ABSTRACT

Title of Dissertation: EFFECT OF CATEGORIZATION ON TYPE I ERROR AND POWER IN ORDINAL INDICATOR LATENT MEANS MODELS FOR BETWEEN-SUBJECTS DESIGNS

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Due to the superiority of *latent* means models (LMM) over the modeling of means on a single measured variable (ANOVA) or on a composite (MANOVA) in terms of power and effect size estimation, LMM is starting to be recognized as a powerful modeling technique. Conducting a group difference (e.g., a treatment effect) testing at the *latent* level, LMM enables us to analyze the consequence of the measurement error on measured level variable(s). And, this LMM has been developed for both interval indicators (IILMM; Jöreskog & Goldberger, 1975, Muthén, 1989, Sörbom, 1974) and ordinal indicators (OILMM; Jöreskog, 2002).

Recently, effect size estimates, post hoc power estimates, and a priori sample size determination for LMM have been developed for interval indicators (Hancock, 2001). Considering the frequent analysis of ordinal data in the social and behavior sciences, it seems most appropriate that these measures and methods be extended to

LMM involving such data, OILMM. However, unlike IILMM, the OILMM power analysis involves various additional issues regarding the ordinal indicators. This research starts with illustrating various aspects of the OILMM: options for handling ordinal variables' metric level, options of estimating OILMM, and the nature of ordinal data (e.g., number of categories, categorization rules). Also, this research proposes a test statistic of the OILMM power analysis parallel to the IILMM results by Hancock (2001).

The main purpose of this research is to examine the effect of categorization (mostly focused on the options handling ordinal indicators, and number of ordinal categories) on Type I error and power in OILMM based on the proposed measures and OILMM test statistic. A simulation study is conducted particularly for the two-populations between-subjects design case. Also, a numerical study is provided using potentially useful statistics and indices to help understanding the consequence of the categorization especially when one treats ordinal data as if they had metric properties.

EFFECT OF CATEGORIZATION ON TYPE I ERROR AND POWER IN ORDINAL INDICATOR LATENT MEANS MODELS FOR BETWEEN-SUBJECTS DESIGNS

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Table of Contents

List of Tables

Table 1: Threshold Values 89

List of Figures

Chapter I: INTRODUCTION

Much research has shown the superiority of *latent* means models (LMM) over the modeling of means on a single measured variable (ANOVA) or on a composite (MANOVA) in terms of power and effect size estimation. More specifically, the measurement error on measured level variable(s) leads to underestimating the magnitude of the treatment effect and decreasing the power of detecting the presence of that treatment effect (Hancock, 2004). Because of these reasons, testing a treatment effect at the latent level (LMM) has been suggested and developed for both cases when that latent variable has *interval* level indicators (IILMM; Jöreskog & Goldberger, 1975, Muthén, 1989, Sörbom, 1974) and when that latent variable has *ordinal* level indicators (OILMM; Jöreskog, 2002).

Recently, effect size estimates, post hoc power estimates, and a priori sample size determination for LMM have been developed for interval indicators (Hancock, 2001, for the between-subjects case, and Hancock, 2003b, for the within-subjects case). Considering the frequent analysis of ordinal data in the social and behavior sciences, it seems most appropriate that these measures and methods be extended to LMM involving such variables (OILMM).

However, the OILMM power analysis procedure necessarily involves the issues regarding ordinal variable, ordinally-scaled variable (e.g., options for treating ordinal variables, number of categories). Therefore, it is very natural to suspect that the OILMM power analysis is also impacted by the effects of the indicators' crude categorization. Although this ordinal variable categorization effect has been studied for many decades (e.g., the attenuation of correlation), no research has been done on OILMM or LMM power analysis.

The main purpose of this research is to examine the effect of categorization on Type I error and power in OILMM, particularly for the between-subjects design case. And, this analysis covers various aspects of ordinal variables: different options for treating ordinal indicators, ordinally-scaled indicators (ignoring or counting ordinal variables' metric), and the nature of ordinal variables (e.g., number of categories, categorization rules). In the literature review chapter, I review several existing methodologies with interval/ordinal indicators (e.g., interval/ordinal indicator confirmatory factor analysis models, interval/ordinal indicator LMM) including various options of treating ordinal variables metric level, and estimation options of OILMM. Also, I illustrate the power analysis procedure introduced by Hancock (2001) and discusse the procedure of the OILMM power analysis.

In the method chapter of this present study, first, I propose important facets of the OILMM power analysis such as the effect size measures and test statistics for the OILMM. Second, I outline a simulation study for investigating the effect of categorization on two-population between-subjects ordinal indicator LMM under various conditions (methods of accommodating ordinal data, sample size, number of indicators, model size, magnitude of loadings, and latent mean effect size). Also, in the simulation method section, the rationale for the choice of simulation design factors (simulation conditions) is discussed using the previous results and findings from interval case LMM research. Lastly, I propose several potentially useful statistics and indices to help understanding the consequence of the categorization especially when one treats ordinal variables as if they had metric properties.

In the results chapter, first, I illustrate the simulation results of convergence rate, empirical Type I error rate, empirical power estimates, the effect size measure, and the construct measure. Of most practical importance, the current simulation research results shows that ignoring ordinal variables' metric option can always yield biased result regardless of the number of category. In other words, there is no "More categories, better results" phenomenon in OILMM, and treating the ordinal indicators as if they were interval indicators can be misleading. Second, further analytical/numerical analysis results are presented to support/understand the prior simulation results using proposed analytical statistics and indices in the method chapter of the current study.

At last, in the discussion chapter, the discussion of the current study and future research directions are discussed. The results of this present work help researchers who are interested in the various facets of power analysis (e.g., effect size estimates, post hoc power estimates, and a priori sample size determination) for OILMM.

Chapter II: LITERATURE REVIEW

Confirmatory Factor Analysis

As a special case of structural equation modeling (SEM), confirmatory factor analysis (CFA; Jöreskog, 1969) plays a very important role and has been used in a variety of research applications in social and behavior sciences. A broad-spectrum aim of CFA can be expressed as testing the hypothesis that the observed covariance matrix for a set of measured indicator variables is equal to the model implied covariance matrix which is based on the hypothesized factor model. And, this relationship can be expressed as

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\theta) = \boldsymbol{\Lambda\Phi\Lambda}' + \boldsymbol{\Theta},$$

where $\boldsymbol{\Sigma}$ represents the population covariance matrix of a set of observed indicator variables and $\boldsymbol{\Sigma}(\theta)$ represents the model implied covariance matrix as a function of θ, a vector of model parameters. More specifically, the model implied covariance matrix is a function of a factor covariance matrix, $\boldsymbol{\Phi}$; a factor loading matrix, $\boldsymbol{\Lambda}$; and an error covariance matrix, $\boldsymbol{\Theta}$.

The fit functions for two most common model parameter estimation methods assume multivariate normality of observed indicator variables are maximum likelihood (ML) and normal theory generalized least square (GLS),

$$F_{\mathrm{ML}} = \ln|\boldsymbol{\Sigma}| + \mathrm{tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}) - \ln(\mathbf{S}) - p,$$

$$F_{\mathrm{GLS}} = \mathrm{tr}[(\boldsymbol{\Sigma}-\mathbf{S})\mathbf{S}^{-1}]^2,$$

where **S** is the sample covariance matrix and p is the number of indicators (Bollen, 1989). These estimation methods can be shown to provide consistent, efficient, and unbiased parameter estimates and asymptotic standard errors along with an omnibus test of model fit if sample size is adequate, the model is properly specified, and observed variables follow multivariate normal distributions (Bollen, 1989; Browne, 1984). Because ordinal data do not have metric properties, this multivariate normality assumption for the ML is not met when the indicators are ordinally-scaled and thus, technically speaking, one should be careful in using the estimation methods that require the normality assumption such as the ML for the ordinal variable models. In the next section of this research, I provide a review of the options for handling ordinal indicators including the estimation methods for CFA.

CFA with Ordinal Indicators

Ignoring Metric (IM) Approach

In the behavioral and social sciences, it is very common to use a self-report questionnaire to try to measure latent constructs. In particular, the Likert response technique is widely used with questionnaires because it is adaptable to many situations and is easy to develop (DiStefano, 2002; Nunnally, 1978). Also, it is a very typical practice in the behavioral and social sciences that once ordinal data have been collected, often using a Likert scale, those data are treated as intervally-scaled data.

Ordinal variables only assume that a response to a given category represents an increased amount of a given latent construct relative to a lower category. Therefore, we don't know the exact difference (metric) at the level of the latent construct (underlying response variable) that underlies two different category responses. In other words, unlike interval or ratio scale variables, ordinal variables do not have metric properties (origin and unit of measurement). For that reason, treating the moments (e.g., means, variances, correlations, and covariances) of ordinal variable responses as if they were interval can be misleading. Therefore, treating ordinal variables as if they had metric properties has been warned, and much research has illustrated the problems resulting from analyzing ordinal variables as such (Bollen & Barb, 1981; Borgatta & Bohrnstedt, 1980; Jöreskog & Moustaki, 2001; Kaplan, 2000; Mayer, 1971; O'Brien, 1985; Ware & Benson, 1975).

While some research suggests that treating data from a Likert scale with five or more categories as continuous is acceptable (Bollen & Barb, 1981), this crude categorization impact research was only on the magnitude of Pearson correlations, that is, the attenuation of Pearson correlations under a limited simulation design. Furthermore, there is no prior analytical research on the attenuation of Pearson correlation by crude categorization.

Poon, Leung, and Lee (2002) conducted research investigating the consequence of treating ordinal measures as if they were interval scales on means and variances of measured variables. In this research, they concluded that treating ordinal variables as interval variables can be misleading. However, this is based on a real data example and limited simulation research. There is no prior research that analytically provides the consequence of treating ordinal variables as interval variables onto mean and variance estimates. Since the parameter estimates of latent variables (e.g., the mean and variance of latent variable) rely on the observed moment estimates in CFA models, it is very reasonable to conjecture the consequence on the observed variables' moment estimates by ignoring ordinal indicators' metric level can also affect the latent variable's moment estimates. For the purposes of the current study specifically, there exists no prior analysis of the ignoring ordinal indicators' measurement level on latent mean estimates (or latent mean differences).

As a consequence of the problems arising when one chooses ignoring metric (IM) options (i.e., treating ordinal variables as interval variables), researchers have argued that the method of analysis should be determined according to the metric level of the data (Muthén & Kaplan, 1985). In CFA, especially with methods that require a normality assumption, such as Maximum Likelihood (ML) estimation, treating ordinal data as if interval data will violate this normality assumption since this assumption implies the metric properties of outcome variables (Kaplan, 2000). It is true that there were developments for handling the nonnormality of interval outcome variables' distribution, such as Browne's (1984) Asymptotic Distribution Free (ADF) estimation or the Satorra-Bentler (S-B) scaling method (Satorra & Bentler, 1994). However, it should be noted that these developments are not for ordinal outcome variables, but for interval outcome variables.

Besides violating the normality assumptions, treating ordinal variables as if interval variables also causes the attenuation of variable relations (MacCallum, Zhang, Preacher, & Rucker, 2002), underestimation of parameter estimates and factor correlations (Babakus, Ferguson & Jöreskog, 1987), and negative bias of standard errors (Babakus et al., 1987). Therefore, handling ordinal data as if interval data should be considered with great caution.

SEM Strategies: The Underlying Response Variable (URV) Approaches

Instead of treating ordinal data as if intervally-scaled data, several methods have been suggested to overcome the problems mentioned in the previous section, namely Latent Variable (LV) approaches. Jöreskog and Moustaki (2001) subdivided the latent variable level approaches into the structural equation modeling (SEM) approach, also known as the underlying response variable (URV) approach, and the item response theoretical (IRT) model approach, also known as the response function (RF) approach. Mislevy (1986) also gave an excellent comparison between these two approaches in terms of a factor analysis model with ordinal indicators, including detailed estimation options for IRT (e.g., Bock, Gibbons, & Muraki, 1988). In this particular research, I focused on the URV approach (equivalently, SEM approach) as an option for handling ordinal indicators, and a review of the RF approach (equivalently, IRT approach) follows in next section.

In the educational and psychological domains, it is logical and common to assume that dichotomies or polytomies arise from an underlying continuum. The URV approach is based on the assumption that each observed ordinal variable X is generated by an underlying unobserved continuous variable X^* assumed to be *normally* distributed. In other words, URV approach assumes that the latent variable underlying ordinal data is *normal*. Note that there is a problem in proving that the underlying variable exists and in proving the correctness of distributional assumptions about this underlying variable (Kampen & Swyngedouw, 2000). While there are some developments for testing the bivariate underlying distributional assumptions (Jöreskog, 2002), testing the univariate underlying distribution is generally impossible (see Kampen & Swyngedouw, 2000 more details regarding the potential problems of employing the underlying variable method for ordinal variables).

Nevertheless, it is true that the normal distribution has historical precedent and the practical convenience of well known distributional properties (Muthén & Hofacker, 1988), and conventional SEM software, such as EQS (Bentler, 2005), Mplus (Muthén & Muthén, 2001), or LISREL (Jöreskog, & Sörbom, 2004), use the normal distribution as the underlying distribution for URV approach. More recently, Flora and Curran (2004) showed that the parameter estimates of CFA are robust to the moderate violation of normality assumption for underlying response variables using a Monte Carlo simulation study.

URV approach estimates the model either in two or three stages. For handling mixed type variables including ordinal polytomous, Muthén (1984) and Jöreskog (1990, 1994) proposed a three-stage estimation method. At the first stage, first order statistics such as thresholds, means and variances are estimated by ML. In the second stage, second order statistics such as polychoric correlations are estimated by ML using first stage estimates. At the third stage, Muthén (1984) proposed a generalized least squares (GLS) method, and Jöreskog (1990, 1994) proposed a weighted least squares method (WLS) where the weight matrix is an estimate of the inverse of the asymptotic covariance matrix of the polychoric correlations to estimate the parameters of the structural part of the model. Lee, Poon, and Bentler (1990, 1992) also proposed a two-stage estimation procedure as an extension. Details of these estimation options for URV approach are discussed in a later part of this work.

IRT Strategies: The Response Function Approach

Historically, the response function approach was developed within the IRT model with dichotomous variables and a single latent factor. This approach is based on the conditional independence assumption that responses to different items (variables) are independent from each other given a value of latent variable. And, this approach specifies the conditional distribution of response patterns as a function, either the logit or the probit, of the latent factor(s) (see Samejima, 1969, for more details about a logit and a probit model to model ordinal responses). Also, the response functions proposed in that article are composed of a slope parameter (discrimination parameter) for each item and an item response parameter (difficulty parameter). Muraki (1990) discusses the estimation of the unidimensional graded response model using a marginal ML method with an Expectation Maximization (EM) method.

SEM Approach vs IRT Approach

Much research about the similarity of both approaches has been shown repeatedly; an analytical map exists between sets of parameter estimates from both approaches (e.g., Muthén, 1984, 1993; Muthén & Christoffersson, 1981; Takane & de Leeuw, 1987). Jöreskog and Moustaki (2001) presented a comparison of these methods in terms of parameterizations and estimation methods. Glöckner-Rist and Hoijtink (2003) also discussed IRT and SEM approaches in terms of the dimensional structure and the measurement invariance issues. More recently Lu, Thomas, and Zumbo (2005) discussed the connection between IRT and SEM based latent regression modeling for discrete data. Also, this comparison of both methods was extended to the case of the covariate effects on manifest and latent variables (Moustaki, Jöreskog & Mavridis, 2004).

Due to the different parameterization of the two approaches, there also exist distinctions. The two clear distinctions would be the different estimation techniques and the different measurement level requirement according to those estimation techniques. As I briefly illustrated above, SEM approaches use marginal frequency information instead of each response patterns. By using these marginal frequencies, we estimate the moments information of data, that is, thresholds, means, variances, polychoric correlations (tetrachoric in dichotomous cases), and then estimate the weight matrix, by using previously estimated thresholds and polychoric correlations (SEM estimation methods are discussed in more detail in a later part of this work). So, the SEM approach can be characterized as a *Summary-Information Method* which uses summary information of data for estimation (e.g., a weighted least square (WLS) or ML estimation method). In contrast, the IRT approach can be characterized as a *Full-Information Method* which uses full information of data for estimation (e.g., the marginal ML method by Bock and Aitkin, 1981).

Even though both the SEM approach and IRT approach give us standard errors, tests of fit, comparable and consistent parameter estimates, each estimation approach yields distinct computational issues according to the number of variables and/or factors, and sample sizes in practical implementation. The computational burden of the SEM approach increases sharply as the number of observed ordinal variables increases and requires a substantially large sample size for the stable estimate of the weight matrix (we discuss this issue in detail later). However, IRT uses integration over the factor space for multidimensional factor model and this integration needs to be approximated by various numerical techniques, such as Gauss-Hermit quadrature, adaptive quadratic points, and Monte Carlo methods. But, this numerical integration yields a geometric computational burden as the number of factors increases (Mislevy, 1986), and several methods (e.g., Markov chain Monte Carlo) has been suggested to overcome this methodological problem in the IRT field. This is not the case for the SEM approach since it uses the dependency structure, that is, polychoric correlations, to estimate the multifactor relationships. Considering those computational aspects of each approach, researchers have to choose ordinal variable option according to their own research circumstances for the above (Mislevy, 1986).

Specifically for our current purpose, testing factor mean differences, I focused on the SEM approach because: a) LMM has initially been developed under the SEM paradigm, b) we can easily implement this model via popular SEM software (e.g., Mplus, LISREL, or EQS) for either the multiple group design or the repeated measure design, c) there is no conventional program for IRT LMM.

Thresholds and Polychoric Correlation Estimation

As discussed previously, ordinal variables do not provide metric information (origins or units) and thus the only information we can glean is frequencies in a contingency table. To overcome these properties of ordinal variables, an option using a normal underlying variable for an observed ordinal variable has been often employed in educational and psychological domain. Consequently, each *m*-category ordinal variable, *X*, will be considered to have come from a normal underlying variable, X^*, which has a range from $-\infty$ to $+\infty$. If X has m categories coded a_1, a_2, $\ldots$, a_m, the connection between X and X^* is

$$X = a_i \leftrightarrow \nu_{i-1} < X^* < \nu_i, \ i = 1, 2, \ldots m,$$

where

$$-\infty = \nu_0 < \nu_1 < \ldots \ \nu_{m-1} < \nu_m = +\infty,$$

are thresholds. As we can see in Figure 1, the relation between the underlying latent variable, X^*, and the m-category ordinal variable, X, can be constructed by establishing thresholds, ν_i. The function for computing ν_i follows:

$$\nu_i = \Phi_1^{-1}(\pi_1 + \pi_2 + \ldots + \pi_i), \quad i = 1, \ldots, m,$$

where Φ_1 is the standard normal univariate density function, and π_i is the probability of an ordinal response in the ith category (Jöreskog, 2002). This probability can be estimated by the ith category sample proportion, p_i. Also, a measure of association between two ordinal variables, polychoric correlation, can be estimated using estimated thresholds and their marginal distribution from a contingency table. More specifically, in a two-step procedure (see Olsson, 1979), the polychoric correlation, ρ, can be estimated by maximizing the log likelihood function,

$$\ln L = \sum_{i=1}^{m_1} \sum_{j=1}^{m_2} n_{ij} \log \int_{\upsilon_{i-1}}^{\upsilon_i} \int_{\upsilon_{j-1}}^{\upsilon_j} \Phi_2(u,v)\,du\,dv,$$

where $\Phi_2(u,v)$ is the standard normal bivariate density function with correlation ρ.

Then, these estimated thresholds and polychoric correlation(s) are used for conducting CFA under the various estimation options. More detailed information about estimation options for CFA with ordinal indicators is described in the next section of this work.

Estimation Options for CFA with Ordinal Indicators

S-B Scaling Option

Unlike other estimation methods I discuss later, Satorra-Bentler (S-B) scaling method does not consider the metric of the data. Instead of metric consideration, after assessing the degree of nonnormality from the data, this option performs a statistical correction on the χ^2, fit indices, and standard errors with the assessed nonnormality. Therefore, this option is more appropriate as a nonnormality cure solution.

The benefits of this approach over normal estimators, e.g., ML, have been studied in terms of standard error (DiStefano, 2002) and model fit (Green, Akey, Fleming, Hershberger, & Marquis, 1997). Results from the above studies indicate that the S-B scaling option may be an alternative in case of extremely small sample size and/or extremely large model to consider the latent variable level options. Moreover, Green et al. (1997) found that the S-B scaling option produces a χ^2 value very close to the expected χ^2 value even when there were *few* categories (less than three) with various distributions of data (symmetric, uniform and negatively skewed distributions).

ADF/WLS Estimation Options

Browne (1984) developed asymptotically distribution free estimators (ADF) for nonnormal data and this estimator is often also called Weighted Least Squares (WLS). This estimation option applies the fitting function,

$$F_{\mathrm{WLS}} = [\mathbf{s} - \sigma(\theta)]'\mathbf{W}^{-1}[\mathbf{s} - \sigma(\theta)],$$

where is **s** and $\boldsymbol{\sigma}$ refer to the vectors of $p(p+1)/2$ distinct elements of the sample covariance matrix and the model implied covariance matrix, and **W** is a positive-definite weight matrix. If a consistent estimator of the asymptotic covariance matrix of **s** is chosen for **W**, this estimator provides asymptotically efficient parameter estimates and correct standard errors as well as omnibus test of model fit (Browne, 1984).

Since this option has the capability of taking into account the metric of data, it also can be an option for an ordinal indicator measurement model. Muthén (1984) suggested a strategy that takes into account the metric level of the data by including this metric information in the estimation procedures by using a correct weight matrix to employ ADF/WLS estimation. By using polychoric/tetrachoric correlation matrix to construct an asymptotic covariance matrix used as the weight matrix **W** in the WLS estimation, the ADF/WLS estimation option gives us appropriate standard error information for model parameters with ordinal variables. Also, except for the theoretical superiority of this estimation by taking into account the metric of variables, the major advantage of this approach is the fact that the model parameter estimates appear robust to non-normally distributed data (DiStefano, 2002).

However, there exists computational intensiveness in the ADF/WLS technique when inverting the weight matrix as the number of variables increases. Furthermore, this estimator requires a large sample size to get convergent and stable estimates of the weight matrix. Specifically, Jöreskog and Sörbom (1996) suggested a minimum sample size of $(p+1)(p+2)/2$, where p is the number of indicators in a

CFA model. Also, a lack of sensitivity to model misspecification, and failure to reject incorrect models, have been reported (Curran, West, & Finch, 1996).

WLSM and WLSMV Estimation Options

For helping computational intensity along with the large sample size requirement of the ADF/WLS option dealing with categorical variables, Muthén (1993) suggested two robust WLS estimators: a) WLSM, using a mean-adjusted chi-square in scaling, b) WLSMV, using both mean- and variance-adjusted chi-square in scaling. Since WLSM and WLSMV use only the diagonal elements of the weight matrix to estimate parameters, this option can reduce the computational burden and the large sample size requirement from inverting the weight matrix. Also, this option incorporates scaling similar to the S-B scaling method to correct the inflated test-statistic and standard errors due to using only the diagonal part of the full weight matrix (Muthén, 1993).

Unlike other options for ordinal variables, currently this option is only available via Mplus. Recently, Flora and Curran (2004) conducted an empirical evaluation research of alternative estimation methods of ordinal variable CFA. In this research, they concluded that the WLS performed adequately only at the largest sample size (1000 sample in that simulation design) but led to substantial estimation difficulties with smaller samples. But a robust WLS option, WLSMV, performed well across all conditions of this simulation research design (Flora & Curran, 2004). Unlike other estimators, e.g., ML or WLS, relatively newly developed WLSMV's performance has not been fully investigated yet. More intensive empirical research for performance of this option in a variety of conditions will be required. I used

WLSMV estimation method at the simulation research part of this work because 1) this estimation method is newly developed and the default estimation method for ordinal indicator CFA in Mplus, 2) this estimation method has been known as better performance estimator than the traditional estimation methods such as WLS (Flora & Curran, 2004).

Markov chain Monte Carlo (MCMC) Estimation Options

As seen above, the current SEM approach estimation options can be characterized as a special case of WLS (again, WLSM, WLSMV can be characterized as a special case of WLS). And, those options require multiple estimation stages (either two stages or three stages).

Stochastic estimation methods known as Markov chain Monte Carlo (MCMC) techniques have drawn an increasing amount of attention within the last twenty years. MCMC provides a virtually universal tool to deal with integration (and optimization) problems (Andrieu, Freitas, Doucet, & Jordan. 2003; Dyer, Frieze, & Kannan, 1991; Jerrum & Sinclair, 1996). MCMC estimation approaches have been shown to have methodological advantages in the SEM field, e.g., reliable parameter estimation with small sample, flexibility of handling missing data, and so forth (Arminger, & Muthén, 1998; Scheines, Hoijtink, & Boomsma, 1999).

However, MCMC estimation often requires large numbers of iterations (Gilks, Richardson, & Spiegelhalter, 1996), necessitating efficient computational strategies. Due to its computational intensity and complexity, MCMC has not been widely used yet in social science and educational methodology. In situations involving large amounts of data and many parameters, as is often the case in SEM, the complexity and sometimes computational burden of the MCMC process can prove frustrating.

More recently, Arnold-Berkovits (2003) proposed a Bayesian method using MCMC estimation method for small sample size SEM. While this method has been developed for the general ordinal variable SEM, it is more appropriate to categorize this method as an IRT approach in this current work since this MCMC approach uses each subject level responses as data, the full-information methods. Also, because this method uses full-information instead of summary information (e.g., thresholds, means, polychoric correlations), a drawback of this MCMC methods is that the computational burden increases as sample size and model size increase. Therefore, this full-information MCMC method can be impractical, especially when large sample situation.

To overcome computational burden of using full information for MCMC estimation, an ordinal CFA MCMC estimation method using summary information would be practically very useful since there are many situations involving large data and many parameters in the ordinal variable CFA. Unfortunately, such methodology has not been yet developed. Furthermore, for our current purpose specifically, testing factor mean differences using MCMC estimation method also has not yet been suggested. Therefore, I did not adapt the MCMC estimation option in this current study and remains as a future work.

The previous sections reviewed CFA options of handling ordinal indicators. As I mentioned early, LMM is an extension of CFA and is based on the CFA methodological framework such as parameterization scheme, and estimation methods to test latent mean differences. Next, I discuss in detail the LMM methods with interval indicators and ordinal indicators.

Latent Means Models (LMM)

LMM and MANOVA

In social and behavioral sciences, the research questions regarding the comparison on the means of scores observed from the groups' subjects are very popular. And, these types of questions can be addressed using observed variable(s) such as t-test, ANOVA, or MANOVA. Especially, for the research situations with multiple dependent variables, a multivariate approach, such as MANOVA, can be used to answer whether the groups, e.g., the treatment group and the control group, differ on that variable system as a whole. And, MANOVA requires these variables have the theoretical optimal to form a meaningful linear composite, i.e., an emergent variable system which is the formative measurement model with cause indicators (Bollen & Lennox, 1991).

Instead of testing at the level of observed variables, if a single construct underlies the observed variables (a latent variable system; the reflective measurement model with effect indicators), we are able to conduct a statistical test on the construct mean difference as well as estimate the standardized effect size associated with that differences in latent means, LMM. Research (e.g., Bollen & Lennox, 1991) advocates that one should determine whether the variable is emergent or latent before selecting a method of analysis. It is also true that the researchers can develop their own research design, e.g., an experimental design to test a new educational policy, either for an emergent variable system method (MANOVA) or for a latent variable system (LMM).

In many social and behaviors sciences, the variables we have and the variables we wish we had are different because the variables we wish we had often can't be directly observable (latent; error-free), and we must work with the variables we can measure (observed; error-laden). In such cases, one should be aware of the deviation between the two types of variables (latent and observed) and also concern in the operationalization of theoretically error-free latent variables as error-laden measured variables. The measurement error associated with the measured variables may provide us a distorted view of the critical relations in a population; at worst we might not even have sufficient power to draw statistical inference at all (Hancock, 2003a).

The most important advantage of LMM or CFA as a latent variable methodology could be the fact that it has the potentiality of separating the measurement error (noise) and the true difference (signal). Especially, regarding the methodologies for testing group mean differences, Hancock (2003a) provided an excellent overview of the analytical impact of the measurement error onto the methodological process of testing group means such as MANOVA and LMM. More specifically, he analytically showed that the consequences of measurement error for inference could be the underestimation of the magnitude of the true difference (e.g., the treatment or intervention effect) and the decrease of the statistical power to detect such difference.

Moreover, Hancock also illustrated the potential methodological superiorities of LMM over MANOVA with both the numerical results and methodological syntheses: 1) the fact that LMM does not require the estimation of the variables' reliability since this information was implicit within the LMM process in the estimation of the factor loadings (I illustrate this procedure in detail later), 2) the smaller sample size requirement of LMM than that of MANOVA to achieve same level of power, 3) the flexibilities of LMM in terms of the possibility of relaxing the measurement invariance assumption (the equal covariance matrix assumption), 4) the ease of LMM to complex factorial designs by the creative use of group code predictors, and 5) the possibility of LMM to incorporate a latent covariate.

MIMIC and SMM

LMM may be conducted using any SEM software (e.g., EQS, LISREL, Mplus) and can be further divided into two different approaches, MIMIC and SMM. A part of larger class of models known as multiple-indicator multiple-cause (MIMIC) models has been suggested for assessing latent population differences (Jöreskog & Goldberger, 1975; Muthén, 1989). This procedure is not without its own assumptions and restrictions, although some of which may be released in a somewhat more complicated strategy known as Sörbom's (1974) structured means modeling (SMM).

