NNFI, RNI, and CFI).

4. We found that all seven fit indices were estimation method specific. Incremental fit indices from GLS were much less biased than that from ML under small to medium sample sizes ($N \leq 200$). Stand-alone indices from GLS can either appear as under estimation (χ^2) or upward bias (d and m), while estimates from ML appear as overestimation (χ^2) or downward bias (d and m).

5. Chi-square (χ^2) appears to be a poor fit index. Even under perfect conditions, it either under estimated (with GLS) or over estimated (with ML). χ^2 was seriously affected by sample size and p/m ratio. When $N \leq 200$ and $p/m \geq 4$, χ^2 was very inaccurate.

6. NFI values with ML were affected by all the factors examined here. Severe bias occurred when $N \leq 200$, or $L \leq 0.7$ and $p/m \geq 3$. Even with $N = 500$, the bias did not completely disappear. NFI values with GLS were relatively unbiased once N reached 100 or L reached 0.7.

7. NNFI values with ML were biased downward when $N \leq 100$ and $L = 0.50$. There was no bias at all when either N reached 200 or L reached 0.70. The p/m ratio had no significant effect on NNFI. NNFI values with GLS were relatively unbiased under all conditions studied here.

8. Noncentrality d Index and Centrality m Index were affected by p/m ratio when $N \leq 100$. The bias increased when p/m ratio become larger. GLS produced upward bias for these two indices while ML produced downward bias. However, once N reached 200,

no bias occurred with either GLS or ML estimation.

9. RNI and CFI were not seriously affected by all four factors examined in this study. However, downward bias can occur under small sample size ($N \leq 100$) when ML is used. There was no bias occurring when GLS was used under all conditions.

10. The sample size had a strong effect on the variabilities of all seven fit indices studied here. In general, when N increased, the SDs of fit indices decreased.

11. The loading size had a strong effect on the variabilities of four incremental fit indices (NFI, NNFI, RNI, and CFI). When L increased, SDs of these fit indices decreased. The loading size had no effect on the variabilities of d and m .

12. The p/m ratio had a strong positive effect on the variability of NNFI and a small positive effect on the variability of RNI. When p/m ratio goes up, the SDs of NNFI and RNI go down. The p/m ratio had a strong negative effect on d and m . When p/m ratio goes up, so do the SDs of these two indices. The p/m ratio had no effect on the variabilities of NFI and CFI.

13. GLS produced much smaller SDs for all seven fit indices than ML did in general.

14. Among all seven fit indices examined here, RNI and CFI were not only the two indices with the smallest bias, they also have the least variabilities.

15. Based on the findings from this study, we recommend that χ^2 and NFI should not be used, due to their inaccurate and severe bias even under perfect conditions studied here. The other five fit indices (NNFI, d , m , RNI and CFI) were relatively unbiased once sample size was 200 or larger. However, they need to be tested for sensitivity under

misspecification conditions.

16. Although GLS seems to produce smaller bias and smaller variabilities for all the fit indices examined in this study, this could either because GLS is more robust or because GLS is insensitive. Therefore, before these two estimators are examined under misspecification, GLS should not be assumed to be better than ML.

17. While parsimony is clearly a problem for Stand-alone indices (χ^2 , d and m) and Type I Incremental fit index NFI, parsimonious adjusted indices (PIs) do not appear to be the solution. This is because the optimal values of PIs varied from model to model, depending on the model's df_i/df_n ratio. Type II Incremental fit indices (NNFI, RNI and CFI) do not appear to need this adjustment, because they already take df into account.

APPENDIX A

Table A-1

MANOVA summary table for Normed Fit Index

Sources	SS	DF	MS	F	P	ETA SQUARED
<u>BETWEEN FACTORS</u>						
WITHIN CELLS	19.64	5744				
N	17.69	3	5.90	1725.00	.000	.11
L	19.62	2	9.81	2869.01	.000	.13
k	5.00	4	1.25	365.85	.000	.03
N BY L	5.13	6	.85	249.85	.000	.03
N BY k	1.36	12	.11	33.16	.000	.01
L BY k	1.53	8	.19	55.82	.000	.01
N BY L BY k	.45	24	.02	5.45	.000	.00
<u>WITHIN FACTOR</u>						
WITHIN CELLS	18.32	5744				
E	33.17	1	33.17	10402.41	.000	.21
E BY N	13.17	3	4.39	1377.08	.000	.08
E BY L	11.78	2	5.89	1846.78	.000	.08
E BY k	3.23	4	.81	253.40	.000	.02
E BY N BY L	3.40	6	.57	177.48	.000	.02
E BY N BY k	1.20	12	.10	31.42	.000	.01
E BY L BY k	.83	8	.10	32.44	.000	.01
E BY N BY L BY k	.32	24	.01	4.22	.000	.00

N : SAMPLE SIZE
L : LOADING SIZE
k : NUMBER OF INDICATORS PER FACTOR
E : ESTIMATION METHOD

Table A-2

MANOVA summary table for Nonnormed Fit Index

Sources	SS	DF	MS	F	P	ETA SQUARED
<u>BETWEEN FACTORS</u>						
<u>WITHIN CELLS</u>						
N	50.79	5744				
L	.63	3	.21	23.73	.000	.01
k	.09	2	.04	4.82	.008	.00
N BY L	.39	4	.10	11.10	.000	.00
N BY k	.14	6	.02	2.63	.015	.00
N BY L	.37	12	.03	3.45	.000	.00
L BY k	.24	8	.03	3.35	.001	.00
N BY L BY k	.25	24	.01	1.17	.262	.00
<u>WITHIN FACTOR</u>						
<u>WITHIN CELLS</u>						
E	45.67	5744				
E BY N	.62	1	.62	78.34	.000	.01
E BY L	.87	3	.29	36.48	.000	.01
E BY k	.17	2	.08	10.55	.000	.00
E BY N BY k	.43	4	.11	13.54	.000	.00
E BY N BY L	.22	6	.04	4.51	.000	.00
E BY N BY L BY k	.41	12	.03	4.35	.000	.00
E BY L BY k	.28	8	.03	4.34	.000	.00
E BY N BY L BY k	.28	24	.01	1.49	.059	.00
N						
L						
k						
E						

Table A-3

MANOVA summary table for Noncentrality d Index

Sources	SS	DF	MS	F	P	ETA SQUARED

<u>BETWEEN FACTORS</u>						

WITHIN CELLS						
N	39.79	5747				
L	.45	3	.15	21.61	.000	.01
k	.00	2	.00	.32	.724	.00
N BY L	.14	4	.03	5.05	.000	.00
N BY k	.02	6	.00	.43	.859	.00
L BY k	.32	12	.03	3.83	.000	.00
N BY L BY k	.25	8	.03	4.56	.000	.00
N BY L BY k	.58	24	.02	3.50	.000	.01

<u>WITHIN FACTOR</u>						

WITHIN CELLS						
E	4.28	5747				
E BY N	8.49	1	8.49	11409.29	.000	.11
E BY L	11.49	3	3.83	5143.07	.000	.14
E BY k	.02	2	.01	12.36	.000	.00
E BY L BY k	5.77	4	1.44	1937.84	.000	.07
E BY N BY L	.05	6	.01	10.27	.000	.00
E BY N BY k	8.10	12	.67	906.46	.000	.10
E BY L BY k	.05	8	.01	9.21	.000	.00
E BY N BY L BY k	.14	24	.01	8.00	.000	.00

N	: SAMPLE SIZE					
L	: LOADING SIZE					
k	: NUMBER OF INDICATORS PER FACTOR					
E	: ESTIMATION METHOD					

Table A-4

MANOVA summary table for Centrality Index m Index

Sources	SS	DF	MS	F	P	ETA SQUARED

<u>BETWEEN FACTORS</u>						

WITHIN CELLS	407.93	5747				
N	9.88	3	3.29	46.41	.000	.01
L	.52	2	.26	3.67	.026	.00
k	2.68	4	.67	9.43	.000	.00
N BY L	1.59	6	.26	3.73	.001	.00
N BY k	6.30	12	.52	7.39	.000	.01
L BY k	5.53	8	.69	9.73	.000	.01
N BY L BY k	13.38	24	.56	7.86	.000	.02

<u>WITHIN FACTOR</u>						

WITHIN CELLS	239.48	5747				
E	42.98	1	42.98	1031.42	.000	.05
E BY N	61.97	3	20.66	495.72	.000	.07
E BY L	.80	2	.40	9.62	.000	.00
E BY k	23.32	4	5.83	139.89	.000	.03
E BY N BY L	1.97	6	.33	7.88	.000	.00
E BY N BY k	33.96	12	2.83	67.91	.000	.04
E BY L BY k	3.38	8	.42	10.15	.000	.00
E BY N BY L BY k	8.43	24	.35	8.43	.000	.01

N : SAMPLE SIZE
 L : LOADING SIZE
 k : NUMBER OF INDICATORS PER FACTOR
 E : ESTIMATION METHOD

Table A-5

MANOVA Summary Table For Relative Noncentrality Index

Sources	SS	DF	MS	F	P	ETA SQUARED

<u>BETWEEN FACTORS</u>						

WITHIN CELLS	336.46	5747				
N	.44	3	.15	2.50	.058	.00
L	.07	2	.04	.61	.543	.00
K	.51	4	.13	2.17	.070	.00
N BY L	.08	6	.01	.22	.972	.00
N BY K	.71	12	.06	1.02	.430	.00
L BY K	.50	8	.06	1.07	.384	.00
N BY L BY K	.85	24	.04	.60	.935	.00