Hancock (1997) also gave a didactic treatment of these two approaches. The MIMIC approach adapts group code (e.g., dummy code) for group membership, and this group code plays a role as independent variables for the factor within a structural equation model (similar to the regression approach with group code). Consequently, this approach uses a single set of data across all groups of interest. In contrast, SMM pursues to model variable's mean structure along its the covariance structure for the inference regarding the populations' underlying construct means (similar to ANOVA or t-test). So, SMM can have the methodological flexibility to allow for some loading differences across populations, e.g., the partial measurement invariance (Byrne, Shavelson, & Muthén, 1989). More specifically, SMM can release bias (equal intercepts) and tau-equivalence (equal factor loadings) constraints while a MIMIC approach implicitly assumes that all sources of bias and (co)variation among observed variables are equivalent across groups.

Although there are differences in data structure and constraint options between two methods, under the conditions of strong measurement invariance across groups (constraining corresponding intercept and loading parameters to be equal across groups), two options yields equivalent estimates. That is, MIMIC is a special case of SMM. For reasons of generality of SMM, I focused on the SMM framework as an LMM in this particular research.

<u>Interval Indicator Latent Means Models (IILMM)</u>

Each j_{th} population latent means on a single factor can be estimated by the following equation,

$$\mu_j = E[X_j] = \tau_j + \Lambda_j E[\eta_j] = \tau_j + \Lambda_j \kappa_j,$$

where $\boldsymbol{\mu}_j$ is the j^{th} group px1 mean vector of p indicators, τ_j is the j^{th} group a px1 constrained vector containing intercept values, Λ_{j} is the j^{th} group a px1 vector of variable constrained loadings on the common factor correlations, η_j is the j^{th} group factor, and κ_j is the j^{th} group the common factor mean when constraining one population latent mean as 0 for identification. These estimated latent means for each population can be used for the hypothesis test of J-group construct mean equivalence: $H_0 : \kappa_1 = \ldots = \kappa_J$.

As we can easily see from the above expression, the latent mean estimate can be viewed as a function of the loadings and observed means, since we solve the above equation for κ during the estimation process. Therefore, if we treat ordinal indicators as interval indicators and apply the interval indicator approach (e.g., ML estimation method) for LMM, we could be exposed to the categorization impact of ordinal data not only on loading estimates but also on latent mean estimates. Again, even though the categorization impact regarding the measures of association (e.g., attenuation on correlation or loading magnitude in CFA) has been studied before, there is no study on the categorization impact on the latent mean difference test as a consequence of the categorization impact on observed variable estimates. This categorization impact on both observed and latent variable estimates were analyzed in the current study using a simulation design.

Ordinal Indicator Latent Means Models (OILMM)

By the nature of the ordinal variable and underlying response variable approach (outlined above), all underlying variables X^* are standardized to have zero means and unit variances. However, since LMM requires means and variances of indicator variables to estimate the mean of construct, performing OILMM requires additional procedures and/or techniques which are different from those used with interval variables.

For this problem, Jöreskog (2002) suggested a framework of OILMM in the between-subjects case and the within-subjects (longitudinal) case. The key characteristic of a between- or within-subjects research design is that the *same* measurement instruments are used on the different groups or on the same individuals across occasions, respectively. Therefore, how to apply the same measurement instrument across groups or across occasions is an important issue in the case of between- or within-subjects ordinal data because we have to construct a metric system (origin and units) for all groups or occasions. Jöreskog (2002) illustrated a method of applying the same measurement instrument by constraining the set of thresholds on a given ordinal variable to be equal. This process of applying the same measurement by constraining thresholds is identical for both the between- and within-subjects cases. However, the focus of this research is between-subjects OILMM.

Figure 2 illustrates the process of estimating indicator level (or observed variable) means for two populations. Setting two sets of thresholds to be equal, and concurrently setting the mean of first population to be 0 and have unit variance (for identification), it is possible to estimate the mean and variance of the second population relative to the first population, so called the *relative mean* and the *relative variance*, respectively.

Latent means modeling with ordinal indicators, OILMM, can easily be extended using the estimates from ordinal indicators as described above. Specifically, we can generalize the J=2 case to the more general $J \geq 2$ case, either between- or within-subjects designs. However, I focused on the J=2 between-subjects case in this work for simplicity.

After estimating the means and variances of each indicator for the second population (again, where the means of first population's indicators are constrained as to be 0 and the variances of first population's indicators are constrained to have unit variance for identification), we can estimate the latent mean of the second group using the following equation, $\boldsymbol{\mu}^*_2 = \mathrm{E}[X^*_2] = \boldsymbol{\tau}^*_2 + \boldsymbol{\Lambda}^*_2\mathrm{E}[\eta^*_2] = \boldsymbol{\tau}^*_2 + \boldsymbol{\Lambda}^*_2\kappa^*_2$, where $\boldsymbol{\mu}^*_2$ is the second group px1 mean vector of ordinal indicators, $\boldsymbol{\tau}^*_2$ is a px1 vector containing the second group's intercept values, $\boldsymbol{\Lambda}^*_2$ is a px1 vector of the second group factor loadings on the common factor estimated by polychoric correlations and variances, η^*_2 is the second group factor, and κ^*_2 is the second group common factor mean. Since we constrained the first group latent mean as 0, this common factor latent mean (equivalently, second group factor mean) also implies the latent mean difference between two populations ($\kappa^*_2 - \kappa^*_1 = \kappa^*_2 - 0 = \kappa^*_2$).

Power Analysis in LMM

Power Analysis in IILMM

Only recently, effect size estimates, post hoc power estimates, and a priori sample size determination have been articulated for analyses involving between-subjects latent means (Hancock, 2001). And, those measures and methods have already become a routine part of univariate analyses involving measured variables (e.g., ANOVA or MANOVA) with intervally-scaled indicators. Also, Hancock (2003b) suggested effect size estimates, post hoc power estimates, and a priori sample size determination strategies for latent means models with two occasions for the within-subjects case. In this part of the present study, I introduce the basic process of between-subjects LMM power analysis and factors affecting this power introduced by Hancock (2001). Note that this development is based on following scenarios: 1) intervally-scaled indicators, 2) ML estimation method, 3) under the Satorra and

Saris's SEM power analysis framework which use the noncentral chi-square distribution (Satorra & Saris, 1985).

In SMM, a special case of LMM, the multisample discrepancy function G across J groups may be expressed as

$$G = \sum_{j=1}^{J} (n_j / N) F_j \ ,$$

where $N = \sum_{j=1}^{J} n_j$ and F_j is fit function for the j-th group. In the case of ML estimation method,

$$F_j = [\ln\left|\hat{\mathbf{\Sigma}}_j\right| + tr(\mathbf{S}_j \hat{\mathbf{\Sigma}}_j^{-1}) - \ln\left|\mathbf{S}_j\right| - p] + (\mathbf{m}_j - \hat{\boldsymbol{\mu}}_j)' \hat{\mathbf{\Sigma}}_j^{-1} (\mathbf{m}_j - \hat{\boldsymbol{\mu}}_j),$$

where $\mathbf{S}_j$ is the jth group observed covariance matrix, $\hat{\mathbf{\Sigma}}_j$ is the jth group model-implied covariance matrix composed of optimum estimates, $\mathbf{m}_j$ is the jth group vector of observed sample means of the indicator variable, and $\hat{\boldsymbol{\mu}}_j$ is the jth group model-implied indicator mean vector, $\hat{\boldsymbol{\tau}}_j + \hat{\mathbf{\Lambda}}_j \hat{\kappa}_j$ equivalently. Also, when the sample covariance matrix has been fit to the properly specified model implied covariance matrix and the mean structure model (with mean constraint for identification), the test statistic, $T_1=(N-1)G$, will asymptotically follow central χ^2 distribution with ν_1 degrees under large sample conditions (Hancock, 2001; Satorra & Saris 1985).

And, if all correct population parameters were substituted into the fit function T_1 with the only latent mean constraint $\kappa_j = \kappa.$ for j = 1 to J, where $\kappa. = \sum_{j=1}^{J} n_j \kappa_j / N$, the model test statistic, T_1, would reduce to T_0,

$$\begin{aligned} T_0 &= (N-1)\sum_{j=1}^{J}(n_j / N)\left[(\boldsymbol{\mu}_j - \boldsymbol{\tau}_j - \mathbf{\Lambda}_j \kappa.)' \hat{\mathbf{\Sigma}}_j^{-1} (\boldsymbol{\mu}_j - \boldsymbol{\tau}_j - \mathbf{\Lambda}_j \kappa.)\right] \\ &= (N-1) g_0 . \end{aligned}$$

And, Hancock illustrated that this latent mean constraint will introduce badness of fit into the multisample mean structure if the hypothesis, the latent means equality, is wrong, and T_0 follows noncentral χ^2 distribution with J -1 degrees of freedom and noncentrality parameter $\lambda_0 = (N\text{-}1)g_0$. Therefore, the power of this test is simply the area of this noncentral χ^2 distribution exceeding the critical value from the corresponding central distribution with given α value.

Under several assumptions (Hancock, 2001), this noncentrality parameter can be substantially simplified as,

$$\lambda_0 = (N-1)g_0 = (N-1)f^2 H \ ,$$

where f is J-group standardized latent effect size measure introduced by Hancock,

$$f = \sigma_\kappa / \phi^{1/2},$$

where ϕ is the variance of η and σ_κ is the standard deviation of population means on the construct η,

$$\sigma_\kappa = \left[\sum_{j=1}^{J} (\kappa_j - \kappa.)^2 / J \right]^{1/2} ,$$

with $\kappa.$ being the grand mean of construct ($\kappa. = \sum_{j=1}^{J} n_j \kappa_j / N$,). And, H, the maximal construct reliability coefficient (Hancock & Mueller, 2001) can be defined as,

$$H = \phi \mathbf{\Lambda}' \mathbf{\Sigma}^{-1} \mathbf{\Lambda} \ ,$$

which is assumed to be homogeneous across groups.

For the simple J=2 between-group case, the noncentrality parameter can also be simplified as,

$$\lambda_0 = (N-1)g_0 = (N-1)[n_1 n_2 / N^2] d^2 H \ ,$$

where d is a standardized effect size measure for two group case latent mean difference proposed by Hancock (2001). And, this can be expressed as

$$d = |\kappa_1 - \kappa_2| / \phi^{1/2},$$

where ϕ is the variance of η, assumed to be homogeneous across both populations. The d value may then be estimated from sample data as

$$\hat{d} = |\hat{\kappa}_1 - \hat{\kappa}_2| / \hat{\phi}^{1/2},$$

where $\hat{\kappa}_1$ and $\hat{\kappa}_2$ are sample means on the η construct for each group and $\hat{\phi}$ is an average variance estimate for scores on η. A value for $\hat{\phi}$ may simply be determined as the average of the latent variances across the two-groups; similarly, one could constrain construct variances equal across groups and use the single estimate as $\hat{\phi}$. I investigated this effect size measure as a key facet of power in the simulation study of this present work.

Several points about the noncentrality parameter expression are worth stating explicitly. First, as expected, an increased effect size and sample size results in increased noncentrality and consequently results in increased power (due to the increased noncentrality). Second, a more reliable construct measure as reflected in a larger H (bigger magnitude of factor loadings, equivalently), yields greater noncentrality, and hence more power. In other words, effect size estimate, sample size, and magnitude of loading estimates are crucial components to determine the power in the LMM.

Power Analysis in OILMM

Using the results of the interval indicator case, it is very reasonable to speculate those components (effect size estimate, sample size, and magnitude of loading estimates) could also be important facets of determining OILMM power. However, there is no prior analytical research on OILMM power analysis. Considering the frequent analysis of ordinal data in the social and behavior sciences, it seems most appropriate that the LMM power analysis procedure be extended to the one involving such indicators. However, there are several difficulties in understanding/developing the power analysis for OILMM. Details of these difficulties follow.

As I've reviewed in early sections of current study, multiple options exist for handling ordinal indicators (e.g., IM or URV option). And, as we have also discussed, the OILMM parameter estimates (either of observed variables or of latent variables) can vary according to those options. As discussed already, it is reasonable to conjecture that different options for handling ordinal data may yield different power estimates for detecting latent means equivalence and Type I error. However, the impact of these options on LMM power analysis has not been studied.

Furthermore, the estimation options can also differ according to the options for handling ordinal indicators (e.g., IM option with ML estimation or URV option with WLSMV estimation). Note that IILMM power analysis has been developed based on the ML fit function (Hancock, 2001), and this analytical development was benefited by the known/favorable analytical properties of the ML fit function. WLS, WLSM, or WLSMV do not possess such good analytical properties as ML. And, it seems to be infeasible to analytically decompose the facets determining OILMM power from those fit functions, and the facets of OILMM (e.g., standardized effect size measures or a relevant measure of construct reliability measure) have not been developed yet. Even the distributional properties of estimates from the developed ordinal variable estimation methods' (WLSM or WLSMV) estimates have not been fully known yet.

As a consequence, a full range of empirical analysis of the categorization impact on Type I error and power of OILMM is needed. In this present work, I investigated this issue through both analytical study and an intense simulation study across various conditions. First, the facets of OILMM power analysis (e.g., standardized effect size measures or a relevant measure of construct reliability measure) were proposed as the ordinal indicator case extension of the developments by Hancock (2001).

Second, most practically importantly, I present several coefficients developed to study the consequences of IM option. Using these proposed indices, I numerically analyzed the consequence of IM option onto the OILMM parameter estimates. For this specific research question, the number of category plays a very important element to answer the questions such as "The more categories for ordinal indicators, the better (e.g., less bias) OILMM results? Consequently, can we ignore the metric of ordinal indicators in OILMM if we have many categories for ordinal indicators?" Due to the very common practice of choosing IM option in social and behavioral sciences, in depth answers to those questions could be very important information and guideline for applied researchers who consider LMM.

Third, through an intensive simulation design, the empirical performance test of WLSMV were analyzed. Most recently WLSMV, a robust WLS estimator for ULV approach, was developed to overcome the limitations of conventional estimations methods (e.g., WLS). And, this estimator is the default estimator for OILMM in Mplus. However, research regarding the performance of this estimator is lacking, and much research regarding this new estimator's performance is needed. Practical questions needed to be answered would be "Do the fit statistics of WLSMV asymptotically follow chi-square distribution?" I analyzed the performance of this estimator using a simulation research using several distributional properties of the WLSMV fit statistics (e.g., Type I error rate or the upper 5 percentile score of empirical sampling distribution) in variety of conditions such as sample size, loading magnitude, effect size and model size.

Chapter III: METHODS

Overview

This chapter covers three subsections: the development of OILMM power analysis facets, the development of IM impact coefficients, and the simulation method.

In the development of OILMM power analysis facets section, I present (1) standardized measures of effect size for latent mean differences inferred from SMM approaches when indicators are ordinal, (2) a construct reliability coefficient with ordinal indicators, and (3) a OILMM test statistic paralleling Hancock's (2001) "development for interval indicators" scenario. These proposed measures are used to investigate the power analysis of OILMM.

In the section on the simulation method, I provide a Monte Carlo simulation design that investigates the effect of categorization on power estimates and Type I error under a variety of conditions. The details of simulation study design conditions and the rationale for choosing each condition were discussed.

Finally, in the development of IM impact coefficients section, I propose several analytical expressions for understanding the effects of the IM option on the observed variable-level statistics. As mentioned in a previous chapter of this work, since the OILMM parameter estimates are based on the observed variable level statistics, these proposed measures are used to understand the consequences of IM option on the OILMM parameter estimates and the power of OILMM.

Development of OILMM Power Analysis Facets

Standardized Measures of Effect Size for OILMM

As we reviewed in the previous chapter, Hancock (2001) showed the noncentrality parameter, an important facet of LMM power analysis, can be substantially simplified as

$$\lambda_0 = (N-1) f^2 H ,$$

where *f* is the *J*-group standardized latent effect size measure introduced by Hancock. As an extension of this measure for the ordinal indicator scenario, the *J*-group standardized latent effect size measure for ordinal indicator with URV option, f^*, can be defined as

$$f^* = \sigma_{\kappa*} / (\phi^*)^{1/2}$$

where ϕ^* is the variance of η^* and $\sigma_{\kappa*}$ is the standard deviation of population means on the construct η^*,

$$\sigma_{\kappa*} = \left[\sum_{j=1}^{J} (\kappa_j^* - \kappa_{.}^*)^2 / J \right]^{1/2},$$

with $\kappa_{.}^*$ being the grand mean of the construct ($\kappa_{.}^* = \sum_{j=1}^{J} n_j \kappa_j^* / N$).

For simple J=2 between-group cases, a standardized effect size measure for two groups with URV options can be expressed as

$$d^* = |\kappa_1^* - \kappa_2^*| / (\phi^*)^{1/2} = |0 - \kappa_2^*| / (\phi^*)^{1/2} = |\kappa_2^*| / (\phi^*)^{1/2} ,$$

where ϕ^* is the variance of η^*, assumed to be homogeneous across both populations if one constrained κ_1^* as 0 for the identification. The d^* value may then be estimated from sample data as

$$\hat{d}^* = \left|\hat{\kappa}_2^*\right| / (\hat{\phi}^*)^{1/2},$$

where $\hat{\kappa}_2^*$ is the sample mean on the η^* construct and $\hat{\phi}^*$ is an average variance estimate of η^*. A value for $\hat{\phi}^*$ may be determined simply as the average of the latent variances across the two-group cases; similarly, one could constrain the construct variances equally across both groups and use a single estimate as $\hat{\phi}^*$. I investigate this effect-size measure as a key facet of power estimates in the simulation study in the present work.

Construct Reliability Coefficients with Ordinal Indicators

Hancock and Mueller (2001) suggested a measure of *construct* reliability, the *H* coefficient, for use within latent variable systems. While equivalent analytical forms of *H* have shown up in other articles as a reliability index of composites (Bentler, 1968; Li, 1997; Li, Rosenthal, & Rubin, 1996), Hancock (2001) illustrated that *H* is a useful facet in an SEM issue, power analysis of latent means modeling. Hancock and Mueller (2001) also illustrated other applications of *H* in SEM, including the attenuation effect of factor correlation due to the measurement error. More detailed information about the properties of this coefficient was discussed in a later part of this work.

As shown by Hancock (2001), in the single factor and interval indicators case *H* can be expressed as follows:

$$H = \phi \mathbf{\Lambda}' \mathbf{\Sigma}^{-1} \mathbf{\Lambda},$$

where ϕ is factor variance, $\mathbf{\Sigma}$ is a population covariance matrix of indicators and $\mathbf{\Lambda}$ is a population unstandardized loading matrix from factor to indicators. *H* also can be expressed in a standardized form:

$$H = \mathbf{L}'\mathbf{P}^{-1}\mathbf{L}$$
$$= \frac{\sum_{i=1}^{p}[\lambda_i^2/(1-\lambda_i^2)]}{1+\sum_{i=1}^{p}[\lambda_i^2/(1-\lambda_i^2)]},$$

where **L** is a standardized loading matrix, **P** is the population correlation matrix, *i* is 1, 2, …, *p*, *p* is the number of indicators, and λ_i^2 is the standardized squared loading of the *i*th indicator variable on a single latent construct. In this form, $\lambda_i^2/(1-\lambda_i^2)$ represents the ratio of the proportion of the *i*th indicator variance as explained by the construct to the unexplained variance proportion. This implies that *H* is a function of λ_i^2, each indicator's reliability. Equivalently, *H* is a function of each indicator's error variance proportion, $1-\lambda_i^2$. Even though this reliability index has been developed for the one-factor case, it can be extended to multi-factor cases. However, I focus on the one-factor in this work and leave the development of the multifactor case *H* for the future.

Again, as previously illustrated, *H* was developed for interval scaled indicators and is a function of the loadings from a construct to its *observed* and *interval* indicators. However, for the ordinal indicators case, these loadings differ depending on whether one uses the IM approach or the URV approach for handling ordinal variables. As a result, the construct reliability coefficients with ordinal indicators differ according to the ordinal variable option selected. This section provides the two different construct reliability measures for ordinal indicators, one for IM options and one for URV option.

In cases where the IM option is chosen, the IM option construct reliability coefficient for ordinal indicators, $\widetilde{H}$, can be defined as

$$\widetilde{H} = \frac{\sum_{i=1}^{p}[\widetilde{\lambda}_i^2/(1-\widetilde{\lambda}_i^2)]}{1+\sum_{i=1}^{p}[\widetilde{\lambda}_i^2/(1-\widetilde{\lambda}_i^2)]},$$

where $\widetilde{\lambda}$ is the standardized loading based on the IM option for ordinal indicators. Note that $\widetilde{\lambda}$ relies on the correlation matrix, which is composed of the IM option correlation, $\widetilde{\rho}$.

If we choose the theoretically more appropriate URV approach for ordinal indicators, the URV option construct reliability coefficient for ordinal indicators, H^*, can be defined as

$$H^* = \frac{\sum_{i=1}^{p}[\dot{\lambda}_i^2/(1-\dot{\lambda}_i^2)]}{1+\sum_{i=1}^{p}[\dot{\lambda}_i^2/(1-\dot{\lambda}_i^2)]}$$

where $\dot{\lambda}$ is the standardized loading based on the URV option and relies on the *polychoric* correlation matrix (more specifically, on the SEM approach of ordinal indicators). And, if the underlying distribution assumption (the underlying normal distribution) about each ordinal indicators holds, $\dot{\lambda} = \lambda$.

Properties of $\tilde{H}$ and H^*

Because they share the same analytical form for the construct reliability coefficient, the interval indicator scenario coefficient, H, and the ordinal indicator scenario coefficients, $\tilde{H}$ and H^*, share some properties. First, since all of the indicators' loadings are used in squared form, $\tilde{\lambda}^2$ or λ^{*2}, the sign of each loading does not affect $\tilde{H}$ and H^*. The quality of the construct depends on the amount of the indicator's proportion that is explained by the construct. Therefore, $\tilde{H}$ and H^* hold appropriate and desirable properties as construct reliability coefficients in terms of the loading sign effect. Second, additional indicators do not decrease the coefficient's value. Adding any small magnitude loading contributes some amount to the construct quality, unless the loading is totally uncorrelated (i.e., the zero magnitude loading case). Third, $\tilde{H}$ and H^* are never smaller than the reliability of the best indicator. If we already have a reasonably reliable indicator, including another indicator will be at least as dependable as using the best single indicator. As we discussed above, it is totally reasonable that an additional, inferior indicator serves only to enhance construct reliability that has already been achieved by the best indicator. Again, all of the above desirable properties are equally applicable to any of the construct reliability indices (H, $\tilde{H}$, and H^*).

It is clear that if we just ignore the metric properties of ordinal indicators by choosing the IM option, the meaning and implication of $\tilde{H}$ will be the same as the interval indicator case even when we have ordinal indicators. For example, $\tilde{H}$ is defined as an index of proportion of variance shared by the latent construct and the observed level ordinal variables. However, as a consequence of the different levels of indicators (X or X*) and the different types of loadings ($\tilde{\lambda}$ or &), $\tilde{H}$ is also a measure of reliability of a construct indicated by the *observed* level ordinal indictors, X. H*, on the other hand, is a measure of reliability of a construct indicated by the *underlying level* ordinal indicators, X*. Therefore, all implications and explanations of H* have to change to represent the relationship between a construct and the *latent* level indicator, X*. For instance, H* is an index of proportion of variance shared by the construct which is indicated by *underlying response* indicators while H is an index of proportion of variance shared by the construct which is indicated by *observed* indicators.

Development of the OILMM Test Statistic

Returning to the interval indicator case LMM power analysis introduced by Hancock (2001), the fit statistic of κ.-constrained model, g_0, is expected to be asymptotically distributed (under multivariate normality) as chi-square distribution with $J - 1$ degree of freedom and noncentrality:

$$\lambda_0 = (N-1)g_0 = (N-1)f^2 H \ .$$

For the simpler $J = 2$ case, this noncentrality parameter can be expressed as

$$\lambda_0 = (N-1)[n_1 n_2 / N_2]d^2 H \ .$$

Note that the noncentrality expressions for IILMM have been derived analytically from the ML fit function (Hancock, 2001). Moreover, the test statistic of IILMM is asymptotically distributed as a chi-square distribution under the multivariate normal distribution assumption. Because of this known distributional property of IILMM test statistics, one can perform post hoc or ad hoc power analysis of IILMM.

However, there is no prior research on the OILMM test statistics. Unlike the IILMM scenario with ML methods, it seems to be very hard to analytically decompose OILMM test statistics into useful facets (e.g., effect size measure, construct reliability measure) using the WLS estimation methods (e.g., WLS, WLSM, or WLSMV). While WLSMV has recently been suggested for use with/as the URV option for ordinal indicator cases, empirical research on the performance of WLSMV estimations regarding test statistics' distributional property is scarce.

Based on the results of OILMM and the previously proposed measures (d^*, f^*, H^*), I propose an expression of the general $J-1$ group case URL option OILMM test statistic:

$$g_0^* = (f^*)^2 H^*,$$

Also, for two group cases,

$$g_0^* = [n_1 n_2 / N](d^*)^2 H^*.$$

Additionally, I propose an expression of general $J-1$ group case URL option OILMM noncentrality parameter:

$$\lambda_0^* = (N-1)(f^*)^2 H^* = (N-1)g_0^*,$$

And, for two group cases,

$$\lambda_0^* = (N-1)[n_1 n_2 / N](d^*)^2 H^* = (N-1)g_0^*.$$

A point worth noting with the above expressions is that both the proposed test statistic and noncentrality are based on the conjecture made from the IILMM results instead of the analytical derivation. To empirically study these proposed test statistics, I used this as proposed test statistic in a Monte Carlo simulation while manipulating various conditions, such as number of categories or sample sizes. Moreover, since empirical research on the distributional properties of the WLSMV test statistic is rare, this simulation study could provide potentially useful information regarding the performance of WLSMV, a new and popular estimation option for ordinal indicators.

Simulation Method

Overview of Simulation Study Design

As shown in the background section, we suspect Type I error rates and the power detecting latent mean differences might change depending on the different methods of handling ordinal indicators, the IM option or URV option. Furthermore, Type I error rates and the power detecting latent mean differences may also vary across other conditions, e.g., number of categories of ordinal variables or model size. To investigate this suspected variability, I used a Monte Carlo simulation to focus on the effect of categorization on the power estimates and Type I errors across both options for handling ordinal indicators and variety of conditions. The details of the simulation study design conditions and the rationale for choosing each condition were discussed in the following sections. Additionally, see Table 2 for the summary of the simulation study conditions.

Sample Size

Initially, data in the present study were simulated for n = 50, 100, 500 and 1000 observations for each group using Mplus. These sample size were chosen to reflect a small to moderate sample size that might be commonly encountered in practice. As seen in the case of interval indicators, the sample size is an important component of the power estimates. Furthermore, since the different types of options and the number of categories for ordinal data may require different levels of sample sizes for estimation, manipulating sample sizes in the simulation research design should be meaningful.

Model Size: Number of Indicators

Regarding population model characteristics, the number of indicator variables was varied as 3, 5 and 7 for one construct, that is, a one-factor model. These model sizes were chosen to reflect a small to big model size that might be commonly encountered in practice. For each population, the same number of indicators was applied. By varying the number of categories, we investigate the relationship between the number of indicators and the categorization effect with the Type I errors and power estimates.

Loading Magnitude

As shown in the discussion of interval data, the power estimate is a function of the construct reliability, *H*. Furthermore, since this coefficient is also a function of loadings, the magnitude of population loadings is also very important component in determining power estimates in ordinal indicator LMM. This condition provides meaningful information for interpreting and analyzing the relationship between the number of categories and power, especially since the attenuation effect of categorization on loadings has already been studied. The magnitude of the factor loadings for interval data prior to categorization was varied as .3, .5 and .7 values which were chosen to reflect a small to big factor loading that might be commonly encountered in practice (Curran et al., 1996). Loadings were homogeneous within a model and these loading values were used to construct population correlation matrices for generating multivariate normal data within Mplus.

Number of Categories

Given the popularity of ordinal variables and the very common practice of choosing the IM option in social science and behavioral research, the number of ordinal categories would be an interesting component. In this research, the number of categories of each indicator, *m*, were varied as 2, 3, 4, 5, 6, 7, 8, and 9 which were chosen to reflect a small to big number of categories that are commonly encountered in educational and behavioral research. Also, *m* was homogeneous for all indicators within model. This number-of-categories effect in ordinal variable analysis has been known for decades and many researchers have investigated this effect via simulation designs (e.g., Babakus et al., 1987; Bollen & Barb, 1981; DiStefano, 2002; Poon et al., 2002). However, there is no prior research regarding the number of category effect in OILMM. In an effort to repair this oversight, this work more intensively investigates this number-of-categories effect, along with other components of the categorical effect analysis, using a Monte Carlo simulation and other analytical developments proposed in early sections of this work.

Investigating this number-of-categories effect provides a very interesting and practical question for applied researchers considering the IM option: "Can we ignore the metric of ordinal indicators if we have enough many *m* in OILMM?" Also, for the URV option, greater numbers of categories result in more parameter estimates (more thresholds) to be estimated. As a result, for the URV options increasing the number of category may decrease the likelihood of obtaining a converged result. That is, the number of category may also play an important role in OILMM parameter estimates.