<u>WITHIN FACTOR</u>						

WITHIN CELLS	334.59	5747				
E	.46	1	.46	7.84	.005	.00
E BY N	.56	3	.19	3.22	.022	.00
E BY L	.12	2	.06	1.02	.362	.00
E BY K	.55	4	.14	2.38	.050	.00
E BY N BY L	.12	6	.02	.34	.914	.00
E BY N BY K	.79	12	.07	1.12	.335	.00
E BY L BY K	.55	8	.07	1.19	.303	.00
E BY N BY L BY K	.94	24	.04	.67	.883	.00

N : SAMPLE SIZE
L : LOADING SIZE
K : NUMBER OF INDICATORS PER FACTOR
E : ESTIMATION METHOD

Table A-6

MANOVA summary table for Comparative Fit Index

Sources	SS	DF	MS	F	p	ETA SQUARED
<u>BETWEEN FACTORS</u>						
<u>WITHIN CELLS</u>						
N	8.88	5746	.71	457.59	.000	.07
L	2.12	3	.66	429.16	.000	.04
k	1.33	2	.04	24.39	.000	.00
N BY L	.15	4	.21	133.30	.000	.04
N BY k	1.24	6	.03	22.32	.000	.01
L BY k	.41	12	.03	22.36	.000	.01
N BY L BY k	.28	8	.03	20.45	.000	.02
N BY L BY k	.76	24	.03			
<u>WITHIN FACTOR</u>						
<u>WITHIN CELLS</u>						
E	8.00	5746	2.01	1446.43	.000	.06
E BY N	2.01	1	.67	484.58	.000	.07
E BY L	2.02	3	.60	434.04	.000	.04
E BY k	1.21	2	.04	27.16	.000	.00
E BY N BY L	.15	4	.19	138.74	.000	.04
E BY N BY k	1.16	6	.03	23.35	.000	.01
E BY L BY k	.39	12	.03	23.02	.000	.01
E BY L BY k	.26	8	.03	20.78	.000	.01
E BY N BY L BY k	.69	24	.03			.02

N : SAMPLE SIZE
L : LOADING SIZE
k : NUMBER OF INDICATORS PER FACTOR
E : ESTIMATION METHOD

APPENDIX B

Table B-1

Means and standard deviations for parsimoniously adjusted
Normed Fit Index

	Sample size	p/m ratio	GLS			ML		
			Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.4557	0.0052	93	0.3594	0.0502	97
		3	0.6630	0.0112	69	0.8862	4.2023	55
		4	0.7539	0.0059	90	0.4547	0.0659	95
		5	0.7986	0.0082	37	0.4296	0.0624	27
		6	0.8337	0.0056	78	0.4127	0.0553	99
	100	2	0.4600	0.0020	97	0.4045	0.0332	99
		3	0.6765	0.0048	100	0.5455	0.0424	99
		4	0.7594	0.0047	99	0.5696	0.0413	100
		5	0.8027	0.0057	98	0.5688	0.0479	100
		6	0.8291	0.0050	97	0.5609	0.0470	100
	200	2	0.4611	0.0031	100	0.4319	0.0186	100
		3	0.6843	0.0052	99	0.6086	0.0255	100
		4	0.7701	0.0017	100	0.6628	0.0223	100
		5	0.8145	0.0052	100	0.6753	0.0290	100
		6	0.8410	0.0033	100	0.6854	0.0268	100
	500	2	0.4671	0.0046	100	0.4533	0.0083	100
		3	0.6900	0.0000	100	0.6553	0.0108	100
		4	0.7800	0.0000	100	0.7313	0.0109	100
		5	0.8292	0.0027	100	0.7656	0.0123	100
		6	0.8559	0.0049	100	0.7843	0.0129	100
Loading = 0.70	50	2	0.4599	0.0017	100	0.4192	0.0244	100
		3	0.6811	0.0042	100	0.5755	0.0354	100
		4	0.7704	0.0043	99	0.6126	0.0390	100
		5	0.8198	0.0041	98	0.6121	0.0326	100
		6	0.8520	0.0045	94	0.6087	0.0380	100
	100	2	0.4610	0.0030	100	0.4420	0.0131	100
		3	0.6861	0.0049	100	0.6319	0.0187	100
		4	0.7733	0.0047	100	0.6925	0.0192	100
		5	0.8203	0.0030	100	0.7159	0.0223	100
		6	0.8491	0.0032	100	0.7239	0.0227	100
	200	2	0.4652	0.0050	100	0.4542	0.0073	100
		3	0.6898	0.0014	100	0.6620	0.0102	100
		4	0.7800	0.0000	100	0.7388	0.0092	100
		5	0.8282	0.0039	100	0.7730	0.0118	100
		6	0.8559	0.0049	100	0.7930	0.0112	100
	500	2	0.4695	0.0022	100	0.4604	0.0037	100
		3	0.6900	0.0000	100	0.6812	0.0048	100
		4	0.7805	0.0022	100	0.7681	0.0044	100
		5	0.8300	0.0000	100	0.8123	0.0053	100
		6	0.8600	0.0000	100	0.8377	0.0049	100
Loading = 0.90	50	2	0.4687	0.0034	100	0.4476	0.0104	99
		3	0.6900	0.0000	100	0.6478	0.0138	100
		4	0.7875	0.0044	100	0.7170	0.0158	100
		5	0.8374	0.0044	98	0.7437	0.0137	100
		6	0.8699	0.0010	95	0.7547	0.0164	100
	100	2	0.4699	0.0010	100	0.4580	0.0040	100
		3	0.6900	0.0000	100	0.6725	0.0069	100
		4	0.7896	0.0020	100	0.7525	0.0074	100
		5	0.8382	0.0039	100	0.7924	0.0090	100
		6	0.8699	0.0010	100	0.8121	0.0087	100
	200	2	0.4700	0.0000	100	0.4606	0.0028	100
		3	0.6900	0.0000	100	0.6831	0.0051	100
		4	0.7900	0.0000	100	0.7697	0.0030	100
		5	0.8400	0.0000	100	0.8153	0.0052	100
		6	0.8700	0.0000	100	0.8412	0.0041	100
	500	2	0.4700	0.0000	100	0.4657	0.0050	100
		3	0.6900	0.0000	100	0.6900	0.0000	100
		4	0.7900	0.0000	100	0.7800	0.0000	100
		5	0.8400	0.0000	100	0.8300	0.0000	100
		6	0.8700	0.0000	100	0.8598	0.0014	100