Latent Mean Differences: Effect Size

The standardized difference in latent means, *d*, were varied as 0 (absent for null situation to investigate Type I error), .3 (small), .7 (moderate), 1.5 (strong), and 3 (strong) with completely invariant intercepts (Cohen, 1988). As with sample size and loading magnitude, the power estimate is a function of latent mean effect size in the case of interval indicators. In this simulation study, I investigated the impact of categorization on latent mean difference estimates, a key facet of power estimates.

The Categorization Rule

As seen previously, given the ordinal data in the contingency table(s), one can estimate thresholds and use these estimates to estimate model parameters (e.g., factor loadings) for the URV option. For the IM option case, because different sets of thresholds value yield different statistics for the indicators, it is very natural to expect that different categorization rules (different threshold values) yield different parameter estimates of OILMM.

There are an infinite number of possible contingency tables in a given number of category sets; even using only two categories for X_1 and three categories for X_2 yields infinitely many four-contingency-cell-proportion combinations. Therefore, for investigating the categorization rule effect on OILMM parameter estimates, we have to select practical categorization rules in order to provide generalized and useful categorization effect analysis.

These threshold schemes play very important roles in many types of research on ordinal categorization effect analysis (e.g., Babakus et al., 1987; Bollen & Barb, 1981; DiStefano, 2002; Poon et al., 2002). For the sake of simplicity, this simulation study focused on three categorization rules that have appeared in prior research. The first, the normal category option (also called the equal category width option within the range from -3 to 3 in standard normal distribution), is an option categorizing a continuum, X^*, which brings the distribution of categorized data, X, closer to normal as the number of category increases (Bollen & Barb, 1981). Moreover, this holds true for any type of underlying distributions, such as uniform or skewed distributions. The second option is the *uniform* (equal proportions) category option. This option is an abnormal option and brings the distribution of categorized data, X, closer to uniform as the number of category increase. The third option is the *asymmetric* option, in which each category proportions are proportional to the number of category, e.g., for 4 categories, it is 40%, 30%, 20%, and 10%. This is also an abnormal category option; it positively skews distributions of ordinal variables. To summarize, as the number of category increases, the distribution of categorized ordinal data of the normal, uniform, and asymmetric (positively skewed) categorization option approaches normal, uniform, and asymmetric (positively skewed), respectively. And, these categorization rules are homogeneous within the model. See Table 1 for the numerical values of thresholds across all categorization options.

Data Generation and Estimation Methods

Initially, Matlab (The MathWorks, 2003) was used to generate Mplus input files according to each condition of simulation. For each sample size, multivariate normal data was generated based on the population matrix according to each model size, loading magnitude, and effect size measure condition within Mplus. Then, the generated data were also coded into ordinal categories within Mplus. Once again, the number of categories (*m*) of each indicator was varied from two to nine in order to investigate the categorization effect with the homogeneous *m* and homogeneous categorization rule within the model.

With the categorized data generated by Mplus, I applied two different ways of handling categorized ordinal data to study the effect of options of handling ordinal variables on OILMM parameter estimates. First, I analyzed the categorized data using the traditional interval scale data method, ML, i.e., using Mplus to treat ordinal indicators as if they were interval indicators (IM approach). Note that the IM approach can be coupled with the WLS types of estimators as well. I choose the ML method for the IM because this estimation method is common choice for the IM in practice. Second, I analyzed the categorized data categorized data sets using Jöreskog's underlying response variable (URV) approach using the Mplus WLSMV estimation method. I use th Both estimations were performed independently using the population starting values within Mplus.

Statistics Examined and Other Issues

Initially, I began by examining rates of properly converged solutions (RPCS) across all simulation conditions. A properly converged solution (PCS) was defined as a converged solution without Heywood cases. Because the main purpose of this study was to explicitly evaluate the categorization effect analysis for OILMM under conditions commonly encountered in applied researches, I defined proper solutions to be valid empirical observations.

Also, I considered three major outcomes of interest: the empirical Type I error rate, the empirical power estimates, and the parameter estimates. First of all, the empirical Type I error can be defined as,

ETIE = NTPCR/TPCR,

where TPCR s the total number of properly converged solutions, and NTPCR is TPCR such that the noncentrality parameter estimate is greater than the population null sampling distribution's critical value (PCV). PCV is (1- α) percentile score of J-1 degree of freedom central chi-square distribution. For the current research design, J = 2 and α = .05, PCV is 3.84. And, the deviation between ETIE and the alpha value (.05 for this study),

ETIED = .05 - EITE,

was analyzed as a final outcome for the empirical Type I error analysis. Additionally, the empirical critical value (ECV: the 95 percentile score of an empirical null distribution of the proposed test statistic) was saved. Because ECV > PCV if and only if ETIE > α, ECV also provides an information (similar to ETIE) of each empirical null distributions. Appendix A provides ECV and ETIED values for all null conditions.

The empirical power was most importantly analyzed. I used EPD,

$$EPD = EP1 - PP,$$

as major simulation outcome for the empirical power analysis. PP is the theoreical power value, EP1 is an empirical power estimates based on the empirical critical value (ECV),

$$EP1 = ETPCR/TPCR,$$

where ETPCR is TPCR such that noncentrality parameter estimates is greater than the empirical critical value (ECV).

Additionally,

$$EPP = EP2 - PP,$$

was also saved. EP2 is an empirical power estimates based on the population critical value (PCV),

$$EP2 = PTPCR/TPCR,$$

where PTPCR is TPCR such that noncentrality parameter estimates is greater than the population critical value (PCV). I provided both EPD and EPP value with ETIED value in Appendix A for all simulation conditions.

Lastly, estimates of key facet of power analysis (effect size and construct reliability) were also saved and analyzed for the further analysis on the results of Type I error and power. For each cell of this simulation design, the quality (accuracy) of parameter estimates was also assessed by investigating a bias index, mean bias (MBS),

$$\sum_i (\hat{\vartheta}_i - \vartheta)/\text{TPCR},$$

where $\hat{\vartheta}_i$ is *i*th properly converged parameter estimate of a parameter ϑ (either *d* or *H*) Also, I investigated a variability index, mean square error (MSE),

$$\sum_i (\hat{\vartheta}_i - \vartheta)^2/\text{TPCR}.$$

I analyzed the relation of this quality and variability of estimates with other design characteristics (e.g., sample size, number of indicators, magnitude of indicators, number of categories, etc.), focusing in particular on the relations 1) between the number of category and estimates, 2) between the ordinal variable handling option and estimates across various other simulation conditions.

Development of IM Impact Coefficients

IM Option Moments

In this section, I begin by reviewing the definition of moments of univariate and bivariate random variables. If $f(y)$ is the univariate probability density of the random variable Y, the *mean* or *expected value* of Y is defined as

$$\begin{aligned}\mu_Y &= E(Y) \\ &= \int_{-\infty}^{+\infty} yf(y)\,dy.\end{aligned}$$

Also, the *variance* of Y can be defined as

$$\begin{aligned}\sigma_Y^2 &= E(Y - \mu_Y)^2 \\ &= \int_{-\infty}^{+\infty} (y - \mu_Y)^2 f(y)\,dy.\end{aligned}$$

If $f_2(y, z)$ is the bivariate probability density of the random variable Y and Z, the *covariance* of Y and Z is defined as

$$\begin{aligned}\sigma_{YZ} &= E(Y - \mu_Y)(Z - \mu_Z) \\ &= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}(y - \mu_Y)(z - \mu_Z) f_2(y, z)\,dydz \ .\end{aligned}$$

Finally, the Pearson product moment correlation of Y and Z is defined as

$$\begin{aligned}\rho_{YZ} &= \rho \\ &= \frac{\sigma_{YZ}}{\sqrt{\sigma_Y^2 \sigma_Z^2}}.\end{aligned}$$

Using the above expressions, we can develop the moments of ordinal variables in cases where ordinal variables are treated as if they were interval-scaled variables. Let us consider X, an ordinal random variable having m categories, ≥ 2, coded $a_1, a_2, \ldots, a_m$, to have come from an underlying continuous variable, X^*, which has a range from $-\infty$ to $+\infty$. The *IM option mean* of this ordinal variable, X, can be defined as

$$\begin{aligned}\mu_X &= \tilde{\mu} \\ &= \sum_{i=1}^{m} \int_{\nu_{i-1}}^{\nu_i} a_i f(x^*)dx^*.\end{aligned}$$

and the *IM option variance* of X can be defined as

$$\begin{aligned}\sigma_X^2 &= \tilde{\sigma}^2 \\ &= \sum_{i=1}^{m} \int_{\nu_{i-1}}^{\nu_i} (a_i - \tilde{\mu})^2 f(x^*)dx^*.\end{aligned}$$

Additionally, the *IM option covariance* of the ordinal variables X_1 and X_2 can be defined as

$$\sigma_{X_1X_2} = \tilde{\sigma}_{X_1X_2}$$
$$= \sum_{i=1}^{m_i}\sum_{j=1}^{m_j}\int_{\nu_{1_{i-1}}}^{\nu_{1_i}}\int_{\nu_{2_{j-1}}}^{\nu_{2_j}}(a_{1_i} - \tilde{\mu}_{X_1})(a_{2_j} - \tilde{\mu}_{X_2})f_2(x_1^*, x_2^*)dx_1^*dx_2^*$$

where m_i is the number of ordinal categories of X_i, ν_{jk} is the k^{th} threshold of the ordinal variable X_j, and a_{l_m} is the m^{th} category response of the ordinal variable X_l. In conclusion, using the above equations, we can easily define the *IM option correlation* of the ordinal variables X_1 and X_2 as

$$\rho_{X_1X_2} = \tilde{\rho}$$
$$= \frac{\tilde{\sigma}_{X_1X_2}}{\sqrt{\tilde{\sigma}_{X_1}^2\tilde{\sigma}_{X_2}^2}}.$$

To compute these proposed moments, we need to determine the probability density function: either f or f_2. As discussed earlier, in the educational and psychological domains it is common to assume the underlying distribution is the normal distribution such that $f = \Phi$, which is the standard normal distribution, and $f_2 = \Phi_2$, which is the standard bivariate normal distribution with correlation ρ (more specifically $\rho_{X_1^*X_2^*}$). Therefore, I use the proposed moment expressions with these normal distribution functions for the remainder of this work.

IM option Bias Coefficients

Using the statistics proposed in the previous section, we can define useful IM option bias coefficients. First of all, we can define the *IM option deviation coefficient* (D), the deviation between an IM option moment of ordinal variables and the moments of the underlying continuous variables, as follows:

$$D_{\mu} = \tilde{\mu} - \mu_{X^*},$$

is the IM option deviation coefficient of the mean,

$$D_{\sigma^2} = \tilde{\sigma}^2 - \sigma^2_{X^*},$$

is the IM option deviation coefficient of the variance,

$$D_{\sigma_{12}} = \tilde{\sigma}_{X_1 X_2} - \sigma_{X_1^* X_2^*},$$

is the IM option deviation coefficient of covariance, and

$$D_{\rho} = \tilde{\rho} - \rho = \tilde{\rho} - \rho_{X_1^* X_2^*},$$

is the IM option deviation coefficient of correlation.

In addition, the *ignoring metric ratio coefficient* (*R*), the ratio between the IM option moments and the underlying continuous moments, can be defined as

$$R_{\mu} = \frac{\tilde{\mu}_X}{\mu_{X^*}},$$

the IM option ratio coefficient of the mean as

$$R_{\sigma^2} = \frac{\tilde{\sigma}^2}{\sigma^2_{X^*}},$$

the IM option ratio coefficient of the variance as

$$R_{\sigma_{12}} = \frac{\tilde{\sigma}_{X_1 X_2}}{\sigma_{X_1^* X_2^*}},$$

the IM option ratio coefficient of covariance,

$$R_{\rho} = \frac{\tilde{\rho}}{\rho},$$

the IM option ratio coefficient of correlation. Also, note that R_ρ can be an *attenuation coefficient of correlation* (C_ρ), due to the crude categorization.

Several points about these proposed coefficients are noteworthy. First, these proposed coefficients provide us with information on the *categorization effect* on the moments when we ignore metric data, i.e., treat ordinal data as if they were interval data via analytical expressions. Second, because most statistical analyses rely on moment statistics about observed variables, these coefficients can be useful tools for understanding the consequences of IM option not only on the moments themselves, but also on the model parameter estimates based on those the metric-ignored moments. Using these IM option moment expression and coefficients, intensive numerical results regarding IM option categorization effect are provided in the results chapter of this work.

Chapter IV: RESULTS

Overview

In this chapter, I illustrate the categorization effect using two different major components: the simulation results and the additional numerical results. In the simulation results part, I illustrate the simulation results by focusing on the three simulation outcomes (convergence rate, empirical Type I Error rate, and power) under various simulation conditions, such as number of categories, ordinal variable handling options, sample sizes, loading magnitudes, model sizes, categorization options, and latent mean differences.

In the additional numerical results part, I provide the categorization effect analysis especially when for an IM option chosen using the previously proposed IM option moments, the IM option deviation coefficients, and the IM option ratio coefficients. Specifically, I first illustrate the categorization effect on observed-level first and second moments. Later, I also provide an analysis of categorization effect on the construct reliability coefficient *H*.

Simulation Results: Convergence Rate

Sample Sizes

The sample size effect on the convergence rate (specifically, on the rate of property converged solutions, RPCS) is very clear. Simply put, the larger the sample (observations), the better the convergence rates for both IM and URV options. Given the same number of sample sizes, the IM option case shows better convergence rates than the URV option does (Figure 3). Many simulation conditions not only fail to reach 500 converged replications, they also frequently have zero converged replications with the smallest sample size condition (n = 50), especially for the URV option case, as we can easily see in Appendix A. Nevertheless, with a sample size of 1000, most of the simulation conditions achieved 500 converged replications for both IM and URV options (i.e., at least 50% convergence rate for the 1000 sample size case).

Figure 3 depicts the average RPCS across m and sample sizes (n = 50, n = 100, n = 500, and n = 1000). For the IM option case, RPCS tends to increase as the number of categories increases for all sample sizes. For the n = 1000 case, all RPCS are greater than .95 for all m. For the URV option case, most interestingly, the $m = 2$ case shows the lowest convergence rate and the $m = 3$ case shows the highest convergence rate. When $m > 3$, the convergence rate drops as m increases. For the small sample size cases (n = 50 and n = 100), the convergence rate drops quickly as m increases, but for the large sample size cases (n = 500 and n = 1000), the convergence rate drops more slowly as m increases (Figure 3).

Loading Magnitudes

For the IM option case, the loading magnitude effect on RPCS is obvious in Figure 4, which depicts the average RPCS across *m* and the loading magnitudes ($\lambda = .3$, $\lambda = .5$, and $\lambda = .7$). Basically, RPCS increases as the number of category increases. The smallest loading magnitude, $\lambda = .3$, yields the lowest convergence rate, but the middle loading magnitude, $\lambda = .5$, yields the highest convergence for all numbers of categories.

However, for the URV option case, the loading magnitude effect on the convergence rate is not so obvious. As *m* increases, the smallest loading magnitude ($\lambda = .3$) tends to yield the biggest RPCS, while the highest loading magnitude ($\lambda = .7$) yields the smallest RPCS. In general, for the URV option, the $m = 2$ case shows the lowest convergence rate and the $m = 3$ case shows the highest convergence rate. And when $m > 3$, the convergence rate drops as *m* increases (Figure 4).

Model Sizes

For the IM option case, the model size effect on RPCS is also evident in Figure 5, which depicts the average RPCS across *m* and model sizes ($p = 3$, $p = 5$, and $p = 7$). Basically, the convergence rate increases as the number of indicators increases. The smallest number of indicators, $p = 3$, yields the lowest convergence rate, but the largest number of indicators ($p = 7$) yields the highest convergence for all numbers of categories.

However, for the URV option case, the model size effect on the convergence rate is less evident. When $m = 3$, 4, or 5, the greater numbers of indicators (bigger model sizes) tend to yield better convergence rates. When $m = 6, 7, 8$, or 9, smaller numbers of indicators (smaller model sizes) tend to yield the better convergence rates. Generally for the URV option, the $m = 2$ case shows the lowest convergence rate and the $m = 3$ case shows the highest convergence rate. When $m > 3$, the convergence rate drops as m increases (Figure 5).

Categorization Options

For the IM option case, the categorization option effect on RPCS is obvious in Figure 6, which depicts the average RPCS across m and categorization options (Normal, Asymmetric, and Uniform). Basically, RPCS increases with the number of category. The differences among three categorization options, however, are not as big as options of other simulation conditions (sample size, loading magnitude, or model sizes).

For the URV option case, the model size effect on RPCS is clear. The normal categorization option yields the lowest convergence rate, and the convergence rate quickly drops as m increases, while the non-normal categorization options' (Asymmetric and Uniform) convergence rates slowly drop as m increases. Only when $m = 3$ or 4 is the average RPCS greater than .5 for the normal categorization option case. In general the $m = 2$ case shows the lowest convergence rate (except for the normal category option case) and the $m = 3$ case shows the highest convergence rate for the URV option. Once again, when $m > 3$, the convergence rate drops as m increases (Figure 6).

Latent Mean Differences

Figure 7 depicts the average RPCS rate across *m* and the latent mean differences ($\kappa_2 = 0$, $\kappa_2 = .3$, $\kappa_2 = .7$, $\kappa_2 = 1.5$, and $\kappa_2 = 3$). For the IM option case, the convergence rate increases as the number of category increases. The null case ($\kappa_2 = 0$), however, tends to yield the lowest convergence rate across the number of category, while the ($\kappa_2 = 1.5$) case tends to yield the highest convergence rate.

For the URV option case the model size effect on the convergence rate is once again apparent. For the $\kappa_2 = 0$, $\kappa_2 = .3$, and $\kappa_2 = .7$ cases, the differences between the convergence rates of the three cases are not very noticeable. However, the convergence rates of the $\kappa_2 = 1.5$ or $\kappa_2 = 3$ cases are substantially lower than those of the $\kappa_2 = 0$, $\kappa_2 = .3$, and $\kappa_2 = .7$ cases. Notably, the average RPCS is greater than .5 for the $\kappa_2 = 3$ case only when $m = 3$ or 4. In general for the URV option, the $m = 2$ case shows the lowest convergence rate (except for $\kappa_2 = 3$ case) and the $m = 3$ case shows the highest convergence rate. As with variations in model size and loading magnitude when $m > 3$, the convergence rate drops as *m* increases (Figure 7).

Summary for Convergence Rate

As seen in the above results, the IM option generally yields better convergence rates (RPCS) than the URV option does. While the IM option RPCS tends to increase as *m* increases, the URV option RPCS tends to decrease as *m* increases when $m > 2$. The difference is most noticeable when $m = 2$; under such circumstances, the URV option RPCS tend to show its lowest RPCS—about 40% on average—while the IM option yields 85% of RPCS.

Simulation Results: Empirical Type I Error Rate

Sample Sizes

For the IM option, the sample size effect on the empirical Type I error rate is very clear. Basically, the greater sample size, the smaller the ETIED. For example, Figure 8 depicts the average ETIED across *m* and sample sizes. However, no obvious pattern of the number of categories effect on the average ETIED has been observed for all sample sizes. For the URV option, there is also no clear pattern in the average ETIED across the various sample sizes. In contrast, there is tendency for the average ETIED to decrease as *m* increases (Figure 8).

Loading Magnitudes

For the IM option, the loading magnitude effect on the empirical Type I error rate is very clear. Basically, the bigger the loading magnitude, the smaller the ETIED. Figure 9 depicts the average ETIED across *m* and the loading magnitudes. However, there is no obvious number of category effect on the average ETIED for all loading magnitudes. For the URV option, on the other hand, there is a similar pattern in the average ETIED among the magnitudes of loadings. That is, the bigger the loading magnitude, the smaller the ETIED. However, in contrast to the IM option, the average ETIED gets smaller as *m* increases when $m > 2$ for the URV option (Figure 9).

Model Sizes

For the IM option, the model size effect on the empirical Type I error rate is straightforward. Basically, the bigger the model size, the smaller the ETIED. Figure 10 depicts the average ETIED across *m* and number of indicators. However, there is no obvious number of category effect on the average ETIED for all model sizes. For the URV option, the pattern in the average ETIED among the model sizes is similar to the IM option case. That is, the model size is inversely related to the ETIED: as the former increases, the latter decreases. However, unlike the IM option, the average ETIED gets smaller as *m* increases when $m > 2$ (Figure 10).

Categorization Options

For the IM option, the categorization option effect on the empirical Type I error rate is not evident. There are no observable differences in ETIED among three categorization options, as we can see in the Figure 11, which depicts the average ETIED across *m* and the categorization options. Furthermore, there is no obvious number of category effect on the average ETIED for all three categorization options. For the URV option, however, there are the following patterns in the average ETIED among three categorization options. First, the normal categorization option yields the least ETIED. Second, the average ETIED of the normal and asymmetric options tends to get smaller as the number of categories increases. Third, the number of categories does not seem to affect the ETIED for the uniform categorization option case (Figure 11).

Summary for Empirical Type I Error Rate

As we see in the above results, the IM option usually yields ETIED of smaller magnitude (i.e., close to zero) than the URV option does. Furthermore, while the URV option ETIED magnitude tends to decrease as *m* increases, the IM option RPCS does not appear to be affected by the number of categories. Therefore, "the more categories, the better" phenomena is again absent for the IM option but present for the URV option.

Simulation Results: Empirical Power

Sample Sizes

For the IM option, the sample size effect on the empirical power is self-evident. The greater the sample size, the smaller the magnitude of the EPD. This is illustrated by Figure 12, which depicts the average EPD across *m* the sample sizes. Also, there is the number of categories effect on the average EPD for all sample sizes: the average EPD tends to approach to zero as the number of categories increases. For the URV option, there is similar pattern in the average EPD among the number of sample sizes: the greater the sample size, the smaller magnitude EPD when $m > 2$. Additionally, the average EPD also tends to approach to zero as the number of categories increases. And, both the IM and the URV options yield negative EPDs for all cases (Figure 12).

Loading Magnitudes

For the IM option, the loading magnitude effect on the empirical power is also unambiguous. As we can see in the Figure 13, which depicts the average EPD across *m* and the loading magnitudes, larger loading magnitudes yields smaller-magnitude EPDs. Also, there is an obvious number of categories effect on the average EPD for all loading magnitudes: the bigger the magnitude of loading, the smaller the magnitude EPD. For the URV option, the same pattern is evident under more limited conditions; that is, the bigger loading magnitude, the smaller magnitude EPD when $m > 2$. In addition, the average EPD also tends to approach to zero as *m* increases. Both the IM and the URV options thus yield negative EPDs for all cases (Figure 13).

Model Sizes

Figure 14 depicts the average EPD across the number of categories and the number of indicators. As model size increases, the EPD magnitude decreases for both the IM option and the URV options. There is also an obvious number of categories effect on the average EPD for all model sizes using either option: the magnitude of EPD decreases as *m* increases. Both the IM and URV options yield negative EPD for all cases (Figure 14).

Categorization Options

Figure 15 depicts the average EPD across the three categorization options and *m*. For the IM option, the categorization option effect on the empirical power is not apparent. In other words, there are no perceptible differences in the average EPD across three categorization options. However, there is a substantial number of categories effect on the average EPD: the magnitude of average EPD gets smaller as *m* increases. For the URV option, there are the following patterns in the average EPD among three categorization options: first, the normal categorization option tends to yield the smallest magnitude EPD; second, the magnitude of the average EPD also gets smaller as the number of category increases. Both IM and URV option yield negative EPDs for all cases (Figure 15).

<u>Latent Mean Differences</u>

Figure 16 depicts the average EPD across the various numbers of categories and the latent mean differences. For the IM option, the latent mean difference effect on the empirical power is obvious. Simply put, the magnitude of EPD gets smaller as the latent mean difference increases. The magnitude of EPD also gets smaller as *m* increases. For the URV option, the average EPD among four latent mean differences show similar patterns: with increases in *m* and/or the latent mean difference, the magnitude of EPD gets smaller. Both the IM and the URV options yield negative EPDs for all cases (Figure 16).

<u>Summary for Empirical Power</u>

The above results show a general trend:, the IM option yields smaller-magnitude (close to zero) EPDs than does the URV option. Most of the results are very clear: for either option, bigger sample sizes, bigger loading magnitudes, bigger model sizes, and/or bigger latent mean difference all yield better power estimate. Moreover, with both the IM and the URV options, the EPD magnitudes get smaller as *m* increases.

Simulation Results: Effect Size

Sample Sizes

For the IM option, the sample size effect on *d* is self-evident. Basically, the greater the sample size, the smaller the MBS. This is shown in Figure 17, which depicts the average MBS of *d* across *m* and the sample sizes. However, the average MBS tends to get bigger as the number of category increases, especially when $m = 2$, 3, and 4. When $m \geq 5$, there is no apparent effect of *m* across all sample sizes. For the URV option, no clear pattern exists in the average MBS among the number of sample sizes. However, in contrast to the IM options, the average MBS tends to approach to zero as the number of category increases when $m > 2$. In general, the average magnitude MBS of the URV option is smaller than that of the IM option, although both options yield a positive MBS (equivalently, overestimated) for all cases when $m > 2$ (Figure 17).

Loading Magnitudes

Figure 18 depicts the average MBS of *d* across *m* and the loading magnitudes. For the IM option, the loading magnitude effect on the average MBS is clear: the $\lambda = .7$ case shows the smallest MBS magnitude, the $\lambda = .5$ case shows the medium magnitude of MBS, and the $\lambda = .3$ case shows the biggest MBS. This is true for regardless of the number of categories. Also, the number of categories effect on the average MBS is obvious for all loading magnitudes: the magnitude of MBS increases as *m* increases. For the URV option, there is different pattern in the average MBS across the magnitudes of loading. That is, the bigger loading magnitudes are associated with the smaller MBS magnitudes when $m > 2$. In addition, the average MBS also tends to approach to zero as m increases when $m > 2$. In general, the average magnitude MBS of the URV option is smaller than that of the IM option. Both IM and URV option yield positive MBS for all cases except when $m = 2$ (Figure 18).

Model Sizes

For the IM option, the model size effect on the average MBS of d is not apparent. Basically, there is no clear pattern in the average MBS among the three model sizes. We can see this in Figure 19, which depicts the average MBS across m and the numbers of indicators. Nevertheless, there is an obvious number of categories effect on the average MBS for all model sizes: the magnitude of MBS tends to positively increase as the model size increases when $m = 2$, 3, and 4. However, when $m \geq 5$, there is no apparent effect of m across all sample sizes. For the URV option, as with the IM option, there are no apparent differences in the average MBS among the model sizes. However, the average-magnitude MBS tends to get smaller as m increases when $m > 2$. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Moreover, both the IM and the URV options yield positive MBS for all cases except when $m = 2$ (Figure 19).

Categorization Options

Figure 20 depicts the average MBS of d across m and categorization options. For the IM option, the uniform categorization option shows the smallest MBS, but the normal categorization option showed the largest MBS. The average MBS gets bigger as m increases when $m = 2$, 3 and 4. For the URV option, there are several patterns in the average MBS among three categorization options. First, the normal categorization option yields the smallest magnitude MBS when $m > 2$. Second, the normal and asymmetric options' average MBS magnitudes tend to get smaller as the number of categories increases. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Again, both options yield positive MBS for all cases except those where $m = 2$ (Figure 20).

Latent Mean Differences

Figure 21 depicts the average MBS of d across m and the latent mean differences. For the IM option, the latent mean difference effect on the MBS is obvious. The smallest latent mean difference ($\kappa_2 = 0$) yields the biggest MBS. But, when $\kappa_2 = .3$, the average MBS is the smallest among the four levels of latent mean differences. In general, the magnitude of MBS tends to get bigger as m increases. Specifically, the MBS tends to increase as m increases when $m = 2$, 3, and 4, but there is no apparent effect of m across all sample sizes when $m \geq 5$. For the URV option, there are same patterns in the average MBS among four latent mean differences: the magnitude of the MBS gets smaller as the latent mean difference increases and the magnitude of the MBS also gets smaller as m increases. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Also, the IM option yields a positive MBS for all cases, but the URV option yields a positive MBS only when $m > 5$ (Figure 21).

MSE of *d* Across Sample Sizes

Figure 22 depicts the average MSE of *d* across *m* and the four different sample sizes. For the IM option, the sample size effect on the MSE is very obvious. The larger sample sizes yield smaller magnitudes of MSE. Moreover, there is no apparent effect of *m* except for the n = 50 case. For the URV option, the magnitude of the MSE tends to get smaller as *m* increases when $m > 2$. Furthermore, the largest sample size, n=1000, yields the smallest- magnitude MSE when $m > 2$. In general, the average-magnitude MSE of the URV option is smaller than that of the IM option (Figure 22).

Summary for Effect Size

In general, the average magnitude MBS of *d* of the URV option is smaller than that of the IM option. Furthermore, while the magnitude of MBS of the URV option gets smaller as *m* increases, that of the IM option gets bigger as *m* increases. Specifically, "the more categories, the better" phenomena is absent for the IM option; even large numbers of categories tend to yield poor estimates (bigger magnitudes of MBS) of *d*. Also, for the MSE of *d*, the magnitude of MBE of the URV option gets smaller as *m* increases, but that of the IM option does not.

Simulation Results: Construct Reliability

Sample Sizes

For the IM option, the sample size effect on *H* (specifically, the pooled *H* of two groups) is self-evident. Basically, the greater the sample size, the smaller the

MBS of *H*. For an example, see Figure 23, which depicts the average MBS across the sample sizes and *m*. Additionally, the average MBS positively increases as the number of categories increases. Specifically, the average MBS is negative (equivalent, underestimated) when $m = 2$ and monotonically increases as *m* increases for all four sample sizes. Substantially, when $m \geq 5$, the n = 50 case MBS becomes positive. For the URV option, there is a different pattern in the average MBS among the number of sample sizes: the greater the number of samples, the smaller the magnitude of MBS when $m > 2$. Furthermore, the average MBS tends to approach zero as the numbers of categories increases for all four sample sizes. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Moreover, the URV option yields a positive MBS for all cases, while most of the IM options' MBSs are negative (Figure 23).

Loading Magnitudes

Figure 24 depicts the average MBS of *H* across *m* and the loading magnitudes. For the IM option, the loading magnitude effect on the average MBS is clear. Basically, the bigger the loading magnitude, the smaller the MBS of *H*. Also, the number of categories effect on the average MBS is obvious for all loading magnitudes: the bigger *m*, the bigger the average MBS. Specifically, the average MBS is negative when $m = 2$ and monotonically increases as *m* increases. When $m \geq 5$, the $\lambda = .3$ case MBS is positive. For the URV option, different patterns exist in the average MBS among the magnitude of loadings. That is, the bigger the loading magnitudes, the smaller the MBS. In addition, when $m > 2$, the average MBS approaches zero as *m* increases. In general, the average MBS magnitude of the URV option is smaller than that of the IM option. Also, the URV option yields a positive MBS for all cases while most of the IM options' MBSs are negative (Figure 24).

Model Sizes

For the IM option, the model size effect on the average MBS of *H* is also apparent. Basically, bigger models yield increasingly negative MBSs, as we can see in the Figure 25, which depicts the average MBS across m and the number of indicators. Also, the number of categories effect on the average MBS is obvious for all model sizes: the bigger m, the bigger MBS. Specifically, all four model sizes' average MBS are negative when $m = 2$ and monotonically increase as m increases. When $m = 9$, all of the MBSs are close to zero. For the URV option, there is an opposite but equally clear pattern in the average MBS among the model sizes. That is, the bigger the model sizes, the smaller the MBS. In addition, all four model sizes' average MBS approaches zero as m increases when $m > 2$. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Again, the URV option yields a positive MBS while the IM option yields negative MBSs for all cases (Figure 25).

Categorization Options

Figure 26 depicts the average MBS of *H* across categorization options and m. For the IM option, no clear pattern exists among three categorization options. However, the number of categories effect on the average MBS is obvious for all categorization options: MBS increases with the growth of m. Specifically, all three categorization options' average MBS are negative when $m = 2$ and monotonically increase as m increases. For the URV option, there are the following patterns in the average MBS among the three categorization options. First, the normal categorization option yields the smallest magnitude MBS, and the uniform categorization options yields the biggest magnitude MBS. Second, all three categorization options' average MBS magnitude get smaller as the number of categories increases. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. The URV option once again yields a positive MBS while the IM option yields negative MBSs for most cases (Figure 26).

Latent Mean Differences

For the IM option, the latent mean difference effect on the average MBS of H is also apparent. As we can see in Figure 27's depiction of the average MBS across latent mean differences and m, bigger mean differences tend to yield negative MBSs. Also, the number of categories effect on the average MBS is obvious for all mean differences: the bigger m, the bigger the MBS. Specifically, all five latent mean differences' average MBS are negative when $m = 2$ and monotonically increases as m increases. For the URV option, a different pattern is observed in the average MBS among the latent mean differences. That is, the bigger the latent mean difference, the smaller the MBS magnitude. In addition, all five latent mean differences' average MBSs approach zero as m increases when $m > 2$. In general, the average-magnitude MBS of the URV option is smaller than that of the IM option. Also, the URV option tends to yield a positive MBS, but the IM option tends to yield a negative MBS.

MSE of *H* Across Sample Sizes

Figure 28 depicts the average MSE of *H* across the four different sample size and the numbers of categories. For the IM option, the sample size effect on the MSE is quite obvious. The bigger sample sizes yield the smaller MSE when $m > 3$. There is also apparent effect of *m* across all four sample size conditions: the average MSE of *H* gets smaller as *m* increases. This is also true for the URV option: the bigger sample sizes again yield smaller magnitudes of MSE. Furthermore, the magnitude of MSE gets smaller as *m* increases when $m > 2$. In general, the average-magnitude MSE of the URV option is smaller than that of the IM option (Figure 28).

Summary for Construct Reliability

In general, the average magnitude MBS of *H* of the URV option is smaller than that of the IM option. And while the magnitude of MBS of the URV option gets smaller as *m* increases, that of the IM option gets monotonically bigger as *m* increases from negative to positive. However, note that we cannot conclude that "the more categories, the better" phenomena exists for the IM option because the increasing *m* can yield poor estimates (e.g., bigger positive magnitude of MBS) of *H*. Also, for the MSE of *H*, the URV option average MSE is generally smaller than that of the IM option.

Further Numerical Analysis on the IM Option

As seen previously, the IM option shows better a convergence rate, a smaller magnitude ETIED, and a smaller magnitude EPD than the URV option does.

However, the URV option yields better results than the IM option in terms of the effect size measure (*d*) and the construct reliability (*H*) estimates for both MBS and MSE. These results regarding *d* and *H* are very important because the ETIED and EPD results are based on the proposed test statistic which is a function of *d* and *H*.

Note that those estimates (*d* and *H*) are also based on estimates of the indicators' moments (i.e., indicators' means, variances, and/or covariances). In other words, *d* and *H* are estimated using the means and covariances of indicators as data. As mentioned previously, the categorization effect on these observed level statistics (means and covariances) is not fully understood. Therefore, understanding the consequence the categorization onto those observed level statistics is necessary, especially for the IM option. More through analysis of such consequences may provide a better understanding of the simulation results regarding *d* and *H,* which are key components of LMM power analysis.

In the following sections, I provide an intensive numerical analysis of the categorization effect for the IM option using previously proposed the IM option moments functions, focused mostly on the observed variable moments. The IM option categorization effect on the construct reliability coefficient and the effect size measure is also provided, based on previous results and analyses.

Categorization Effect on Observed Variable Statistics

Categorization Effect on Relative Mean

As mentioned earlier, since ordinal variables do not have metric properties, there is no significance to the ignored metric mean, $\tilde{\mu}$. Also, $\tilde{\mu}$ mostly depends on the ordinal data coding rules (e.g., the Likert option used in this research always yields the mean of an ordinal variable *X* as zero if the distribution of *X* is symmetric as in normal or uniform distributions). Therefore, it is not very useful to investigate the categorization effect on the mean as a cross-sectional descriptive statistic.

However, it is also true that this first moment information plays a key role in most statistical procedures (including the t-test, ANOVA, and MANOVA) for either within-subject or between-subject research designs. Thus, considering the common social and behavioral research practice of treating ordinal responses as if they were interval-scaled, it is important to understand the impact of ignoring ordinal variables' metric level on the *relative* mean (e.g., the *mean difference* between two IM means, $\tilde{\mu}_2 - \tilde{\mu}_1$).

In a previous section of this work, I illustrated the URV option procedure to capture the underlying level mean difference between two populations using ordinal category proportions (see Figure 2 for this procedure). Equating two sets of thresholds and concurrently setting the mean of the first population as 0 and unit variance for identification, it is possible to estimate both the relative mean and the relative variance of the second population. However, determining the consequences on this relative mean (that is, the mean difference) would be particularly interesting if IM options were employed. This effect on the relative mean has rarely been investigated (see Poon et al., 2002, for the categorization effect analysis on the relative mean and the relative variance using a limited simulation design).

In this section, I provide an intensive numerical analysis of the categorization effect on the relative mean (the mean of second population with respect to the zero mean reference population or the mean difference) across the categorization rules (normal, uniform, positively skewed, negatively skewed), the underlying variable mean difference levels (zero to three with the unit variance of both underlying populations), and the number of categories (two to nine categories). I did this using the IM option mean expression previously proposed in the method chapter of this particular work. Note that the relative mean estimation also requires estimation of the second group variance; the second group's mean and its variance need to be estimated simultaneously (see Figure 2 for more details). To avoid complexity, I fixed the second group variance as one.

The numerical results of this categorization effect on the relative mean are depicted in Appendix B. Additionally, the findings based on these numerical results are summarized here. First, and most importantly, "the more categories, the better" phenomena is absent here. On the contrary, the lower range of category numbers (e.g., two or three) tends to yield negative bias and the upper range of category numbers (e.g., eight or nine) tends to yield positive bias (see Appendix B). Second, most interestingly, the middle range category numbers, e.g., four, five, or six categories, tends to show less bias than either the lower range (e.g., two or three) or the upper range number (e.g., eight or nine) of categories' bias. For example, categories six and seven, with the normal categorization option, yield almost imperceptible bias until the latent mean difference is two (see Appendix B).

In conclusion, the relative mean can always be biased and the degree of this bias is not negligible in most situations. Moreover, in general, increasing the number of categories does not alleviate this bias. Considering the popularity of the statistical tests regarding the first moment (e.g., ANOVA or t-test) and of ordinal variables in the social and behavioral sciences, these findings cannot be stated too strongly: the results are *always* misleading when the IM option is adapted. Thus, one should be careful in treating ordinal variables as if they belong to the metric.

Categorization Effect on Variance and Relative Variance

As discussed above, the consequences of ignoring variables' metric levels is not yet fully understood, particularly where variance is concerned. Again, since ordinal variables do not have metric properties, the metric ignored variance, $\tilde{\sigma}^2$, has no meaning. Therefore, it is not very useful to investigate the categorization effect on the variance as a cross-sectional descriptive statistic. However, this variance also plays a key role in most statistical procedures (such as t-test, ANOVA, MANOVA), given either within-subject or between-subject research designs. Thus, considering the common social and behavioral research practice of treating ordinal responses as if they were interval-scaled, it is important to understand the impact of ignoring ordinal variables' metric level on the *relative* variance (e.g., the *variance difference* between two IM variances, $\tilde{\sigma}_2^2 - \tilde{\sigma}_1^2$).

In this section, I provide an intensive numerical analysis of the categorization effect on the relative variance. Specifically, I investigated the categorization effect on the relative variance across the categorization rules (normal, uniform, positively skewed, negatively skewed), the underlying variable mean difference levels (zero to three with unit variance of both underlying populations), and the number of categories (two to nine categories).

The numerical results of the categorization effect on the relative variance are depicted in Appendix B. Additionally, the findings based on these numerical results are summarized here. First, and most importantly, “the more categories, the better” phenomena is absent here. On the contrary, the larger category numbers tend to yield the more negative bias (see Appendix B). Second, the relative variances with normal/uniform/negative categorization options always show negative bias. Furthermore, this negative bias gets worse as the number of categories increases and/or as the underlying mean difference increases. For the positive category option case, the positive bias occurs when the underlying mean difference falls between 0 and approximately 1.25, and the negative bias occurs when the underlying mean difference is greater than around 1.25.

In conclusion, the relative variance can always be biased and the degree of this bias is not negligible in most situations. Moreover, in general, increasing the number of categories does not alleviate this bias. The relative variance is especially sensitive to the underlying mean difference level. Thus, one should be careful in treating ordinal variables as if they belong to the metric.

<u>Categorization Effect on Correlation</u>

Unlike the relative mean and relative variance, the categorization effect on the Pearson product moment correlation has been studied for a long time (e.g., Bollen &

Barb, 1981). However, most prior research was limited simulation research, focusing on either the correlation estimate itself or on other model estimates based on this correlation estimate. In this section, I provide an intensive numerical analysis of the categorization effect on the correlation across the categorization rules and the number of categories.

Numerical results of this categorization effect on the correlation are depicted in Appendix B. Findings based on these numerical results include, first, that the bias, based on the IM option coefficients of correlation (D_ρ and C_ρ), is always negative for all cases and gets smaller as the number of category increases for all categorization options. Second, in general, the level of bias differs across the levels of the underlying correlation (the correlation between two underlying variables). Third, if both categorization options are symmetric—that is, normal-normal or uniform-uniform—C_ρ is greater than .9 regardless of the magnitude of the underlying correlation as long as the number of categories is greater than 5. Last, for any combination of categorization options and for any magnitude of the underlying correlation, $C_\rho > .8$ as long as the number of category is greater than three.

<u>*Categorization Effect on* H</u>

As we discussed in a previous section of this work, a minor consequence of $\tilde{\rho} = C_\rho \rho$ and $C_\rho < 1$ is that $\tilde{\lambda}^2 < \lambda^2$ and $\tilde{H} < H$. This implies that the attenuation of correlation by the crude categorization consequently yields the attenuation of the construct reliability measure as well. Therefore, the information regarding the difference between $\widetilde{H}$ and H can provide useful tools for understanding the categorization effect on the construct reliability measure.

First, the difference between $\widetilde{H}$ and H, the *construct reliability attenuation deviation coefficient*, can be defined as

$$D_H = H - \widetilde{H}\ .$$

This coefficient represents the construct reliability attenuation size due to the crude categorization.

Second, the ratio between $\widetilde{H}$ and H, the *construct reliability attenuation ratio coefficient*, can be defined as

$$\begin{aligned}
C_H &= \frac{\widetilde{H}}{H} \\
&= \frac{\sum_{i=1}^{p}[\widetilde{\lambda}_i^2/(1-\widetilde{\lambda}_i^2)]\left[1+\sum_{i=1}^{p}[\lambda_i^2/(1-\lambda_i^2)]\right]}{\sum_{i=1}^{p}[\lambda_i^2/(1-\lambda_i^2)]\left[1+\sum_{i=1}^{p}[\widetilde{\lambda}_i^2/(1-\widetilde{\lambda}_i^2)]\right]} \\
&= \frac{\sum_{i=1}^{p}[\widetilde{\lambda}_i^2/(1-\widetilde{\lambda}_i^2)]+\sum_{i=1}^{p}[\lambda_i^2\widetilde{\lambda}_i^2/(1-\lambda_i^2)/(1-\widetilde{\lambda}_i^2)]}{\sum_{i=1}^{p}[\lambda_i^2/(1-\lambda_i^2)]+\sum_{i=1}^{p}[\widetilde{\lambda}_i^2\lambda_i^2/(1-\widetilde{\lambda}_i^2)/(1-\lambda_i^2)]}.
\end{aligned}$$

This coefficient represents the attenuation effect on the construct reliability due to the crude categorization.

Hancock and Mueller (2001) showed that the construct reliability H can be used as a degree of attenuation on factor relationships. Hancock (2001) also showed that that the construct reliability H can be used as a degree of attenuation on the factor mean in the context of LMM with interval indicators. According to that research, H proves useful in analyzing SEM measurement errors. Moreover, in cases with ordinal indicators, I have shown that the construct reliability index with the IM option, $\widetilde{H}$, can be further decomposed into the crude categorization attenuation effect on the construct reliability index, C_H, and the construct reliability index with interval indicators, H. Therefore, C_H can be a helpful element in understanding and/or analyzing the crude categorization effect above and beyond the measurement error effect in various parameter estimates, such as the factor relationships or factor means, including the power estimate associated with the parameter(s) of interest.

Seen previously in the simulation results on H, the MBS of H (specifically, mean of $\hat{\widetilde{H}}$ - H) is negative for most cases and increases as m increases. Those simulation results give us the following conjectures: $C_H < 1$, C_H is a function of m, and C_H increases as m increases.

Chapter VI: DISCUSSION

This chapter discusses the results from the simulation and numerical study on the categorization effect onto the LMM when ordinal indicators are presents. This discussion begins with an overview of the simulation study results, focused mostly on the ordinal indicator options (the IM and URV option) and the number of categories (*m*). The convergence rates (based on RPCS), the empirical Type I errors (based on ETIED), and the empirical power estimates (based EPD) are compared across various simulation conditions. Also, the successfully computed effect size measures (*d*) and the construct reliability (*H*) estimates are compared across various simulation conditions in terms of their accuracy (based on MBS) and variability (based on MSE) relative to the population model. The effect of the number of categories and the ordinal indicator handling options receives the most attention, and explanations of the observed numerical outcomes are included.

Additionally, an overview of the numerical study results, especially for the IM option case statistics, is also provided. The consequences of the IM option on the relative mean, the relative variance, the correlation, and the construct reliability are analyzed, with the focus mostly on the number of categories (*m*) effect. These analyses are based on the IM option moment expressions and the IM option bias coefficients, which are proposed in the method chapter. The analysis concentrates mostly on determining the effect of the number of categories; explanations of the observed numerical outcomes are included. An overall conclusion about the categorization effect on the LMM, based on both simulation and numerical study, is also provided.

This chapter concludes with the potential future research directions of this research. Note that the current simulation study regarding *d* and *H* was a parameter recovery study that specified the correct model when estimating the model parameters. Therefore, the presented results and conclusions are conditional on having the correctly specified model, and the model misspecification effects were not tested in this simulation. The results of the current numerical study are also conditional on the specifications of the numerical study design such as thresholds values and types of underlying distributions.

Simulation Study

Convergence Rate

In general, the IM option yields better convergence rates (RPCS) than the URV option does. While the IM option RPCS tends to increase as m increases, the URV option RPCS tends to decrease as m increases when $m > 2$. Note that these results can be explained by the differences of the estimators of each option. As discussed previously, the URV estimation options (such as WLS, WLSM, and WLSMV) treat the thresholds as model parameters. Therefore, for the URV option, greater m yields more parameters to estimate (bigger weight matrix) and, consequently, creates more difficulty in estimating parameters. In contrast, the IM option estimator ML does not treat the thresholds as model parameters. Therefore, the computational difficulties in the model estimation are not increased as m increases.

Note that the number of parameters is also increased as p increases. However, in contrast to m, the model size does not substantially affect the average convergence rate. In sum, sample size shows mostly apparent impact on RPCS for both IM and URV options. And, the categorization options and latent mean difference yield apparent differences in RPCS only for the URV option.

This particular result may provide practically important information to applied researchers who consider LMM. First, the dichotomous indicator (one of the most common choices in the educational research) LMM with the URV option tends to yield the least successful convergence rate compared to other number of categories, although the model is correctly specified. Second, especially for situations where one can choose m for the factor indicators, the number of categories of indicators should be carefully chosen to balance between the best chance of the converged results and the best parameter estimates. This is important because the RPCS of the URV option tends to decrease as m increases when $m > 2$.

Empirical Type I Error Rate

In general, the IM option yields smaller-magnitude (i.e., close to zero) ETIED than the URV option does. Furthermore, the URV option ETIED magnitude tends to decrease as m increases, while the IM option RPCS does not. Therefore, "the more categories, the better" phenomena is absent for the IM option, but present for the URV option. In sum, sample size shows mostly apparent impact on ETIED for both IM and URV options. And, the categorization options yields apparent differences in ETIED only for the URV option.

This particular result provides us with the following information. First, both IM and URV options' empirical Type I errors are greater than those of the populations, ETIED > 0. Equivalently, the empirical critical value of each simulation condition is greater than the population value, as we can see in Appendix B. This implies that if we applied the population critical value (e.g., 3.84) for the LMM hypothesis testing, especially when sample sizes are small, we will be more likely to incorrectly reject the null hypothesis than we want to bear. Second, the bigger model and bigger loading magnitude tend to yield better ETIEDs (close to zero) for both the IM and the URV options.

Empirical Power

Overall, the IM option yields a smaller magnitude (close to zero) EPD than the URV option does. Most of the results regarding the empirical power estimates are very clear: for both the IM and the URV options, 1) bigger sample size yields better power estimate, 2) bigger loading magnitude yields better power estimate, 3) bigger model size yields better power estimate, and 4) bigger latent mean difference yields better power estimate. Also, both IM and URV options' EPD magnitudes get smaller as m increases. In sum, sample size, loading magnitude, model size, latent mean difference shows apparent impact on EPD for both IM and URV options. However, the categorization option does not yield apparent differences in EPD for both IM and URV options. Note that comparing the IM and URV options regarding the empirical power estimates results is not recommended. As I illustrated in the method chapter, the power estimates for each simulation cell is bounded by each simulation case's null and alternative empirical sampling distributions.

Effect Size

This particular result is d is a population parameter recovery analysis. In general, the average magnitude MBS of d of the URV option is smaller than that of the IM option. While the magnitude of MBS of the URV option gets smaller as m increases, that of the IM option gets bigger as m increases. Specifically, "the more category, the better" phenomenon is absent for the IM option: increasing the number of categories tends to worsen the estimates (bigger magnitude of MBS) of d. Also, for the MSE of d, the magnitude of MBE of the URV option gets smaller as m increases, but that of the IM option does not. In sum, the URV option shows better performance than the IM option not only in terms of accuracy (based on MBS), but also in terms of variability (based on MSE). Furthermore, the number of categories does not improve parameter estimates for the IM option, although it does for the URV option. Therefore, one should be careful in treating ordinal variables as if they belong to the metric

Construct Reliability

This particular result is a population parameter (H) recovery analysis. In general, the average magnitude MBS of H of the URV option is smaller than that of the IM option. While the magnitude of MBS of the URV option gets smaller as m increases, that of the IM option gets monotonically bigger as m increases from negative to positive. Therefore, for the IM option, the number of categories can help estimate H in some situations. However, note that we cannot conclude that "the more categories, the better" phenomena for the IM option exist in here because the increased number of categories can yield even poorer estimates (e.g., bigger positive magnitude of MBS) of *H*. Also, for the MSE of *H*, the URV option average MBE is generally smaller than that of the IM option. In sum, the URV option again shows better performance than the IM option in terms of both accuracy (based on MBS) and variability (based on MSE). Furthermore, the number of categories does not help to get better parameter estimates for the IM option while it does for the URV option. This is further evidence that one should be careful in treating ordinal variables as if they belong to the metric.

Numerical Study

Relative Mean

This particular result is a numerical analysis for the categorization effect on the relative mean of the IM option. In conclusion, the relative mean can always be biased and the degree of this bias is substantial in most situations. Moreover, in general, increasing the number of categories does not alleviate this bias. Considering the popularity of the statistical tests regarding the first moment (e.g., ANOVA or t-test) *and* ordinal variables in the social and behavioral sciences, these findings cannot be stated too strongly: the results are *always* misleading when the IM option is adapted.

Relative Variance

This particular result is a numerical analysis for the categorization effect on the relative variance of the IM option. In conclusion, the relative variance can always be biased and the degree of this bias is not negligible in most situations. Moreover, in general, increasing the number of category does not alleviate this bias. Thus, one should be careful in treating ordinal variables as if they belong to the metric.

Correlation

This particular result is a numerical analysis for the categorization effect on the correlation of the IM option. Unlike the results for the relative mean and the relative variance, the IM option coefficients of correlation are always negative for all cases and gets smaller as the number of categories increases for all categorization options. Also, C_ρ is great than .8 as long as the number of categories is greater than three. As long as only the correlation is considered, the IM option could provide nearly the same estimates of the underlying correlation as the URV option especially when m is big. However, it should be noted that the IM option correlation is always negatively biased, and the IM option should be carefully considered for the models that also take means and variances as data such as LMM.

Overall Conclusion

As seen previously, the URV option yields less biased parameter estimates than the IM option does for both simulation and numerical studies. Because the bias level of the IM option does not be alleviated by m, one should be careful in choosing the IM option regardless the number of category. However, the IM option shows better results in the convergence rates and Type I error rates. Specifically, the IM option always yields better chance of getting properly converged solution than the URV option for most levels of m. Also, the distributional assumption regarding the underlying response variable would be very strong one, and it is hard to apply every indicator variables in practice. When there is no theoretical foundations or justifications regarding the distributional properties of the underlying response variables, adapting methodologically more expensive approach (the URV method) would be riskier. Therefore, in practice, the options of handling ordinal indicators or the number of categories of indicators should be carefully chosen to balance between the best chance of the converged results and the best parameter estimates. Interestingly, the middle rage of m (4, 5, 6, or 7) which is often used in educational and behavioral science (e.g., the Likert scale) generally shows a good performance for both IM and URV options. Additionally, if one could not get the converged solution with the URV option, 1) increasing sample size, 2) employing simpler model (small m and/or p), and 3) adopting the IM option can be recommended.

Potential Topics for Further Research

Throughout the research for this work, the $m = 2$ case tends to show the worst convergence rates for URV option cases. Because the dichotomous indicators (e.g., 1 for true and 0 for false item) are very often chosen in practice, especially in the educational research, understanding the reason for this poor convergence rate for the $m = 2$ case with a comparison of the IRT approach would be interesting and practically important.

While I focused on the between-subjects case in this particular research, the categorization effect analysis of a more complex OILMM such as the within-subjects OILMM is should also be studied due the popularity of such designs in practice.

A comparison of IRT and SEM approaches for OILMM is also recommended. A study of the development of the LMM procedure for the IRT approach is especially necessary and interesting.

Note that the OILMM methodology used in this particular research relies on the underlying normal distribution assumption. Testing the robustness of OILMM parameter estimates from the violations of underlying normal distribution assumptions would also be a potentially interesting area of research.

Since I studied a limited range of the small sample size behavior of OILMM Type I error rates and power estimates, more intensive research on the small sample size behavior for both IILMM and OILMM parameter estimates is needed.

Extending this research to the complex survey scenario (e.g., involving weights and/or multilevel structure) would also be useful to applied researchers.

Finally, the relationship between two LMM approaches, MIMIC and SMM, has been known for the IILMM case (Hancock, 1997). Extending this comparison to the OILMM would also be useful to researchers who consider LMM with such indicators.

Closing Remarks

The current paper makes three contributions to the emerging SEM literature on LMM and ordinal variable estimation. First, this research provides an intensive analysis to understand the consequences of categorization on OILMM parameter estimates, Type I error, and power. Second, it provides useful statistics and indices, enabling us to analytically study the categorization effect. Third, from the results of this study, we learn that the IM option gives us better chance to get converged solution, but the result can be misleading regardless the number of category because the IM option's relative mean and variance are always biased. Consequently, in practice, the options of handling ordinal indicators and/or the number of categories should be carefully chosen to balance between the better chance of the converged results and the better parameter estimates.