Table B-2

Means and standard deviations for parsimoniously adjusted
Nonnormed Fit Index

	Sample size	p/m ratio	GLS			ML		
			Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.4671	0.0111	93	0.3906	0.3748	97
		3	0.6925	0.0159	69	0.8111	3.9163	55
		4	0.7958	0.0104	90	0.7275	0.2187	95
		5	0.8432	0.0108	37	0.7319	0.1576	27
		6	0.8783	0.0069	78	0.7144	0.1170	99
	100	2	0.4681	0.0067	97	0.4735	0.1033	99
		3	0.6976	0.0079	100	0.7070	0.0981	99
		4	0.7903	0.0081	99	0.7688	0.0814	100
		5	0.8420	0.0077	98	0.8148	0.0865	100
		6	0.8720	0.0066	97	0.8213	0.0708	100
	200	2	0.4672	0.0049	100	0.4664	0.0505	100
		3	0.6958	0.0054	99	0.6977	0.0461	100
		4	0.7884	0.0044	100	0.7827	0.0325	100
		5	0.8388	0.0059	100	0.8285	0.0401	100
		6	0.8706	0.0045	100	0.8595	0.0367	100
	500	2	0.4689	0.0031	100	0.4692	0.0185	100
		3	0.6941	0.0049	100	0.6946	0.0160	100
		4	0.7894	0.0024	100	0.7866	0.0133	100
		5	0.8396	0.0020	100	0.8372	0.0153	100
		6	0.8699	0.0010	100	0.8684	0.0135	100
Loading = 0.70	50	2	0.4684	0.0071	100	0.4655	0.0706	100
		3	0.6975	0.0059	100	0.6771	0.0613	100
		4	0.7913	0.0060	99	0.7550	0.0647	100
		5	0.8413	0.0045	98	0.7854	0.0500	100
		6	0.8722	0.0042	94	0.8044	0.0489	100
	100	2	0.4677	0.0045	100	0.4684	0.0305	100
		3	0.6960	0.0049	100	0.6947	0.0299	100
		4	0.7894	0.0042	100	0.7791	0.0281	100
		5	0.8398	0.0038	100	0.8270	0.0291	100
		6	0.8700	0.0025	100	0.8501	0.0253	100
	200	2	0.4684	0.0037	100	0.4673	0.0159	100
		3	0.6951	0.0050	100	0.6949	0.0150	100
		4	0.7895	0.0022	100	0.7860	0.0113	100
		5	0.8392	0.0027	100	0.8339	0.0142	100
		6	0.8702	0.0014	100	0.8652	0.0128	100
	500	2	0.4695	0.0022	100	0.4675	0.0072	100
		3	0.6928	0.0045	100	0.6941	0.0059	100
		4	0.7900	0.0000	100	0.7873	0.0049	100
		5	0.8400	0.0000	100	0.8380	0.0062	100
		6	0.8700	0.0000	100	0.8694	0.0051	100
Loading = 0.90	50	2	0.4693	0.0026	100	0.4597	0.0236	99
		3	0.6945	0.0050	100	0.6871	0.0208	100
		4	0.7900	0.0000	100	0.7760	0.0221	100
		5	0.8400	0.0000	98	0.8186	0.0174	100
		6	0.8700	0.0000	95	0.8456	0.0181	100
	100	2	0.4698	0.0014	100	0.4670	0.0107	100
		3	0.6923	0.0042	100	0.6940	0.0098	100
		4	0.7900	0.0000	100	0.7851	0.0099	100
		5	0.8400	0.0000	100	0.8341	0.0100	100
		6	0.8700	0.0000	100	0.8630	0.0093	100
	200	2	0.4699	0.0010	100	0.4671	0.0050	100
		3	0.6905	0.0022	100	0.6948	0.0058	100
		4	0.7900	0.0000	100	0.7874	0.0044	100
		5	0.8400	0.0000	100	0.8363	0.0053	100
		6	0.8700	0.0000	100	0.8685	0.0054	100
	500	2	0.4700	0.0000	100	0.4681	0.0039	100
		3	0.6900	0.0000	100	0.6936	0.0048	100
		4	0.7900	0.0000	100	0.7895	0.0022	100
		5	0.8400	0.0000	100	0.8397	0.0017	100
		6	0.8700	0.0000	100	0.8698	0.0014	100