Table 1: Threshold Values

Normal

m	2	3	4	5	6	7	8	9
2	0.0000							
3	-1.0000	1.0000						
4	-1.5000	0.0000	1.5000					
5	-1.8000	-0.6000	0.6000	1.8000				
6	-2.0000	-1.0000	0.0000	1.0000	2.0000			
7	-2.1429	-1.2857	-0.4286	0.4286	1.2857	2.1429		
8	-2.2500	-1.5000	-0.7500	0.0000	0.7500	1.5000	2.2500	
9	-2.3333	-1.6667	-1.0000	-0.3333	0.3333	1.0000	1.6667	2.3333

Uniform

m	2	3	4	5	6	7	8	9
2	0.0000							
3	-0.4307	0.4307						
4	-0.6745	0.0000	0.6745					
5	-0.8416	-0.2533	0.2533	0.8416				
6	-0.9674	-0.4307	0.0000	0.4307	0.9674			
7	-1.0676	-0.5659	-0.1800	0.1800	0.5659	1.0676		
8	-1.1503	-0.6745	-0.3186	0.0000	0.3186	0.6745	1.1503	
9	-1.2206	-0.7647	-0.4307	-0.1397	0.1397	0.4307	0.7647	1.2206

Asymmetric (Positive)

m	2	3	4	5	6	7	8	9
2	0.4307							
3	0.0000	0.9674						
4	-0.2533	0.5244	1.2816					
5	-0.4307	0.2533	0.8416	1.5011				
6	-0.5659	0.0597	0.5659	1.0676	1.6684			
7	-0.6745	-0.0896	0.3661	0.7916	1.2419	1.8027		
8	-0.7647	-0.2104	0.2104	0.5895	0.9674	1.3830	1.9145	
9	-0.8416	-0.3113	0.0837	0.4307	0.7647	1.1108	1.5011	2.0099

Asymmetric (Negative)

m	2	3	4	5	6	7	8	9
2	-0.4307							
3	-0.9674	0.0000						
4	-1.2816	-0.5244	0.2533					
5	-1.5011	-0.8416	-0.2533	0.4307				
6	-1.6684	-1.0676	-0.5659	-0.0597	0.5659			
7	-1.8027	-1.2419	-0.7916	-0.3661	0.0896	0.6745		
8	-1.9145	-1.3830	-0.9674	-0.5895	-0.2104	0.2104	0.7647	
9	-2.0099	-1.5011	-1.1108	-0.7647	-0.4307	-0.0837	0.3113	0.8416

Table 2: Simulation Conditions

Conditions	**Levels**
Sample Sizes (n)	50, 100, 500, 1000
Model Sizes (*p*)	3, 5, 7
Loading Magnitudes (λ)	.3, .5, .7
Number of Category (*m*)	2, 3, 4, 5, 6, 7, 8, 9
Latent Mean Differences (*d*)	0, .3, .7, 1.5, 3
Categorization Rules	Normal, Uniform, Asymmetric
Ordinal Data Handling Options	IM, URV

Figure 1: Latent Level X^* and Observed Level X

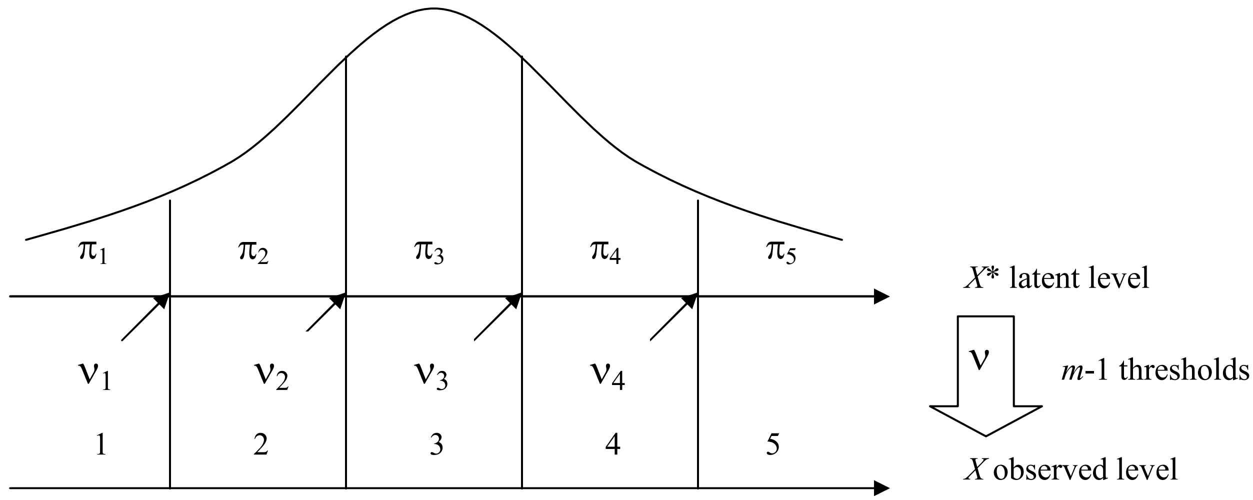


Figure 2: Underlying Response Variable Mean and Variance

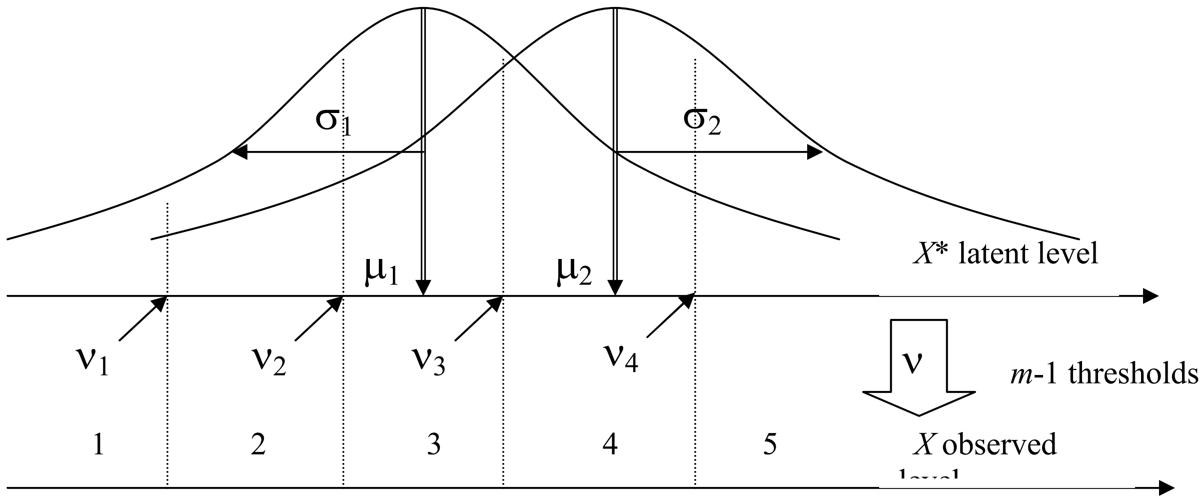
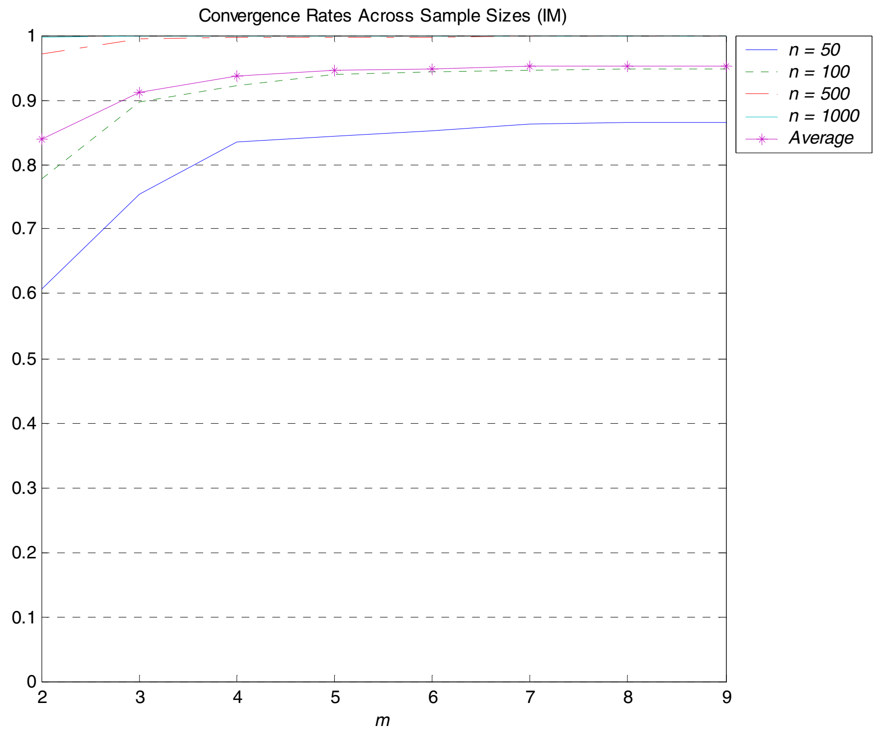


Figure 3: Convergence Rates (RPCS) Across Sample Sizes



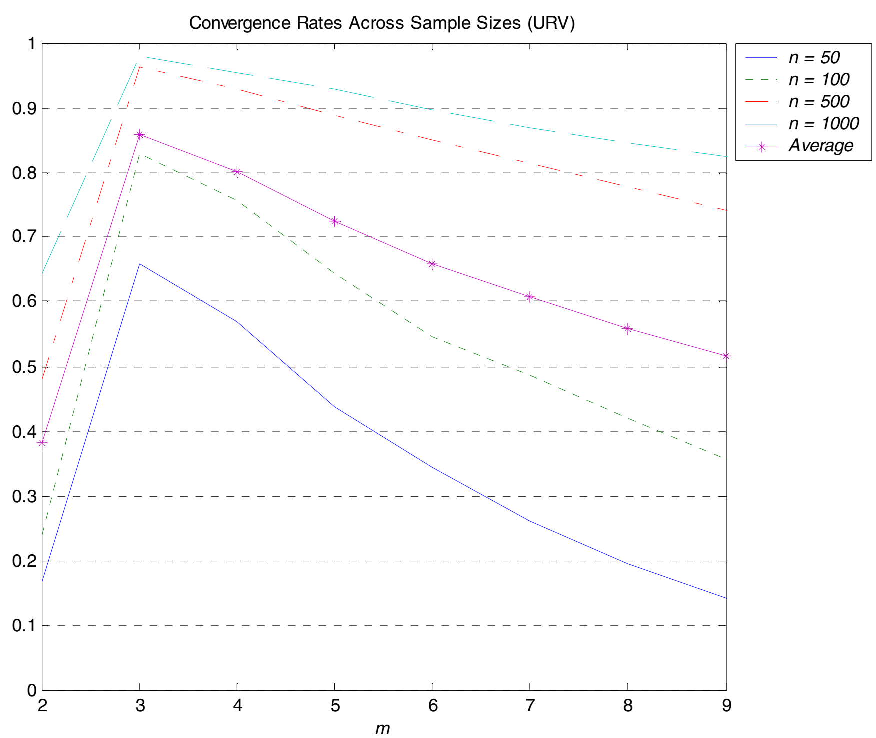
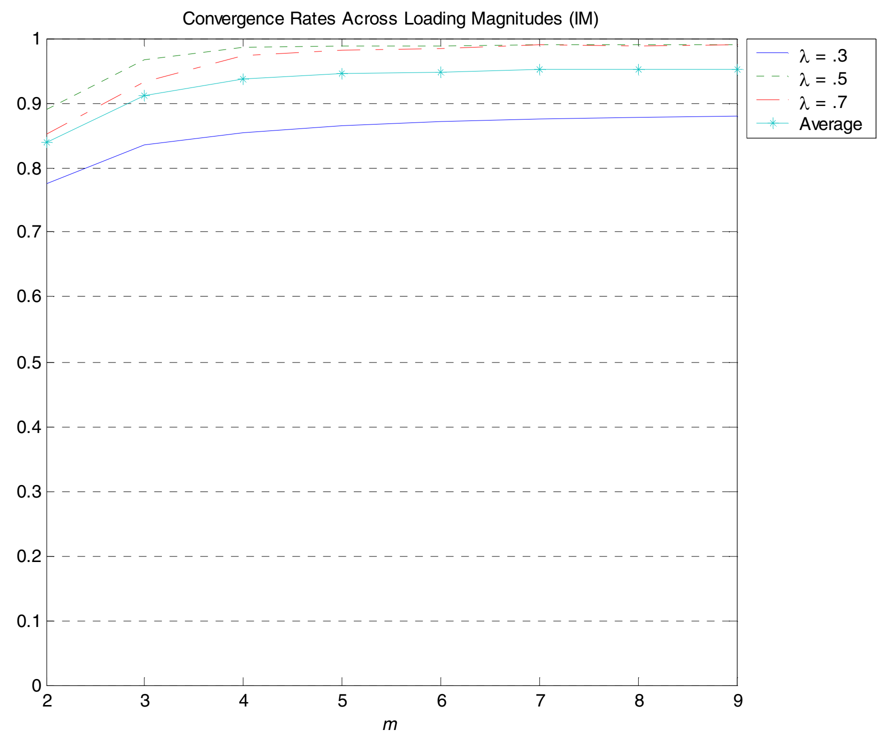


Figure 4: Convergence Rates (RPCS) Across Loading Magnitudes



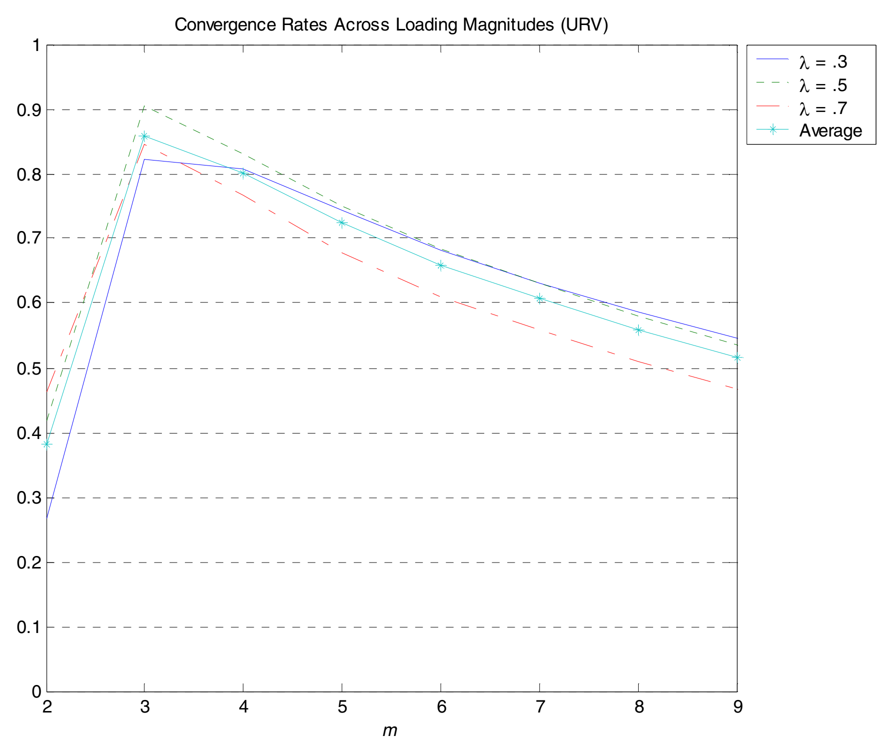
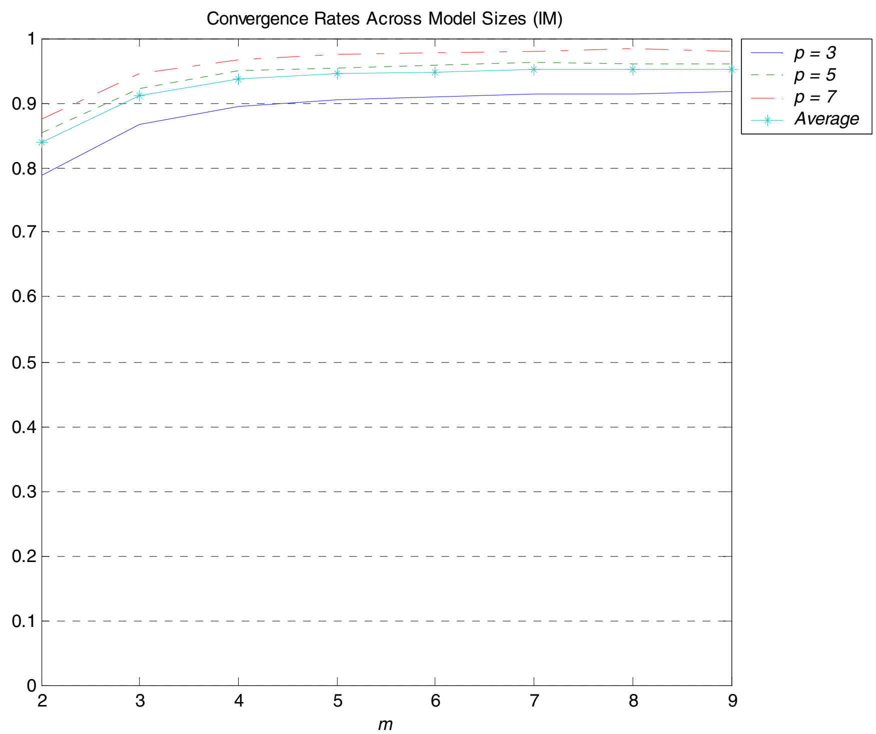


Figure 5: Convergence Rates (RPCS) Across Model Sizes



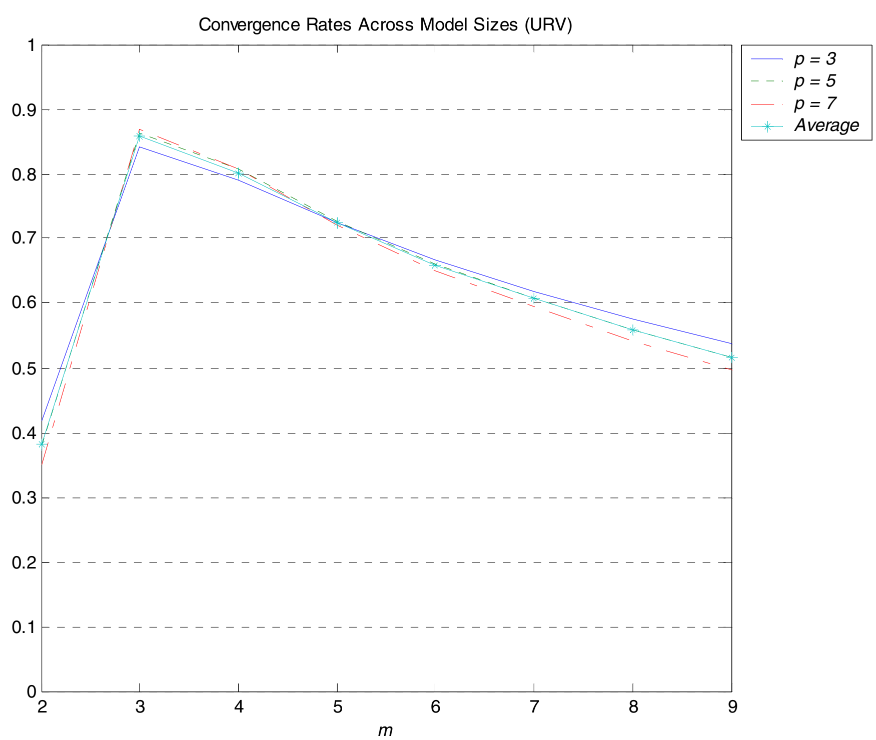


Figure 6: Convergence Rates (RPCS) Across Categorization Options

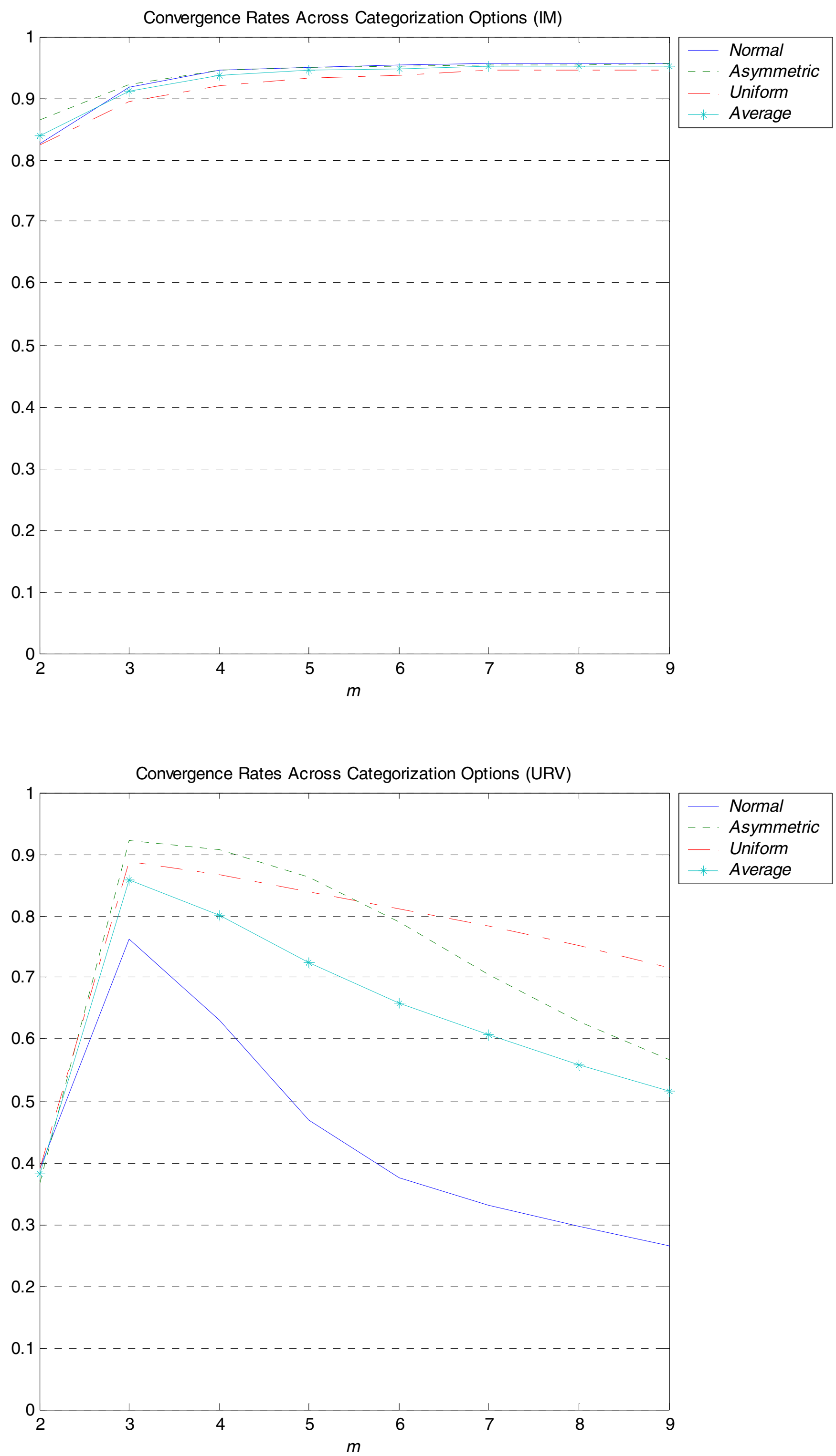
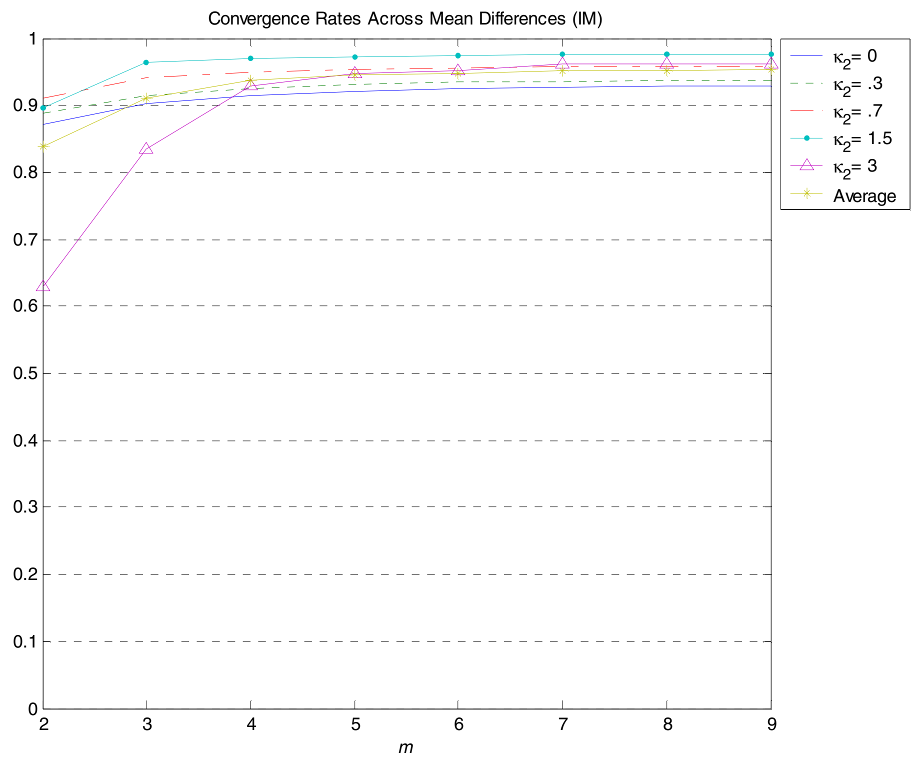


Figure 7: Convergence Rates (RPCS) Across Mean Differences



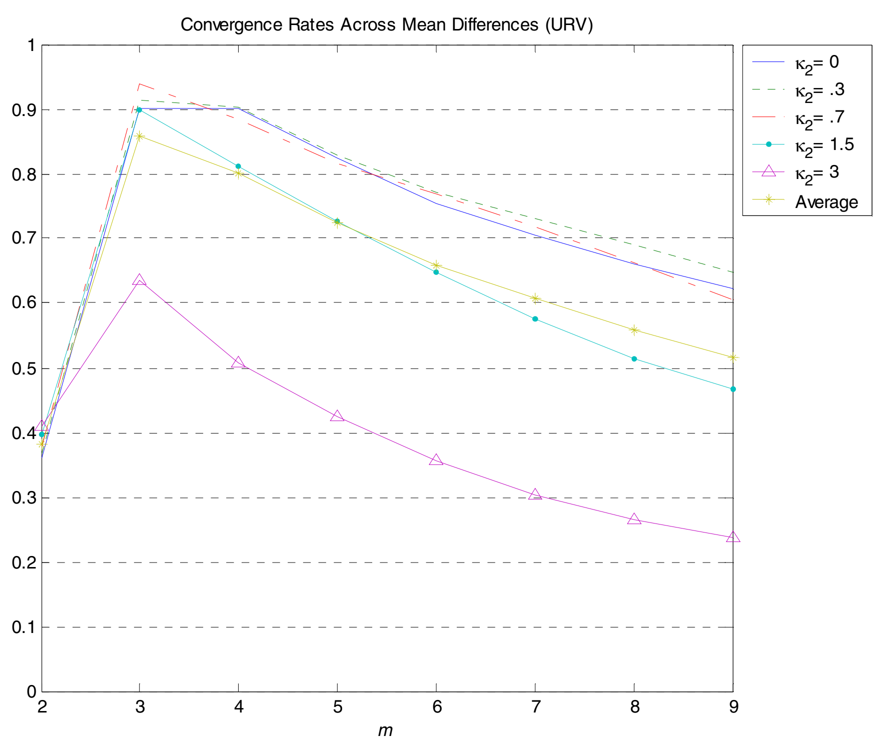
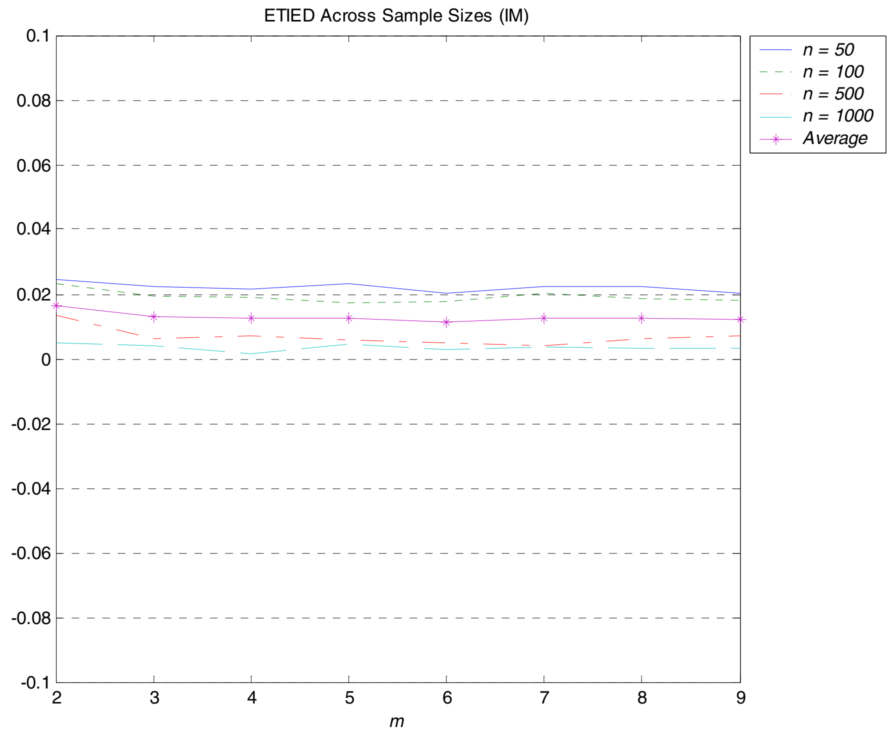