Table B-3

Means and standard deviations for parsimoniously adjusted
Noncentrality δ Index

	Sample size	p/m ratio	GLS			ML		
			Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.0029	0.0309	93	0.0158	0.0437	97
		3	0.0307	0.1277	69	0.6171	1.9987	58
		4	-0.0842	0.1462	90	0.1209	0.1974	95
		5	-0.0976	0.2323	37	0.2385	0.2539	27
		6	-0.2986	0.2280	78	0.4676	0.3162	99
	100	2	-0.0027	0.0125	97	-0.0001	0.0147	99
		3	-0.0158	0.0394	100	0.0004	0.0492	99
		4	-0.0179	0.0757	99	0.0311	0.0866	100
		5	-0.0450	0.1157	98	0.0506	0.1318	100
		6	-0.0413	0.1293	97	0.1260	0.1553	100
	200	2	0.0003	0.0092	100	0.0009	0.0100	100
		3	-0.0043	0.0237	99	-0.0011	0.0255	100
		4	-0.0052	0.0331	100	0.0074	0.0345	100
		5	-0.0060	0.0583	100	0.0179	0.0610	100
		6	-0.0132	0.0696	100	0.0258	0.0822	100
	500	2	0.0006	0.0031	100	0.0007	0.0033	100
		3	-0.0007	0.0093	100	0.0000	0.0093	100
		4	-0.0009	0.0139	100	0.0013	0.0137	100
		5	-0.0027	0.0228	100	0.0020	0.0242	100
		6	-0.0036	0.0301	100	0.0016	0.0299	100
Loading = 0.70	50	2	-0.0055	0.0282	100	0.0058	0.0371	100
		3	-0.0354	0.0824	100	0.0416	0.1112	100
		4	-0.0620	0.1534	99	0.1312	0.2009	100
		5	-0.1338	0.1954	98	0.2911	0.2400	100
		6	-0.2669	0.2254	94	0.4788	0.3188	100
	100	2	-0.0022	0.0162	100	0.0003	0.0176	100
		3	-0.0141	0.0382	100	0.0030	0.0495	100
		4	-0.0125	0.0775	100	0.0339	0.0879	100
		5	-0.0378	0.1179	100	0.0578	0.1319	100
		6	-0.0371	0.1288	100	0.1306	0.1546	100
	200	2	-0.0008	0.0086	100	-0.0006	0.0091	100
		3	-0.0033	0.0237	100	0.0007	0.0255	100
		4	-0.0045	0.0341	100	0.0080	0.0336	100
		5	-0.0046	0.0583	100	0.0192	0.0618	100
		6	-0.0120	0.0710	100	0.0263	0.0820	100
	500	2	0.0000	0.0033	100	0.0000	0.0033	100
		3	-0.0003	0.0099	100	0.0000	0.0095	100
		4	-0.0007	0.0142	100	0.0009	0.0141	100
		5	-0.0031	0.0231	100	0.0013	0.0238	100
		6	-0.0033	0.0297	100	0.0026	0.0297	100
Loading = 0.90	50	2	0.0021	0.0319	100	0.0135	0.0420	99
		3	-0.0315	0.0807	100	0.0474	0.1141	100
		4	-0.0520	0.1621	100	0.1361	0.2070	100
		5	-0.1301	0.1940	98	0.2996	0.2413	100
		6	-0.2503	0.2350	95	0.4846	0.3208	100
	100	2	-0.0020	0.0163	100	-0.0001	0.0184	100
		3	-0.0147	0.0377	100	0.0051	0.0501	100
		4	-0.0132	0.0801	100	0.0336	0.0881	100
		5	-0.0375	0.1194	100	0.0590	0.1326	100
		6	-0.0405	0.1249	100	0.1350	0.1540	100
	200	2	-0.0011	0.0078	100	-0.0007	0.0081	100
		3	-0.0032	0.0231	100	0.0011	0.0255	100
		4	-0.0047	0.0349	100	0.0086	0.0340	100
		5	-0.0009	0.0572	100	0.0218	0.0603	100
		6	-0.0113	0.0718	100	0.0285	0.0828	100
	500	2	0.0007	0.0033	100	0.0010	0.0036	100
		3	0.0000	0.0091	100	0.0003	0.0095	100
		4	-0.0008	0.0151	100	0.0006	0.0143	100
		5	-0.0029	0.0214	100	0.0008	0.0230	100
		6	-0.0035	0.0304	100	0.0016	0.0303	100