Figure 8: Empirical Type I Error Deviations (ETIED) Across Sample Sizes



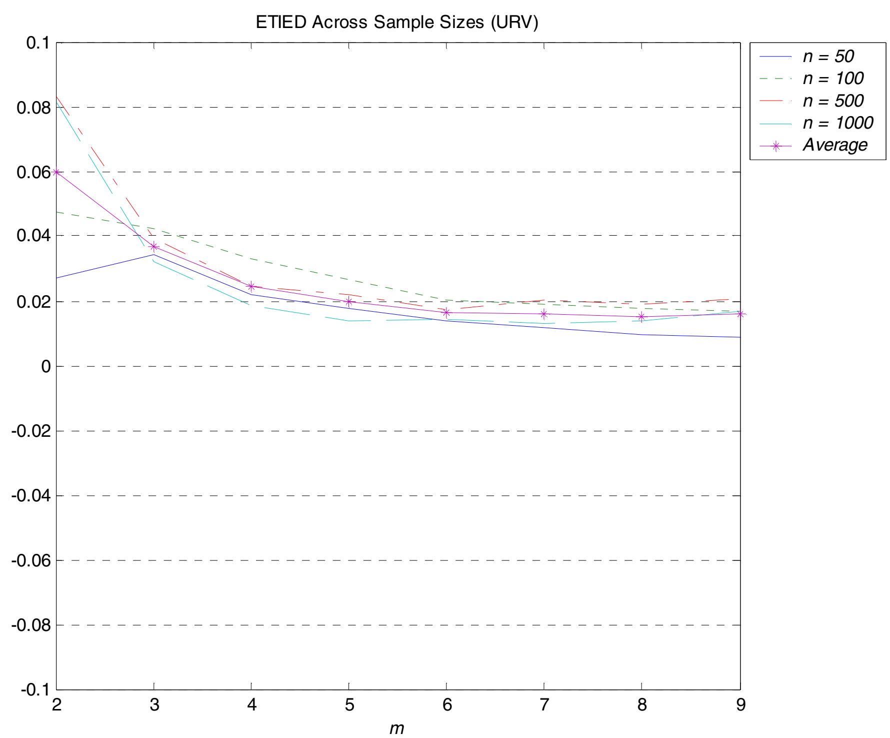


Figure 9: Empirical Type I Error Deviations (ETIED) Across Loading Magnitudes

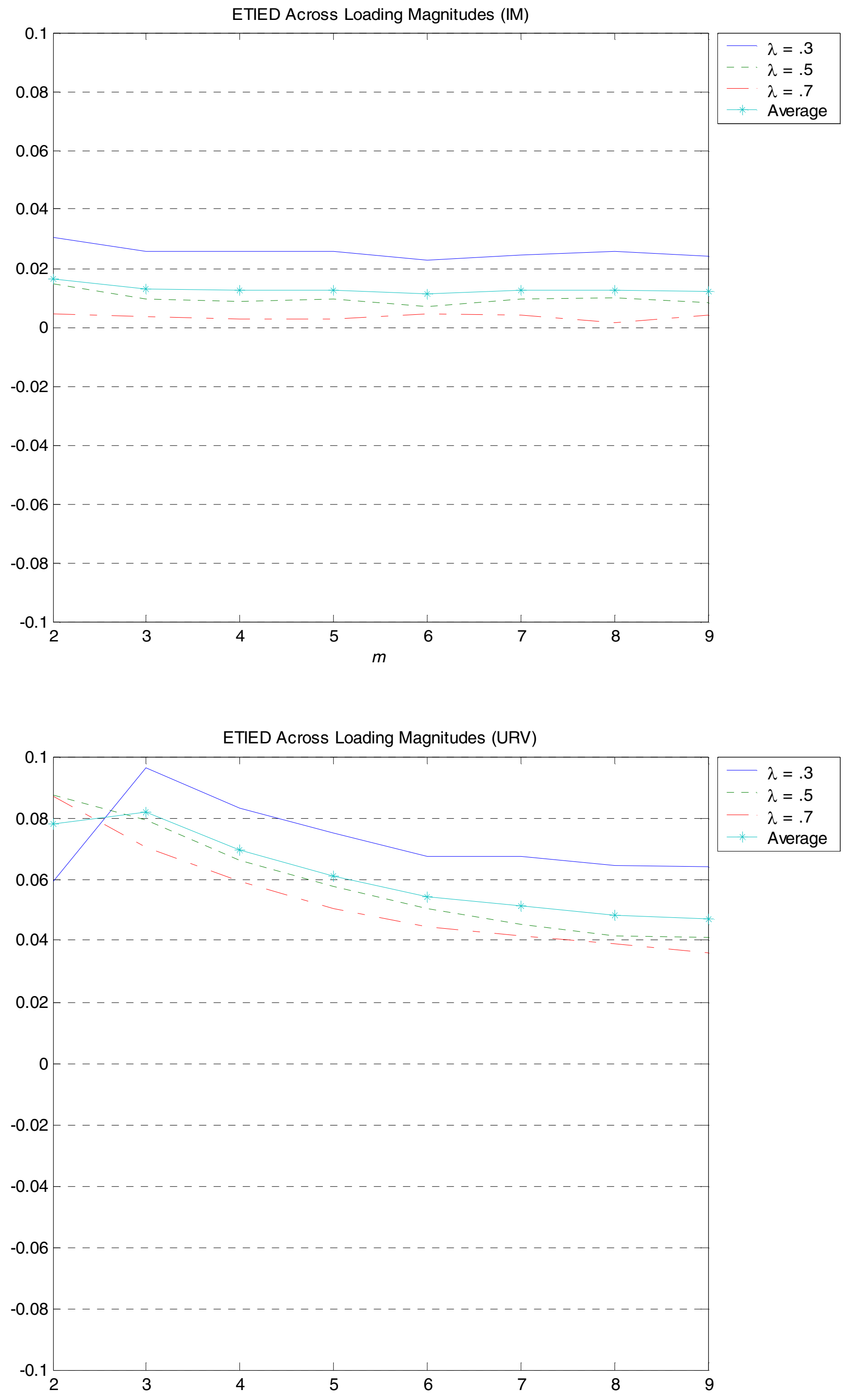
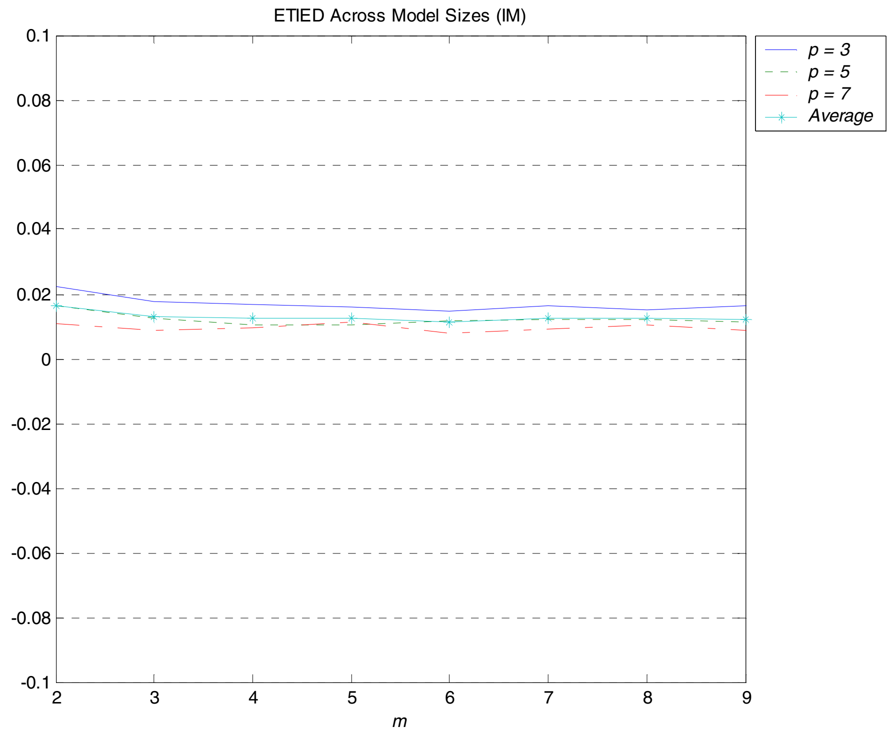


Figure 10: Empirical Type I Error Deviations (ETIED) Across Model Sizes



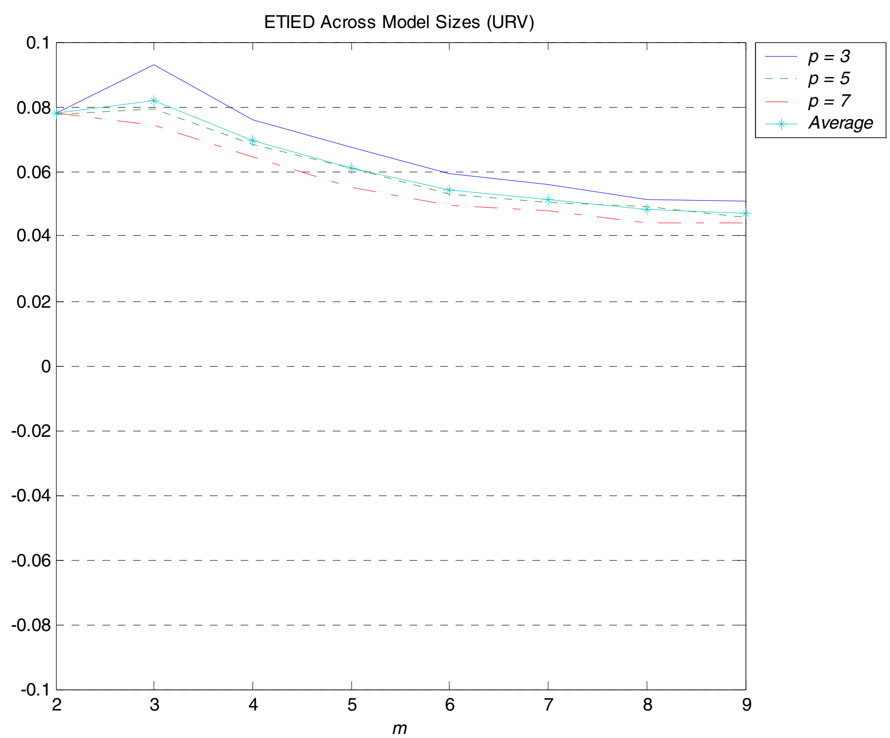
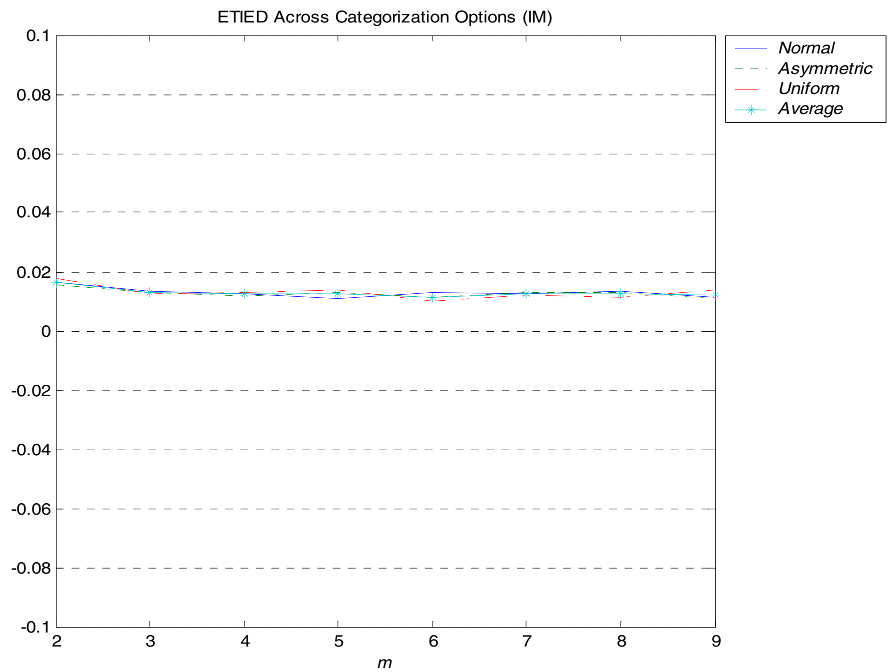


Figure 11: Empirical Type I Error Deviations (ETIED) Across Categorization Options



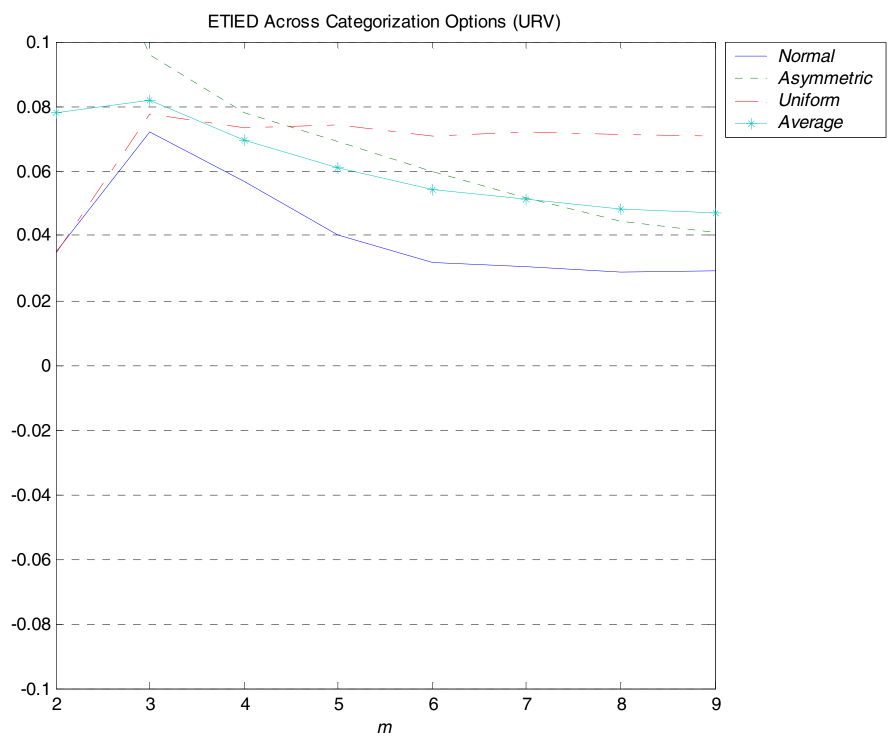
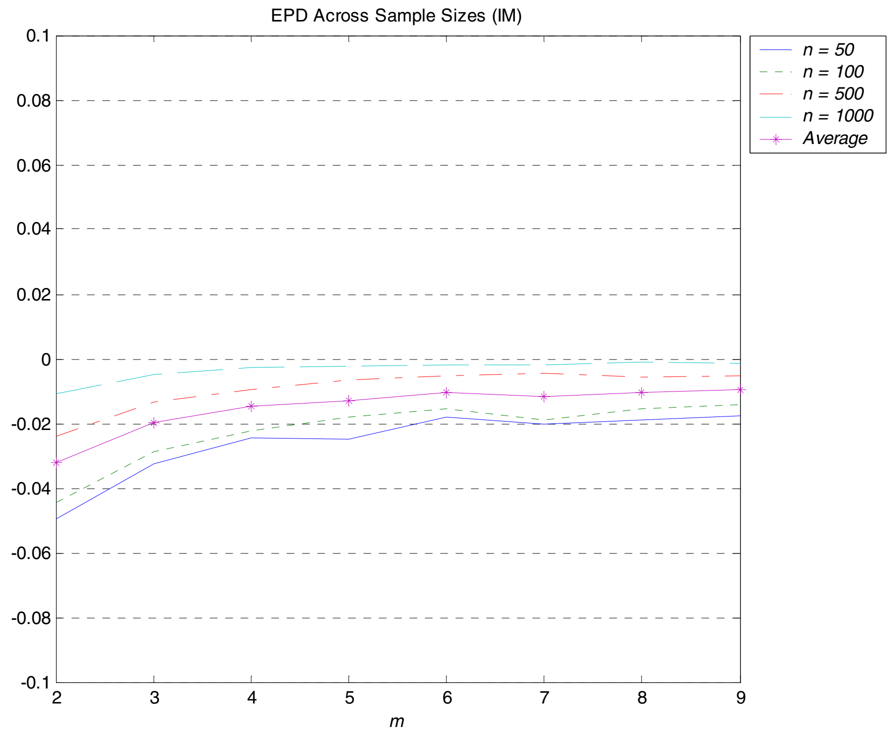


Figure 12: Empirical Power Deviations (EPD) Across Sample Sizes



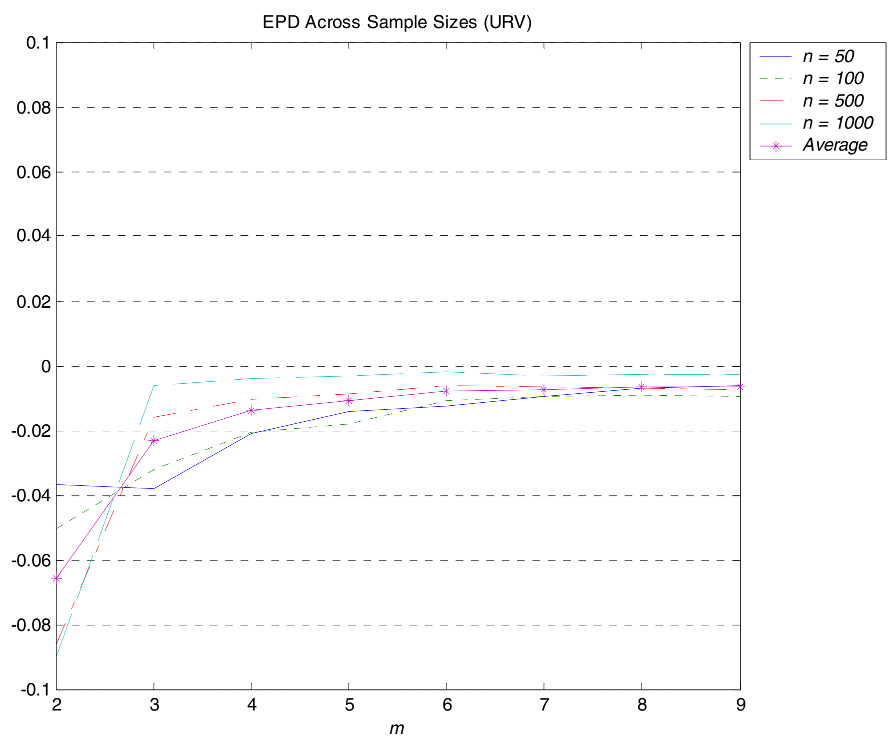
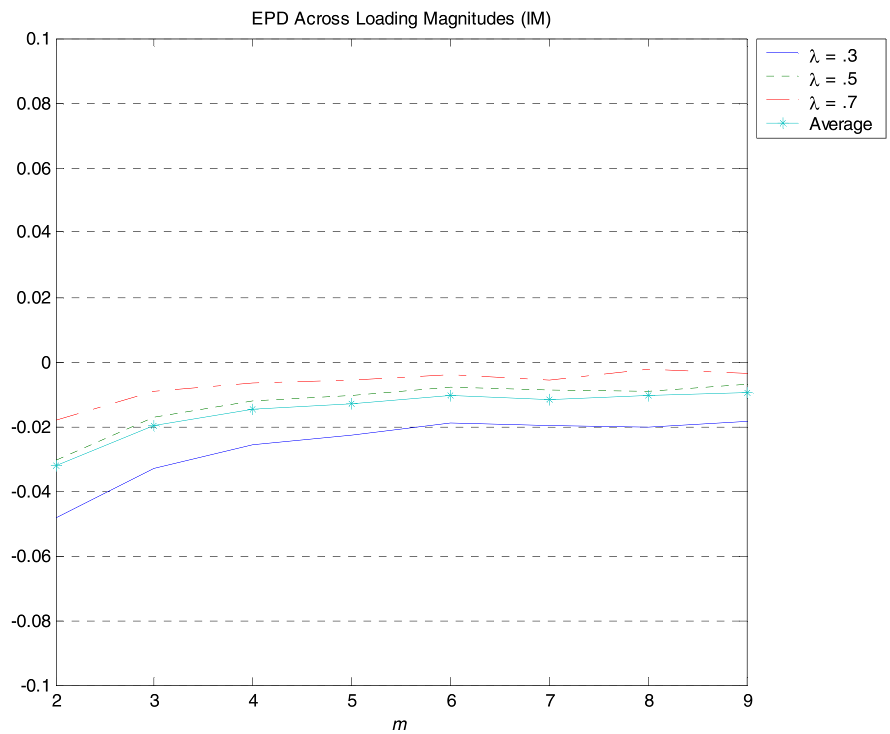


Figure 13: Empirical Power Deviations (EPD) Across Loading Magnitudes



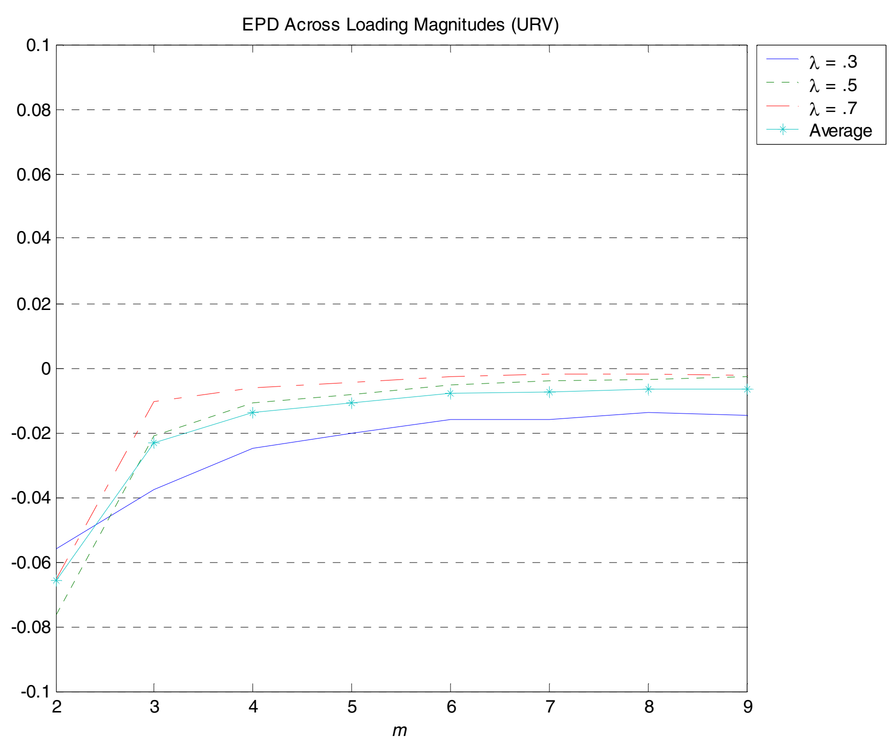


Figure 14: Empirical Power Deviations (EPD) Across Model Sizes

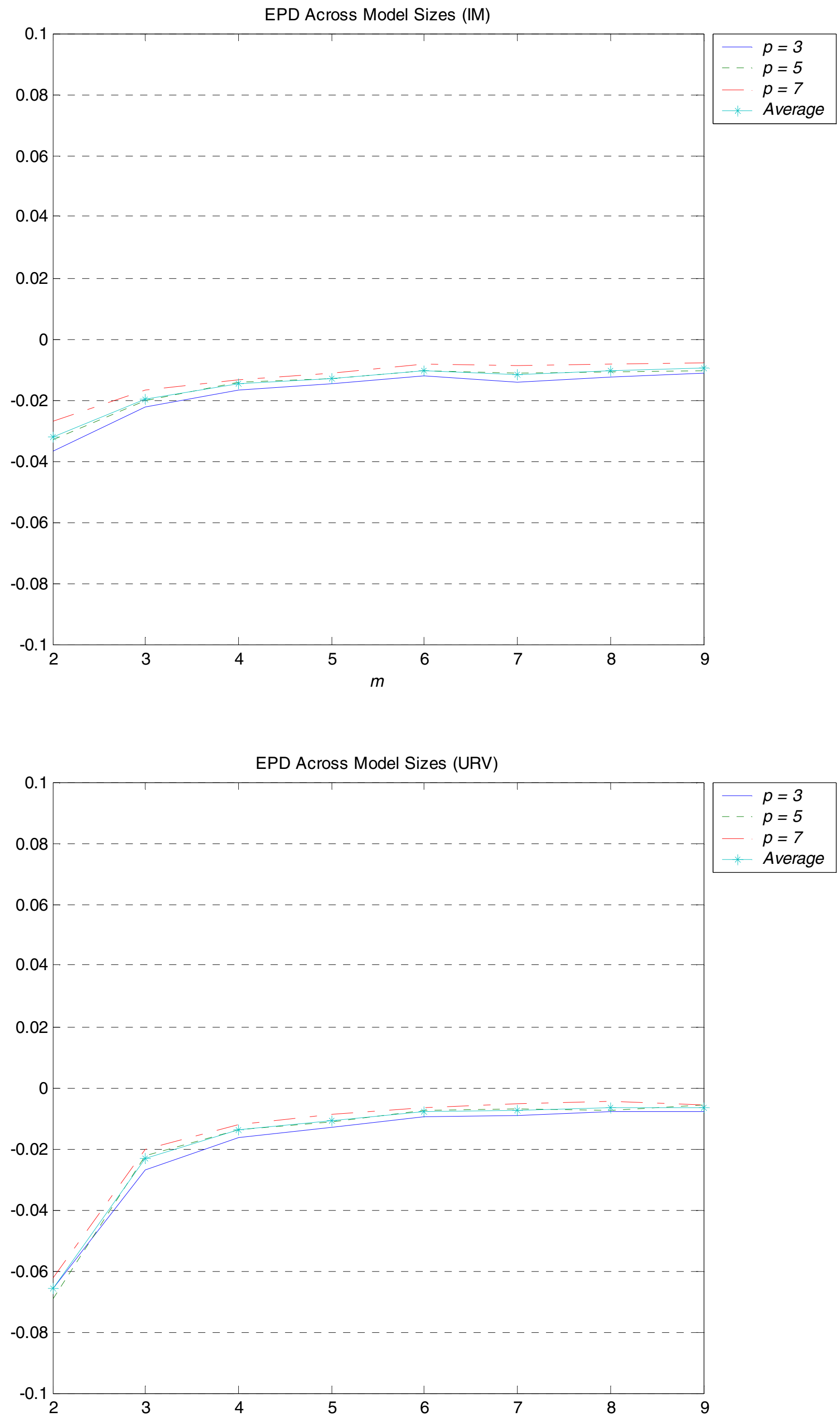
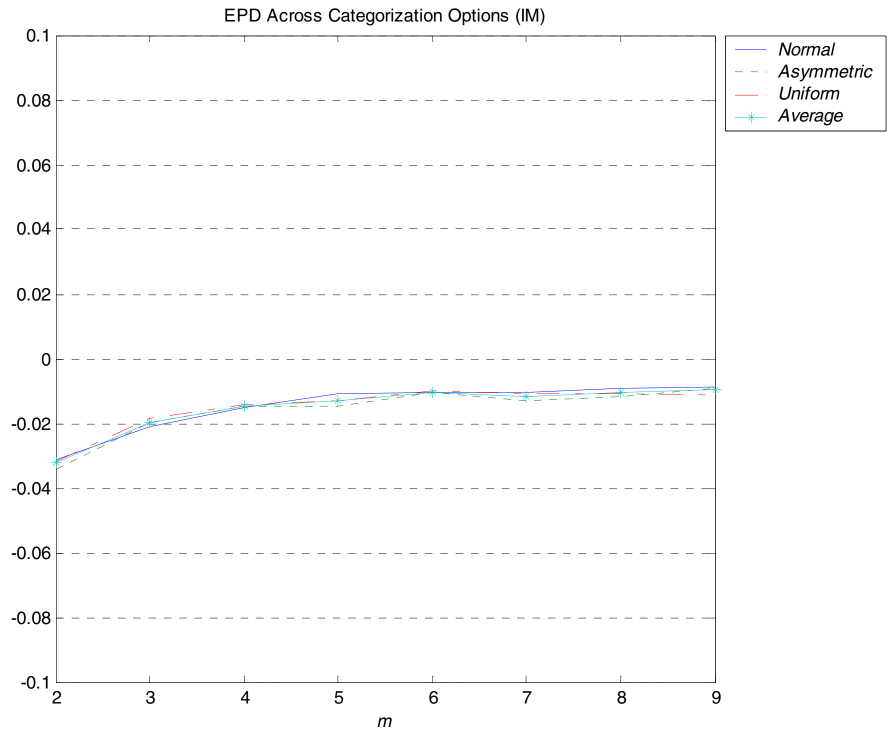


Figure 15: Empirical Power Deviations (EPD) Across Categorization Options



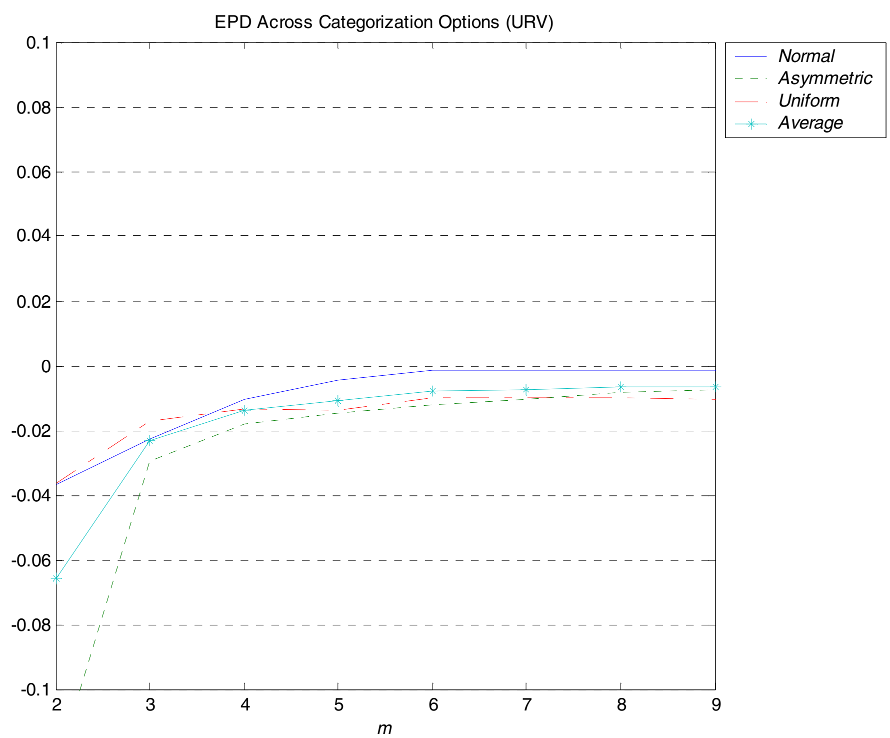
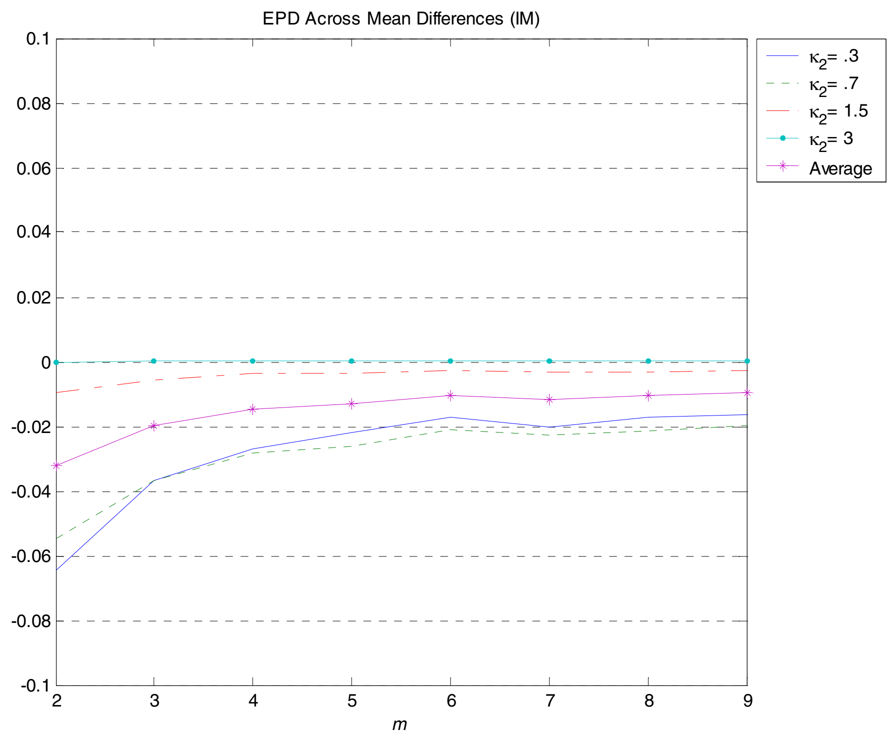