Table B-4

Means and standard deviations for parsimoniously adjusted
Centrality m index

Sample size	p/m ratio	GLS			ML		
		Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.4653	0.0151	0.4591	0.0209	97
		3	0.6820	0.0610	0.5821	0.1891	58
		4	0.8343	0.0755	0.7346	0.0890	95
		5	0.8965	0.1272	0.7356	0.1161	27
		6	1.0412	0.1334	0.6745	0.1210	99
	100	2	0.4680	0.0070	0.4673	0.0077	99
		3	0.7026	0.0201	0.6942	0.0246	99
		4	0.7981	0.0381	0.7739	0.0426	100
		5	0.8629	0.0584	0.8155	0.0637	100
		6	0.8929	0.0658	0.8121	0.0719	100
	200	2	0.4667	0.0055	0.4667	0.0055	100
		3	0.6970	0.0119	0.6948	0.0128	100
		4	0.7906	0.0170	0.7844	0.0176	100
		5	0.8416	0.0293	0.8297	0.0302	100
		6	0.8767	0.0357	0.8573	0.0409	100
	500	2	0.4687	0.0034	0.4687	0.0034	100
		3	0.6947	0.0050	0.6945	0.0052	100
		4	0.7879	0.0074	0.7871	0.0071	100
		5	0.8397	0.0118	0.8373	0.0122	100
		6	0.8711	0.0150	0.8681	0.0151	100
Loading = 0.70	50	2	0.4700	0.0142	0.4644	0.0184	100
		3	0.7132	0.0404	0.6755	0.0520	100
		4	0.8236	0.0789	0.7309	0.0903	100
		5	0.9136	0.1051	0.7114	0.1036	100
		6	1.0220	0.1311	0.6707	0.1216	100
	100	2	0.4676	0.0082	0.4666	0.0090	100
		3	0.7015	0.0196	0.6930	0.0244	100
		4	0.7961	0.0391	0.7730	0.0424	100
		5	0.8595	0.0604	0.8123	0.0634	100
		6	0.8904	0.0653	0.8092	0.0722	100
	200	2	0.4675	0.0046	0.4670	0.0050	100
		3	0.6959	0.0122	0.6943	0.0122	100
		4	0.7906	0.0170	0.7836	0.0168	100
		5	0.8409	0.0295	0.8292	0.0299	100
		6	0.8764	0.0367	0.8564	0.0411	100
	500	2	0.4691	0.0029	0.4689	0.0031	100
		3	0.6946	0.0050	0.6944	0.0050	100
		4	0.7879	0.0077	0.7874	0.0076	100
		5	0.8393	0.0118	0.8378	0.0118	100
		6	0.8711	0.0148	0.8688	0.0147	100
Loading = 0.90	50	2	0.4659	0.0160	0.4611	0.0206	99
		3	0.7120	0.0399	0.6734	0.0546	100
		4	0.8183	0.0822	0.7291	0.0926	100
		5	0.9115	0.1061	0.7081	0.1036	100
		6	1.0127	0.1343	0.6692	0.1230	100
	100	2	0.4677	0.0084	0.4669	0.0093	100
		3	0.7019	0.0191	0.6926	0.0254	100
		4	0.7957	0.0406	0.7724	0.0429	100
		5	0.8597	0.0596	0.8117	0.0635	100
		6	0.8920	0.0637	0.8074	0.0711	100
	200	2	0.4674	0.0046	0.4675	0.0046	100
		3	0.6960	0.0119	0.6941	0.0126	100
		4	0.7910	0.0173	0.7843	0.0171	100
		5	0.8387	0.0288	0.8277	0.0295	100
		6	0.8762	0.0360	0.8559	0.0406	100
	500	2	0.4684	0.0037	0.4684	0.0037	100
		3	0.6945	0.0052	0.6939	0.0055	100
		4	0.7890	0.0078	0.7877	0.0080	100
		5	0.8394	0.0114	0.8380	0.0115	100
		6	0.8711	0.0157	0.8686	0.0154	100