Figure 16: Empirical Power Deviations (EPD) Across Mean Differences



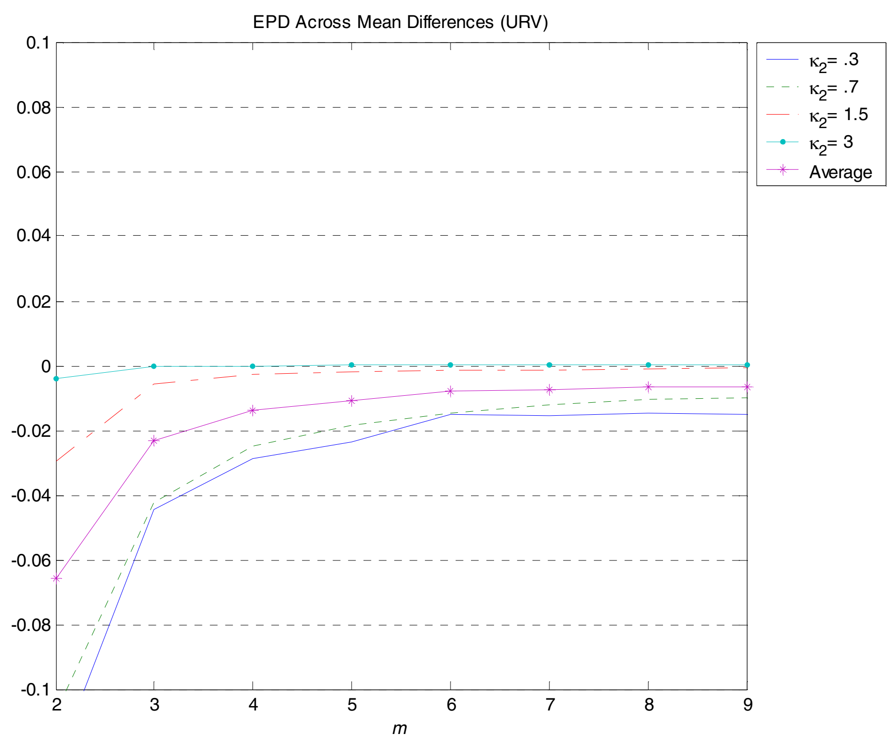
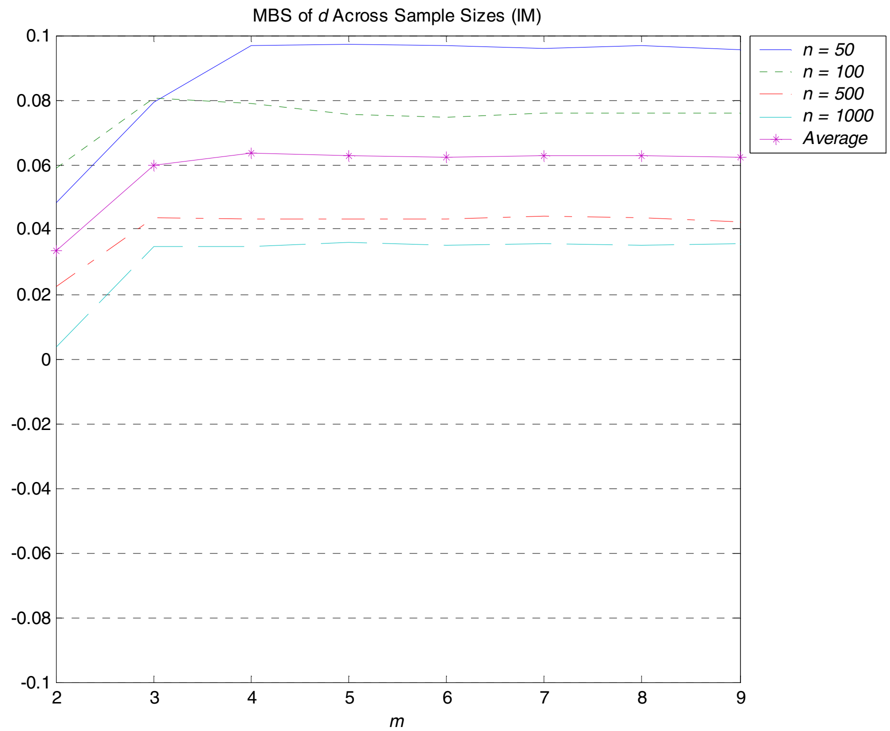


Figure 17: Mean Bias (MBS) of *d* Across Sample Sizes



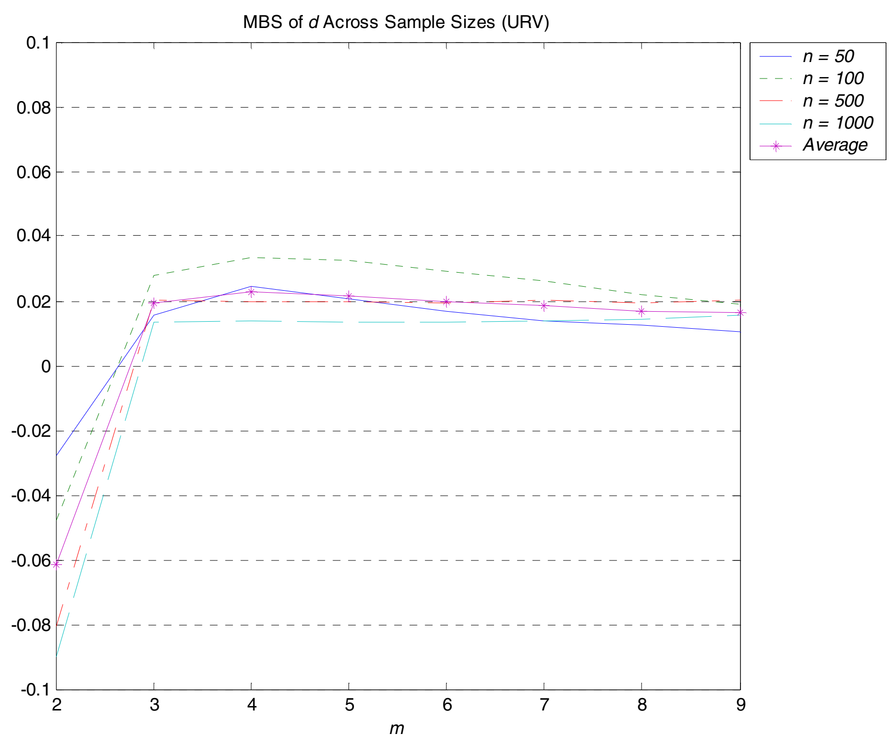
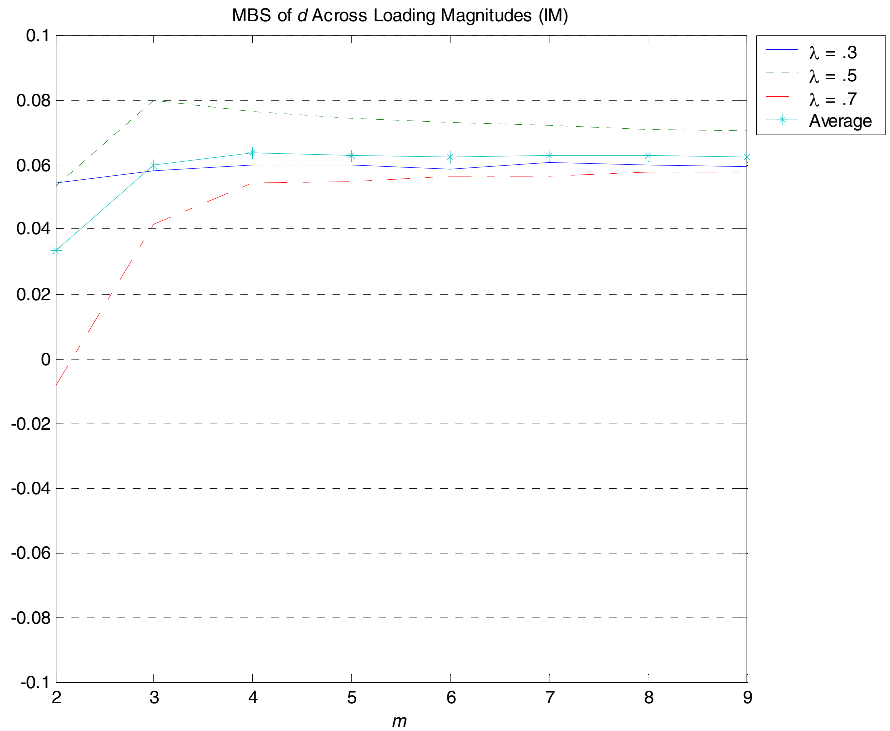


Figure 18: Mean Bias (MBS) of *d* Across Loading Magnitudes



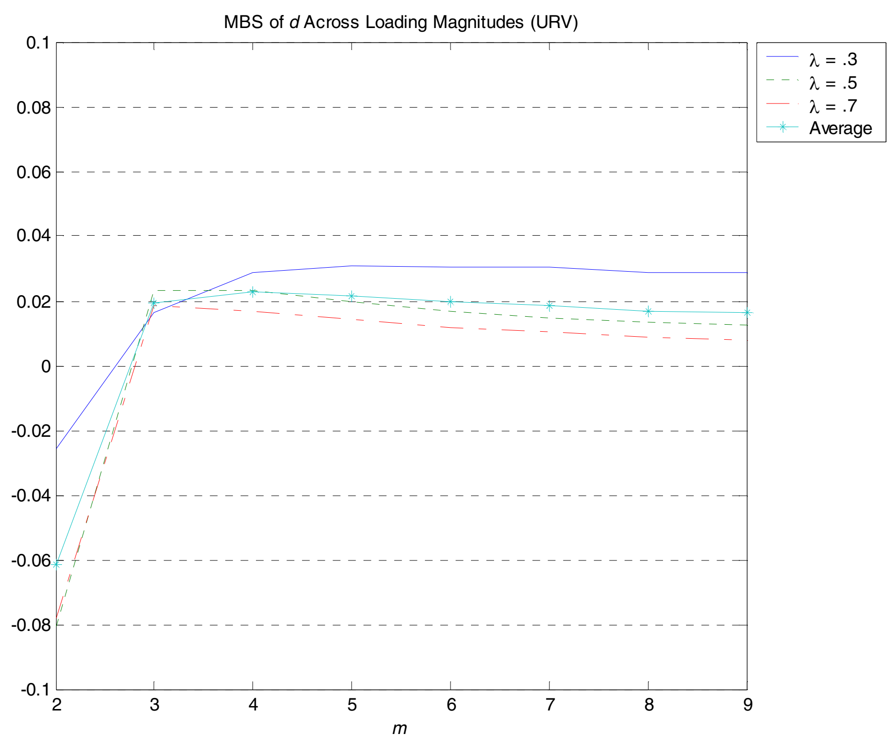
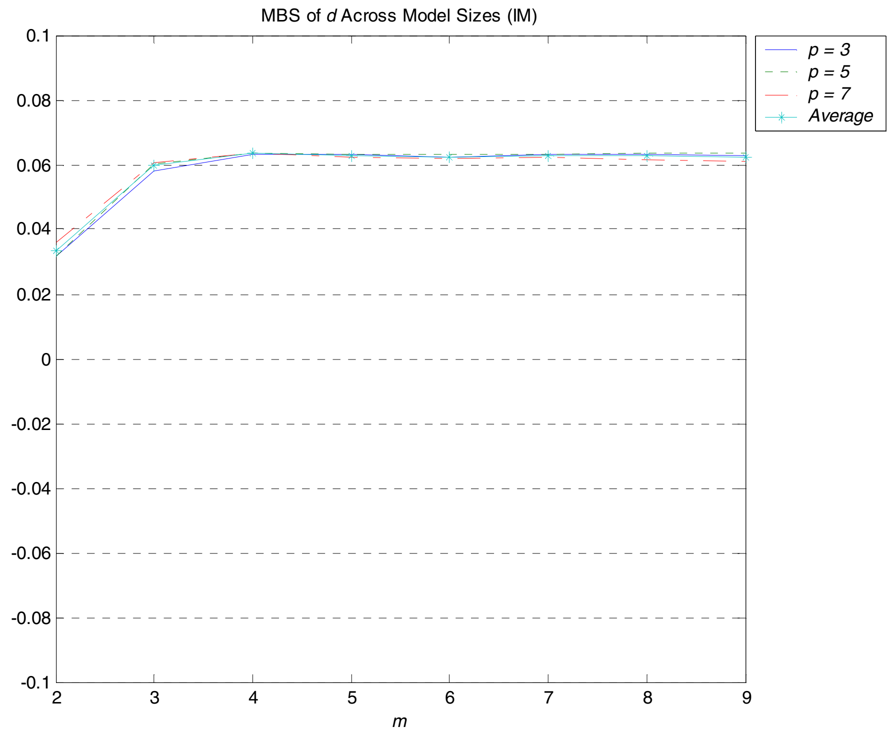


Figure 19: Mean Bias (MBS) of *d* Across Model Sizes



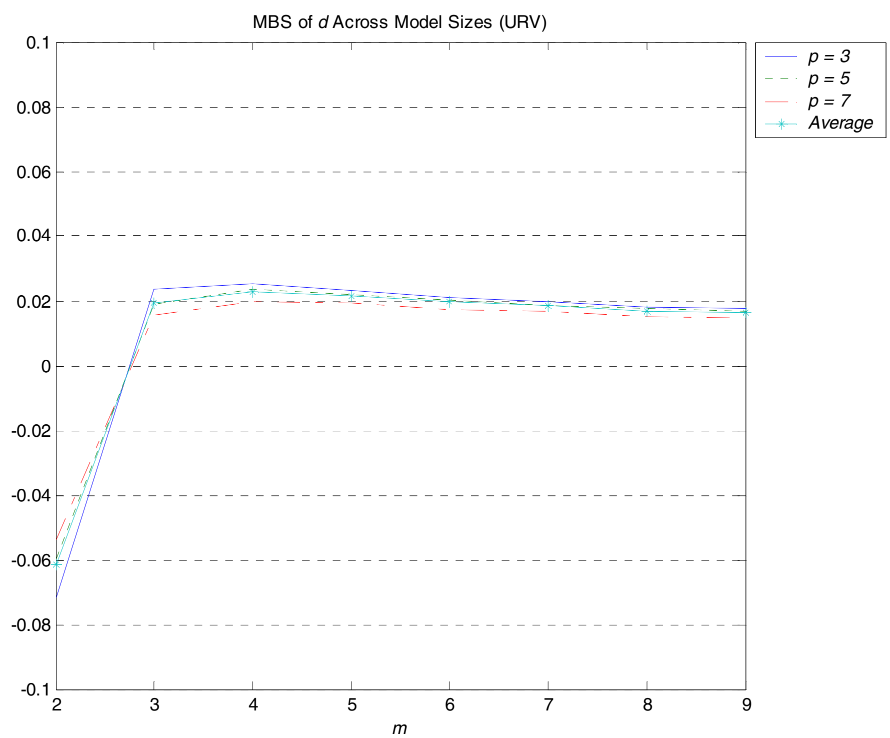
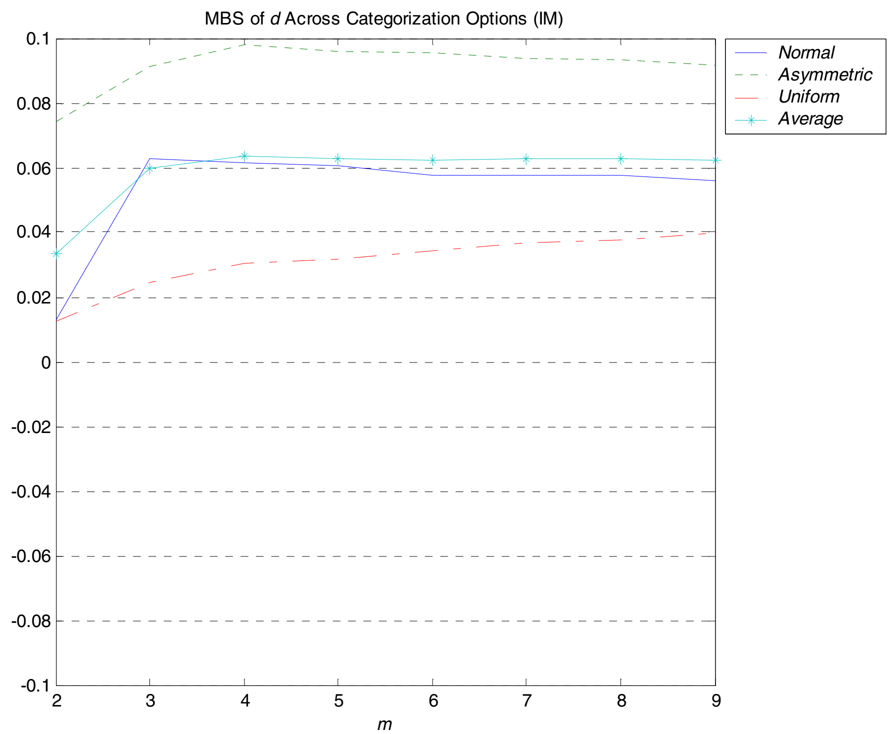


Figure 20: Mean Bias (MBS) of *d* Across Categorization Options



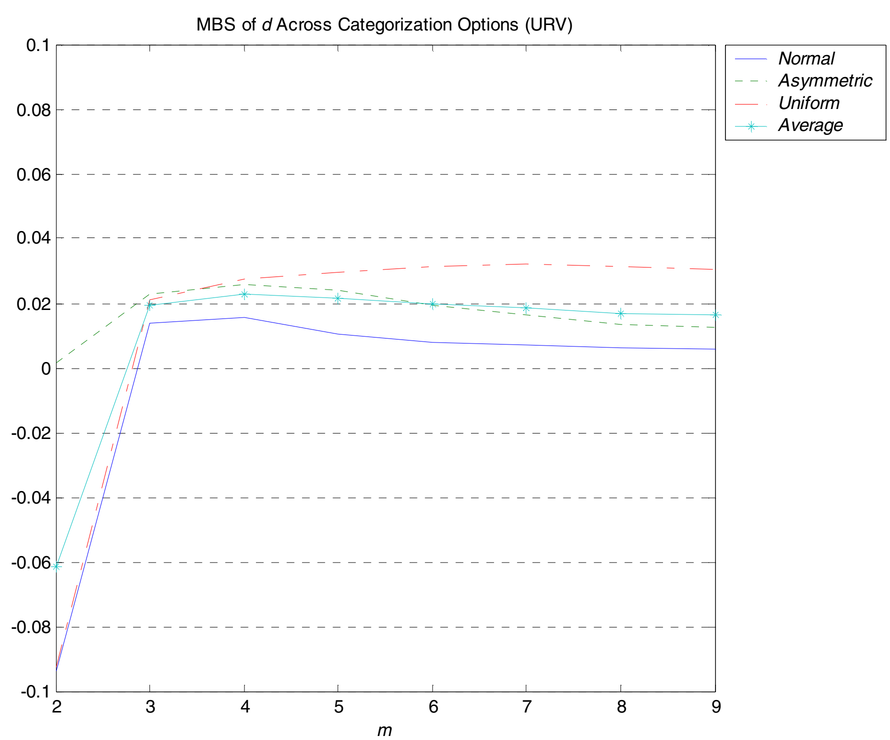
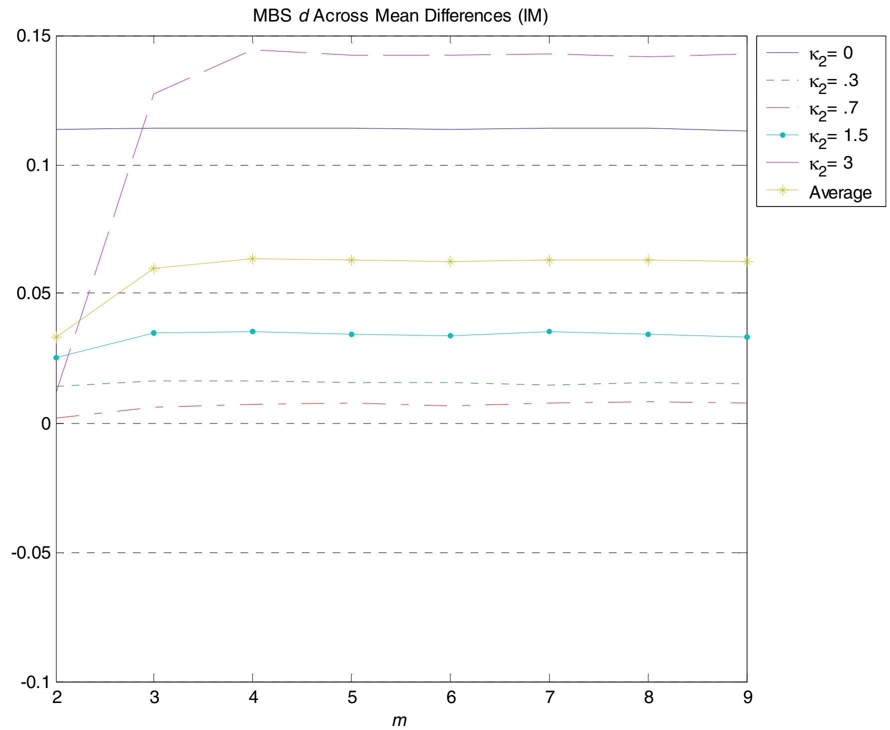


Figure 21: Mean Bias (MBS) of *d* Across Mean Differences



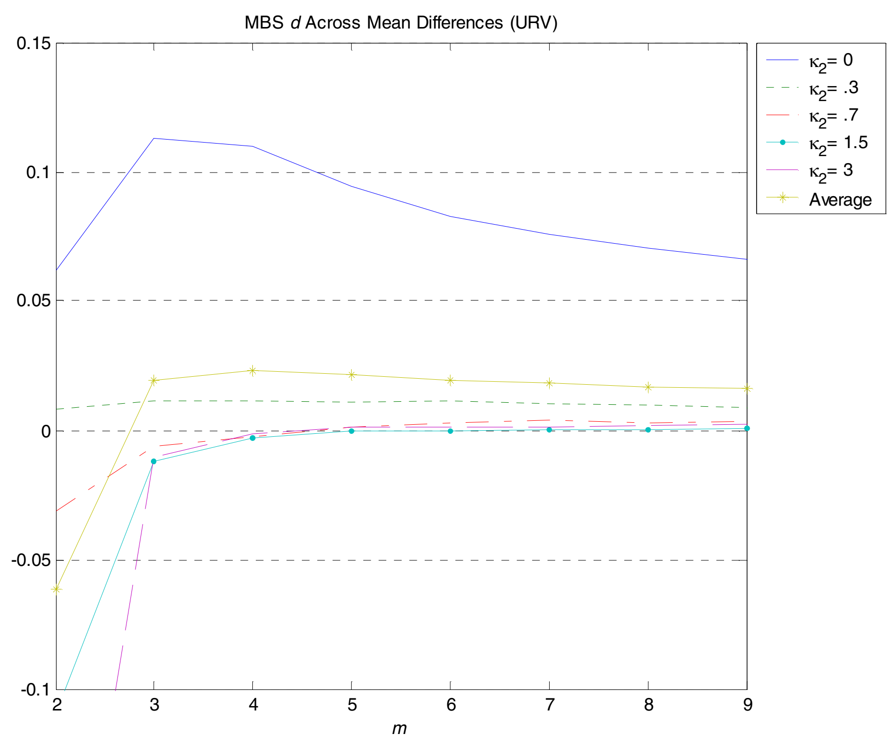
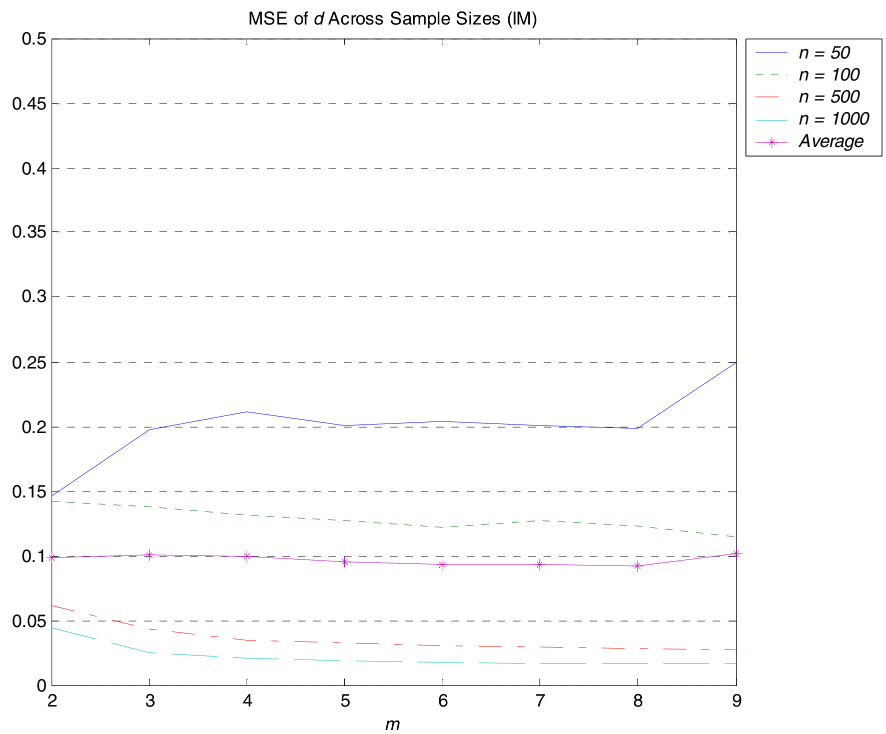


Figure 22: Mean Squared Error (MSE) of *d* Across Sample Sizes



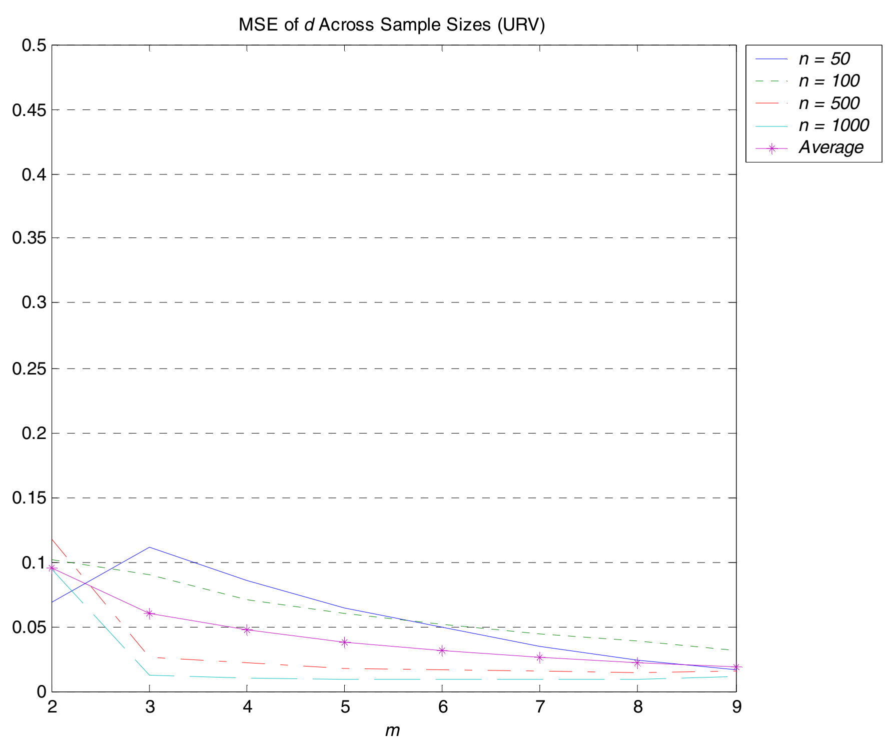
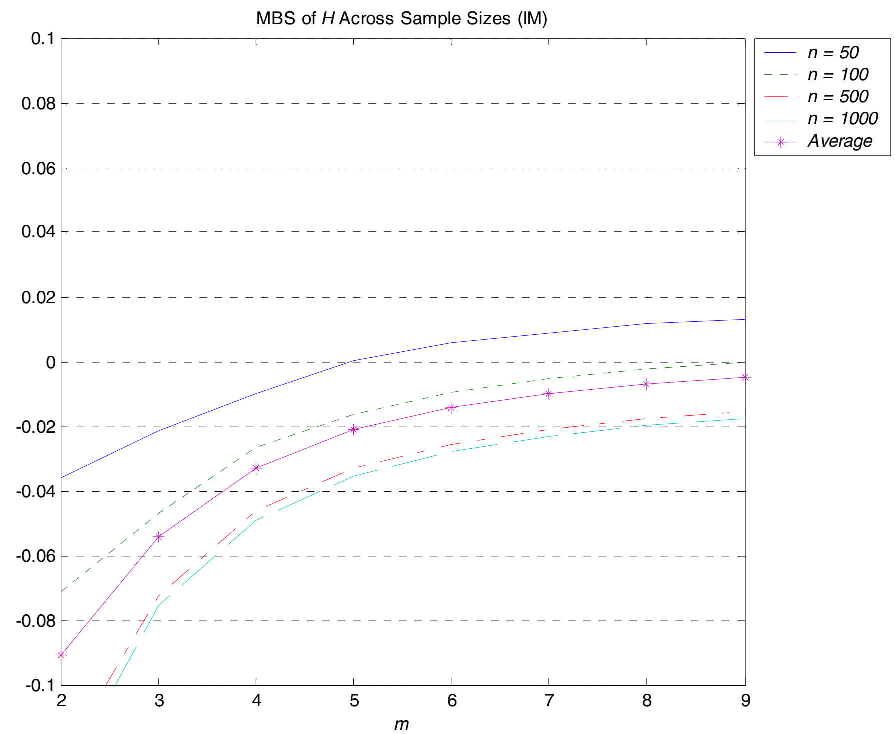