Table B-5

Means and standard deviations for parsimoniously adjusted
Relative Noncentrality Index

	Sample size	p/m ratio	GLS			ML		
			Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.4667	0.0060	93	0.4209	0.2338	97
		3	0.6919	0.0113	69	0.5243	2.3935	58
		4	0.7939	0.0087	90	0.7281	0.1611	95
		5	0.8419	0.0100	37	0.7356	0.1271	27
	6	0.8759	0.0065	78	0.7209	0.0988	99	
	100	2	0.4680	0.0040	97	0.4693	0.0477	99
		3	0.6964	0.0063	100	0.7004	0.0670	99
		4	0.7897	0.0071	99	0.7698	0.0630	100
		5	0.8409	0.0067	98	0.8144	0.0721	100
	6	0.8715	0.0058	97	0.8233	0.0616	100	
	200	2	0.4684	0.0037	100	0.4668	0.0239	100
		3	0.6956	0.0052	99	0.6966	0.0324	100
		4	0.7885	0.0039	100	0.7829	0.0252	100
		5	0.8384	0.0049	100	0.8292	0.0333	100
	6	0.8706	0.0040	100	0.8594	0.0320	100	
	500	2	0.4696	0.0020	100	0.4676	0.0094	100
		3	0.6935	0.0048	100	0.6951	0.0111	100
		4	0.7898	0.0014	100	0.7871	0.0105	100
		5	0.8397	0.0017	100	0.8372	0.0136	100
	6	0.8700	0.0000	100	0.8683	0.0122	100	
Loading = 0.70	50	2	0.4673	0.0045	100	0.4648	0.0330	100
		3	0.6967	0.0049	100	0.6800	0.0423	100
		4	0.7898	0.0040	99	0.7581	0.0508	100
		5	0.8407	0.0036	98	0.7886	0.0411	100
	6	0.8715	0.0036	94	0.8077	0.0425	100	
	100	2	0.4684	0.0037	100	0.4670	0.0149	100
		3	0.6956	0.0050	100	0.6941	0.0204	100
		4	0.7896	0.0028	100	0.7798	0.0220	100
		5	0.8394	0.0031	100	0.8280	0.0244	100
	6	0.8701	0.0017	100	0.8514	0.0220	100	
	200	2	0.4695	0.0022	100	0.4669	0.0072	100
		3	0.6944	0.0050	100	0.6942	0.0112	100
		4	0.7899	0.0010	100	0.7857	0.0091	100
		5	0.8394	0.0024	100	0.8338	0.0112	100
	6	0.8700	0.0000	100	0.8653	0.0113	100	
	500	2	0.4700	0.0000	100	0.4684	0.0037	100
		3	0.6922	0.0042	100	0.6940	0.0049	100
		4	0.7900	0.0000	100	0.7878	0.0042	100
		5	0.8400	0.0000	100	0.8379	0.0050	100
	6	0.8700	0.0000	100	0.8692	0.0049	100	
Loading = 0.90	50	2	0.4700	0.0000	100	0.4634	0.0114	99
		3	0.6928	0.0045	100	0.6882	0.0145	100
		4	0.7900	0.0000	100	0.7772	0.0175	100
		5	0.8400	0.0000	98	0.8202	0.0151	100
	6	0.8700	0.0000	95	0.8466	0.0162	100	
	100	2	0.4700	0.0000	100	0.4667	0.0057	100
		3	0.6912	0.0033	100	0.6939	0.0072	100
		4	0.7900	0.0000	100	0.7847	0.0074	100
		5	0.8400	0.0000	100	0.8341	0.0085	100
	6	0.8700	0.0000	100	0.8633	0.0084	100	
	200	2	0.4700	0.0000	100	0.4683	0.0038	100
		3	0.6900	0.0000	100	0.6948	0.0050	100
		4	0.7900	0.0000	100	0.7879	0.0041	100
		5	0.8400	0.0000	100	0.8369	0.0046	100
	6	0.8700	0.0000	100	0.8686	0.0049	100	
	500	2	0.4700	0.0000	100	0.4694	0.0024	100
		3	0.6900	0.0000	100	0.6929	0.0046	100
		4	0.7900	0.0000	100	0.7900	0.0000	100
		5	0.8400	0.0000	100	0.8398	0.0014	100
	6	0.8700	0.0000	100	0.8700	0.0000	100	

Table B-6

Means and standard deviations for parsimoniously adjusted
Comparative Fit Index

	Sample size	p/m ratio	GLS			ML		
			Mean	SD	n	Mean	SD	n
Loading = 0.50	50	2	0.4663	0.0055	93	0.4201	0.0696	96
		3	0.6862	0.0062	69	0.4705	0.2818	58
		4	0.7886	0.0035	90	0.6997	0.1019	95
		5	0.8378	0.0042	37	0.7178	0.0985	27
		6	0.8700	0.0000	78	0.7186	0.0943	99
	100	2	0.4680	0.0040	97	0.4528	0.0299	99
		3	0.6898	0.0014	100	0.6697	0.0348	99
		4	0.7876	0.0045	99	0.7529	0.0431	100
		5	0.8384	0.0040	98	0.7976	0.0509	100
		6	0.8691	0.0029	97	0.8154	0.0498	100
	200	2	0.4684	0.0037	100	0.4599	0.0175	100
		3	0.6899	0.0010	99	0.6803	0.0175	100
		4	0.7884	0.0037	100	0.7761	0.0175	100
		5	0.8379	0.0041	100	0.8206	0.0234	100
		6	0.8695	0.0022	100	0.8513	0.0207	100
	500	2	0.4696	0.0020	100	0.4656	0.0074	100
		3	0.6900	0.0000	100	0.6880	0.0047	100
		4	0.7898	0.0014	100	0.7845	0.0074	100
		5	0.8397	0.0017	100	0.8332	0.0091	100
		6	0.8700	0.0000	100	0.8644	0.0081	100
Loading = 0.70	50	2	0.4673	0.0045	100	0.4542	0.0220	100
		3	0.6900	0.0000	100	0.6686	0.0306	100
		4	0.7891	0.0029	99	0.7522	0.0433	100
		5	0.8397	0.0017	98	0.7859	0.0364	100
		6	0.8700	0.0000	94	0.8070	0.0412	100
	100	2	0.4684	0.0037	100	0.4631	0.0113	100
		3	0.6900	0.0000	100	0.6839	0.0116	100
		4	0.7894	0.0024	100	0.7755	0.0170	100
		5	0.8392	0.0027	100	0.8235	0.0189	100
		6	0.8699	0.0010	100	0.8492	0.0187	100
	200	2	0.4695	0.0022	100	0.4663	0.0065	100
		3	0.6900	0.0000	100	0.6874	0.0058	100
		4	0.7899	0.0010	100	0.7843	0.0074	100
		5	0.8394	0.0024	100	0.8319	0.0088	100
		6	0.8700	0.0000	100	0.8629	0.0078	100
	500	2	0.4700	0.0000	100	0.4684	0.0037	100
		3	0.6900	0.0000	100	0.6900	0.0000	100
		4	0.7900	0.0000	100	0.7878	0.0042	100
		5	0.8400	0.0000	100	0.8375	0.0044	100
		6	0.8700	0.0000	100	0.8684	0.0037	100
Loading = 0.90	50	2	0.4700	0.0000	100	0.4621	0.0098	99
		3	0.6900	0.0000	100	0.6837	0.0100	100
		4	0.7900	0.0000	100	0.7755	0.0153	100
		5	0.8400	0.0000	98	0.8194	0.0136	100
		6	0.8700	0.0000	95	0.8463	0.0155	100
	100	2	0.4700	0.0000	100	0.4666	0.0055	100
		3	0.6900	0.0000	100	0.6889	0.0031	100
		4	0.7900	0.0000	100	0.7842	0.0067	100
		5	0.8400	0.0000	100	0.8333	0.0074	100
		6	0.8700	0.0000	100	0.8626	0.0073	100
	200	2	0.4700	0.0000	100	0.4683	0.0038	100
		3	0.6900	0.0000	100	0.6900	0.0000	100
		4	0.7900	0.0000	100	0.7879	0.0041	100
		5	0.8400	0.0000	100	0.8369	0.0046	100
		6	0.8700	0.0000	100	0.8680	0.0040	100
	500	2	0.4700	0.0000	100	0.4694	0.0024	100
		3	0.6900	0.0000	100	0.6900	0.0000	100
		4	0.7900	0.0000	100	0.7900	0.0000	100
		5	0.8400	0.0000	100	0.8398	0.0014	100
		6	0.8700	0.0000	100	0.8700	0.0000	100

APPENDIX C

Figure C-1. Mean values of Parsimonious Normed Fit Index across all conditions under GLS estimation

Figure C-2. Mean values of Parsimonious Normed Fit Index across all conditions under ML estimation

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