Figure 23: Mean Bias (MBS) of *H* Across Sample Sizes



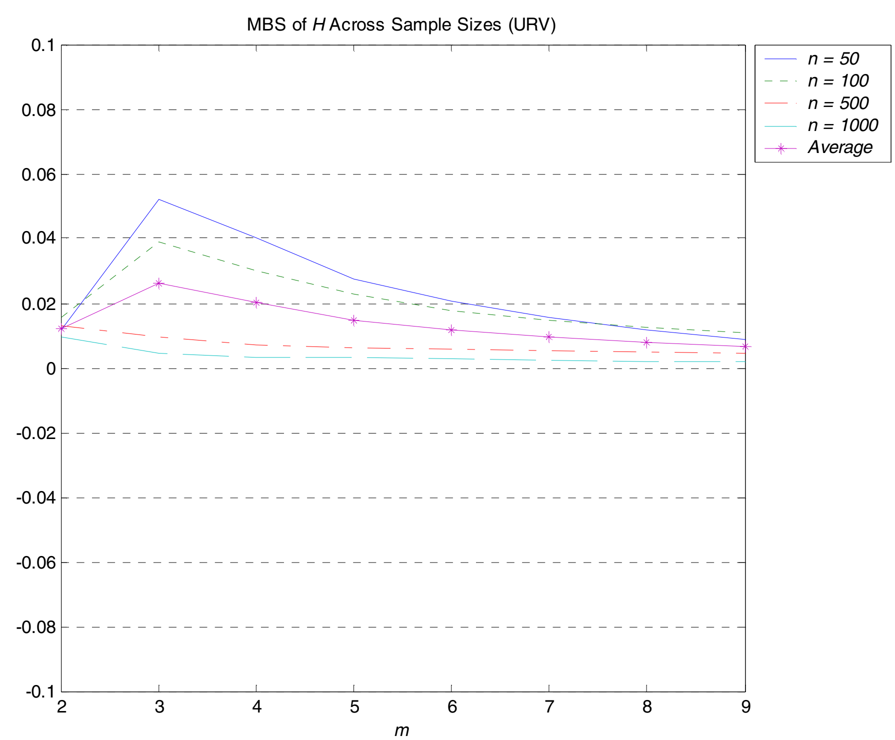
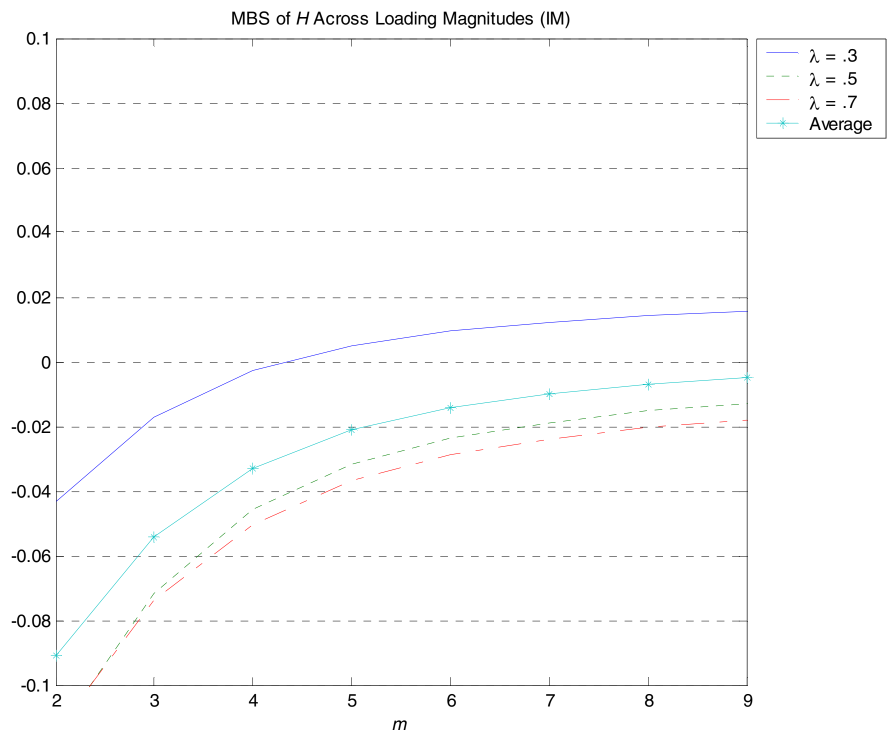


Figure 24: Mean Bias (MBS) of *H* Across Loading Magnitudes



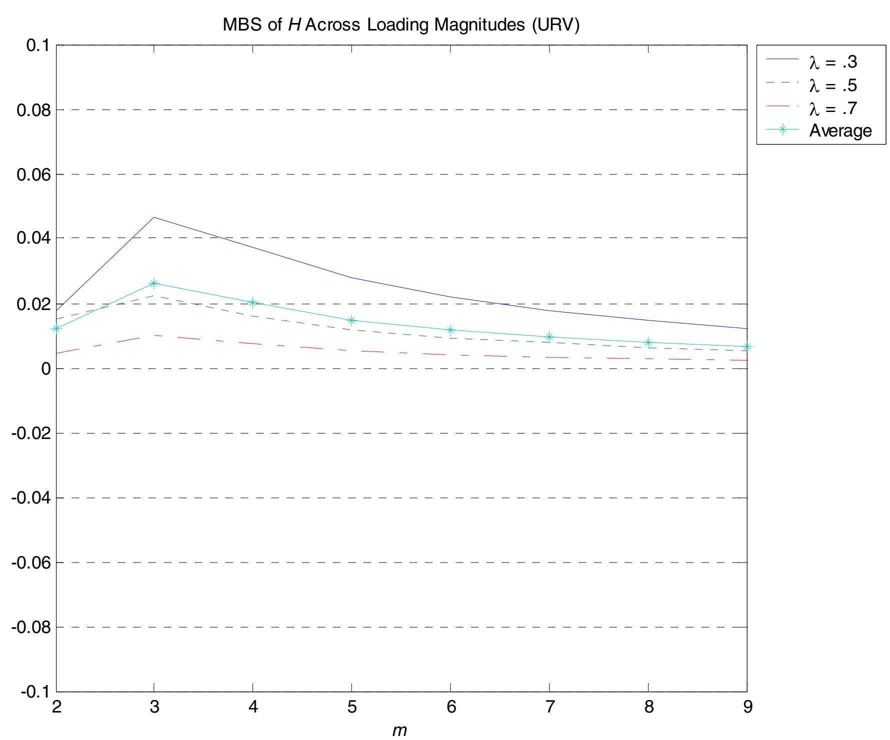
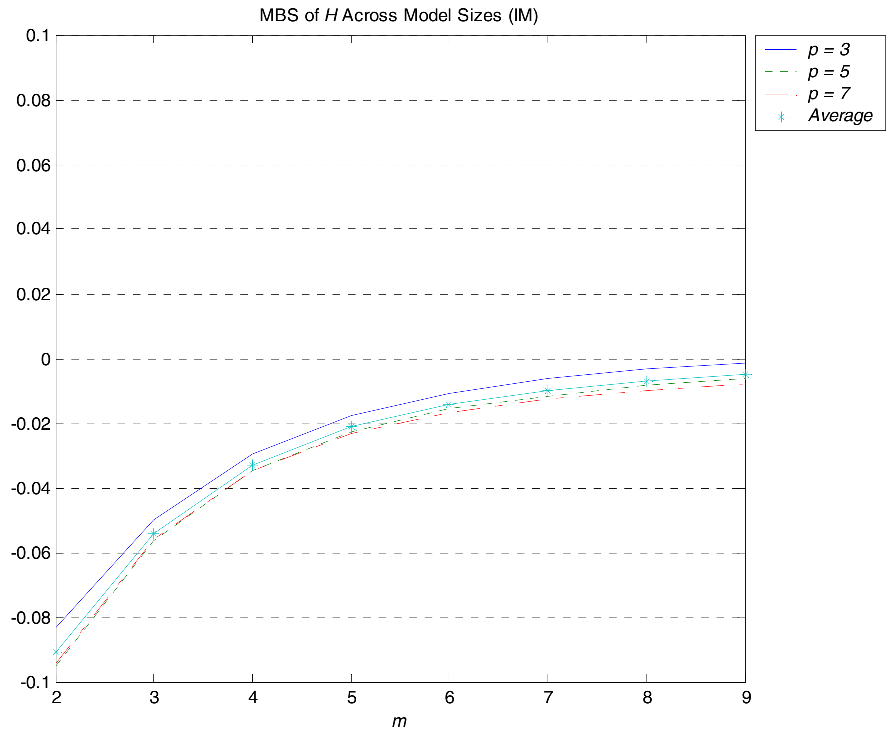


Figure 25: Mean Bias (MBS) of *H* Across Model Sizes



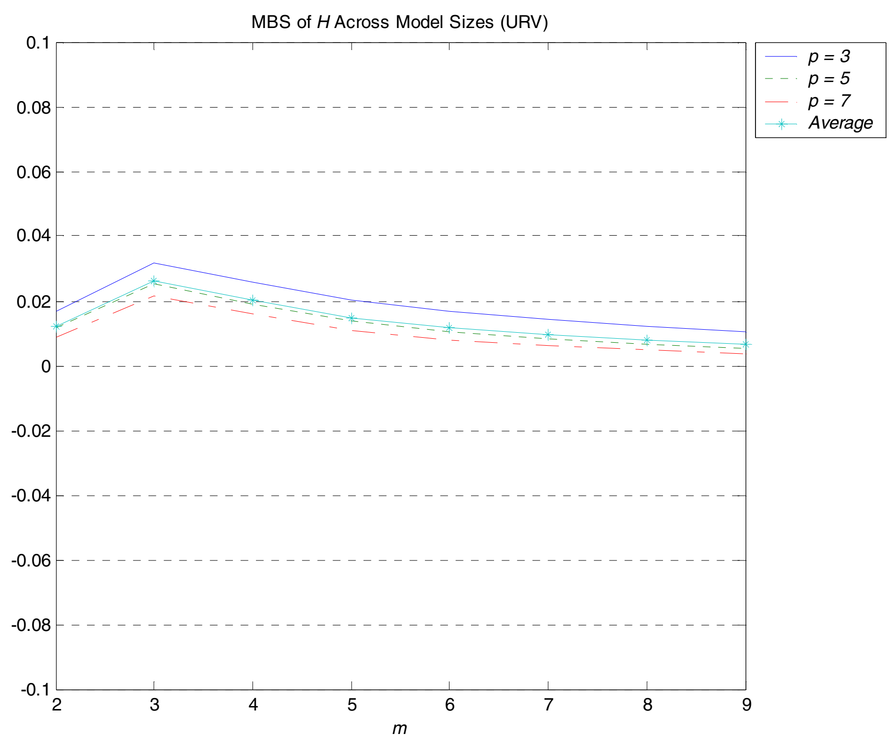
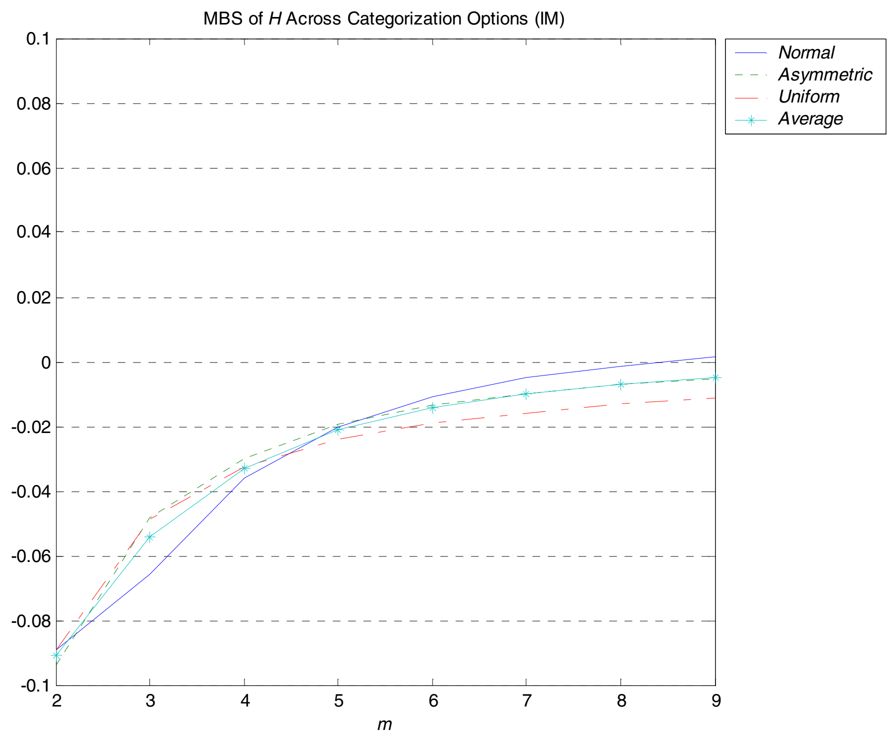


Figure 26: Mean Bias (MBS) of *H* Across Categorization Options



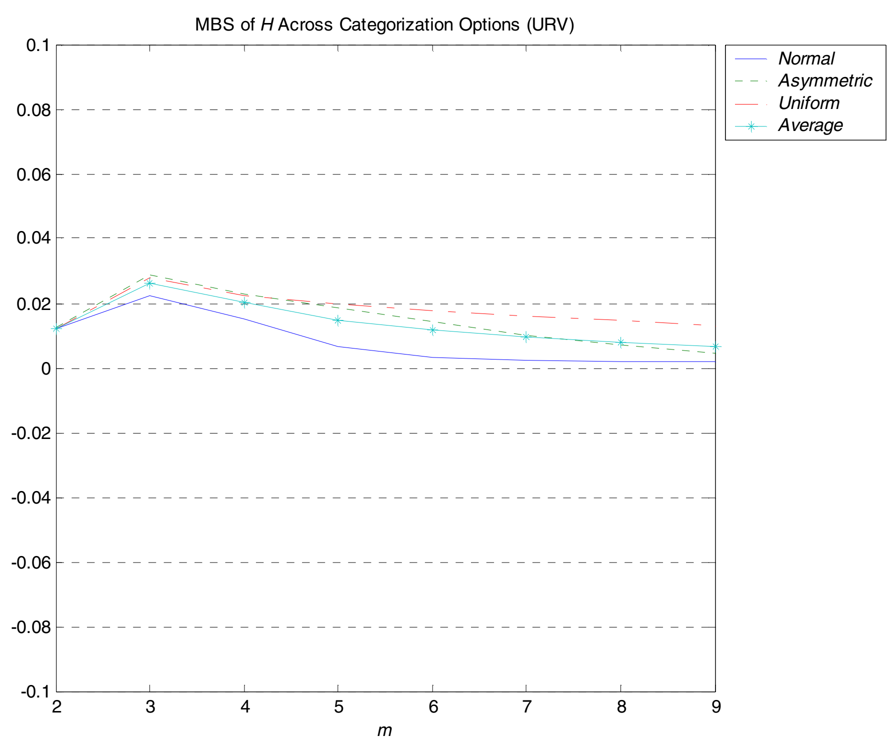
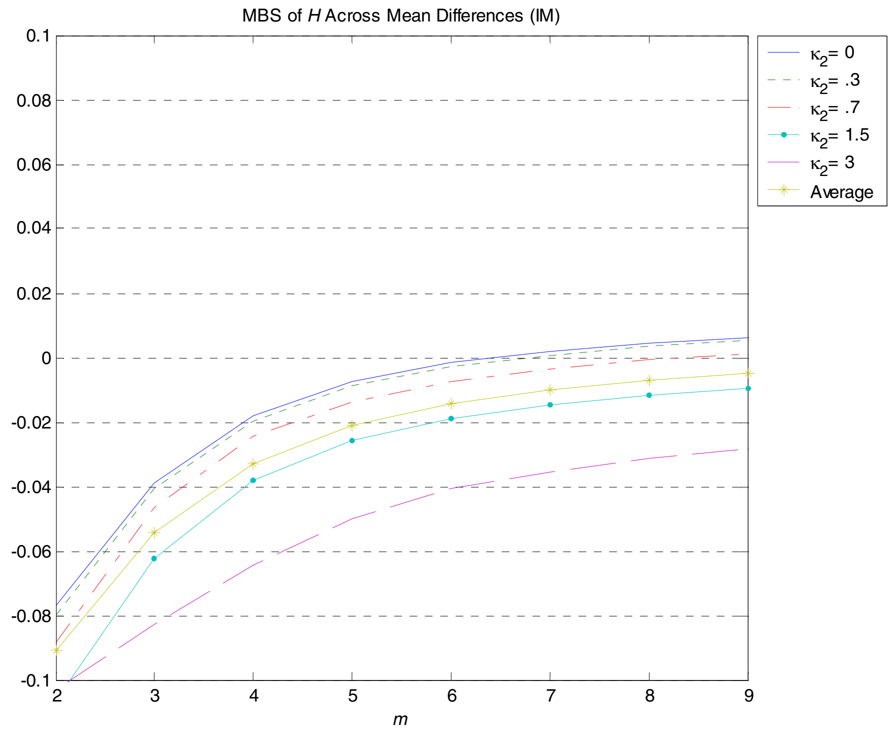


Figure 27: Mean Bias (MBS) of *H* Across Mean Differences



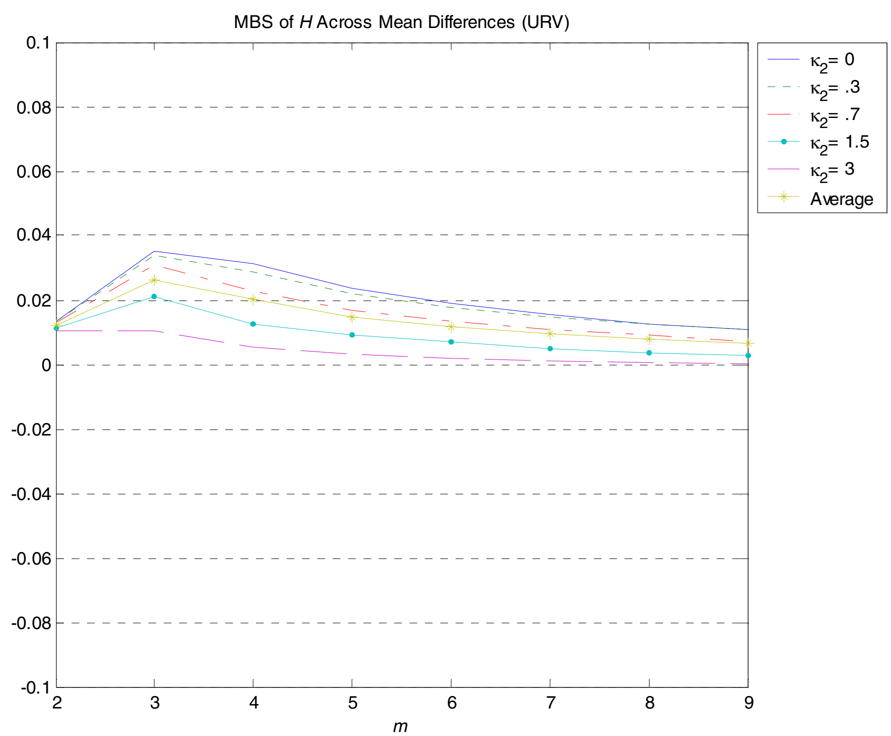
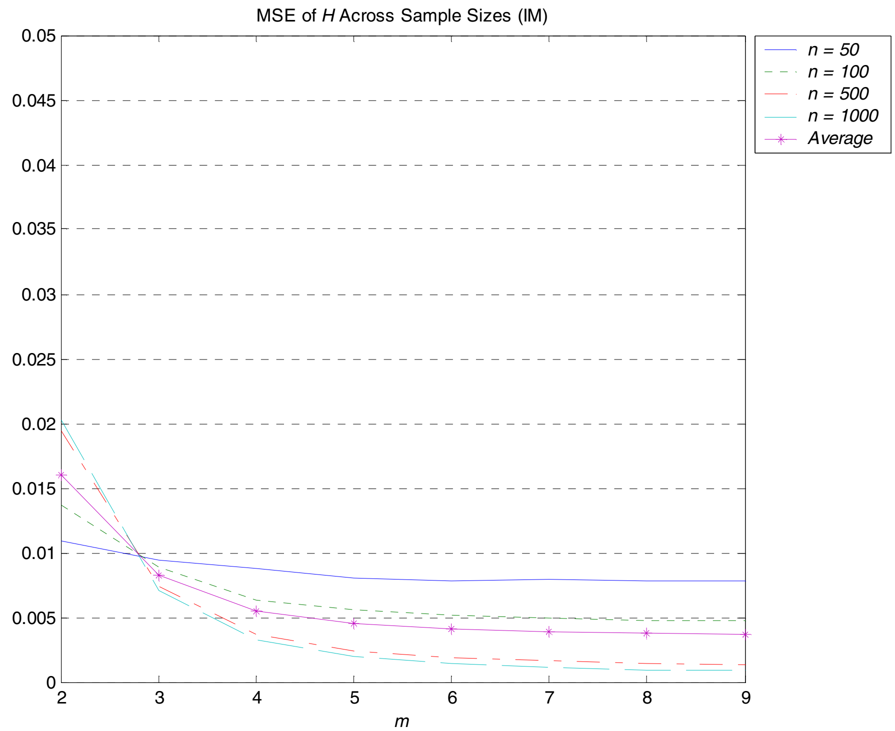
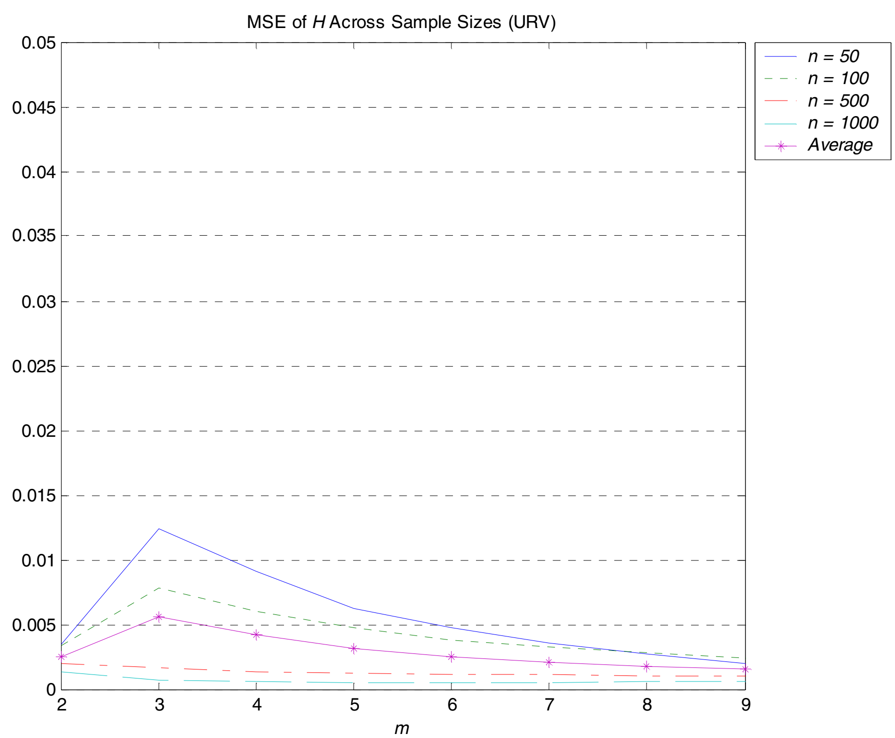


Figure 28: Mean Squared Error (MSE) of H Across Sample Sizes





Appendix A: Simulation Results

IM Option Results when n = 50, $\lambda = .3$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.132*	0.124*	0.113*	0.116*	0.116*	0.104*	0.125*	0.101*
		ET2	6.341*	6.555*	6.866*	6.465*	6.505*	6.328*	7.448*	6.608*
	CO2	ET1	0.123*	0.121*	0.094*	0.119*	0.074*	0.102*	0.109*	0.109*
		ET2	7.127*	6.934*	6.037*	6.790*	6.074*	6.949*	6.237*	6.695*
	CO3	ET1	0.164*	0.114*	0.112*	0.109*	0.096*	0.115*	0.108*	0.091*
		ET2	6.943*	6.488*	6.320*	6.632*	6.011*	6.296*	6.543*	6.261*
$\kappa_2 = 0.3$	CO1	EPD	0.124*	0.150*	0.158*	0.163*	0.149*	0.144*	0.133*	0.106*
		EPP	-0.008*	-0.015*	-0.024*	-0.002*	-0.009*	0.009*	-0.048*	-0.023*
	CO2	EPD	0.121*	0.147*	0.133*	0.144*	0.139*	0.130*	0.112*	0.140*
		EPP	-0.048*	-0.027*	-0.006*	-0.015*	0.007*	-0.030*	-0.026*	-0.013*
	CO3	EPD	0.133*	0.163*	0.151*	0.123*	0.154*	0.134*	0.104*	0.142*
		EPP	-0.021*	-0.009*	0.002*	-0.025*	0.000*	-0.004*	-0.032*	0.006*
$\kappa_2 = 0.7$	CO1	EPD	0.100*	0.145*	0.127*	0.130*	0.148*	0.139*	0.145*	0.159*
		EPP	-0.124*	-0.127*	-0.111*	-0.118*	-0.088*	-0.087*	-0.140*	-0.091*
	CO2	EPD	0.073*	0.124*	0.130*	0.136*	0.153*	0.126*	0.126*	0.153*
		EPP	-0.160*	-0.131*	-0.070*	-0.124*	-0.064*	-0.134*	-0.077*	-0.091*
	CO3	EPD	0.045*	0.142*	0.112*	0.157*	0.140*	0.119*	0.151*	0.135*
		EPP	-0.178*	-0.086*	-0.072*	-0.088*	-0.063*	-0.094*	-0.078*	-0.074*
$\kappa_2 = 1.5$	CO1	EPD	-0.060*	-0.031*	-0.005*	-0.004*	0.007*	0.003*	0.014*	0.011*
		EPP	-0.215*	-0.174*	-0.136*	-0.104*	-0.083*	-0.082*	-0.128*	-0.081*
	CO2	EPD	-0.075*	-0.017*	-0.009*	-0.012*	-0.001*	-0.003*	0.004*	0.001*
		EPP	-0.276*	-0.165*	-0.094*	-0.125*	-0.085*	-0.121*	-0.077*	-0.104*
	CO3	EPD	-0.076*	-0.010*	-0.010*	0.001*	0.004*	-0.001*	-0.004*	-0.003*
		EPP	-0.270*	-0.132*	-0.108*	-0.116*	-0.073*	-0.085*	-0.105*	-0.092*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, $\lambda = .3$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.106*	0.098*	0.095*	0.087*	0.065*	0.063*	0.069*	0.073*
		ET2	6.788*	6.741*	6.582*	6.910*	6.183*	6.054*	6.307*	6.205*
	CO2	ET1	0.095*	0.079*	0.066*	0.083*	0.078*	0.082*	0.085*	0.070*
		ET2	6.757*	6.911*	6.007*	6.419*	6.232*	6.234*	6.107*	5.794*
	CO3	ET1	0.113*	0.074*	0.083*	0.087*	0.077*	0.073*	0.093*	0.095*
		ET2	7.426*	7.119*	6.266*	6.392*	5.934*	5.881*	6.332*	6.487*
$\kappa_2 = 0.3$	CO1	EPD	0.120*	0.085*	0.104*	0.105*	0.101*	0.080*	0.097*	0.094*
		EPP	-0.041*	-0.052*	-0.031*	-0.043*	-0.012*	-0.019*	-0.033*	-0.033*
	CO2	EPD	0.086*	0.078*	0.111*	0.091*	0.083*	0.104*	0.104*	0.077*
		EPP	-0.049*	-0.044*	0.004*	-0.032*	-0.028*	-0.015*	-0.009*	-0.020*
	CO3	EPD	0.109*	0.104*	0.104*	0.094*	0.092*	0.093*	0.093*	0.108*
		EPP	-0.047*	-0.044*	-0.030*	-0.041*	-0.018*	-0.005*	-0.018*	-0.028*
$\kappa_2 = 0.7$	CO1	EPD	0.001*	0.051*	0.061*	0.067*	0.067*	0.081*	0.081*	0.075*
		EPP	-0.241*	-0.172*	-0.155*	-0.177*	-0.131*	-0.104*	-0.109*	-0.130*
	CO2	EPD	-0.026*	0.042*	0.027*	0.047*	0.065*	0.055*	0.054*	0.056*
		EPP	-0.239*	-0.195*	-0.152*	-0.152*	-0.127*	-0.128*	-0.123*	-0.098*
	CO3	EPD	0.021*	0.049*	0.055*	0.062*	0.067*	0.059*	0.073*	0.053*
		EPP	-0.238*	-0.200*	-0.138*	-0.147*	-0.098*	-0.106*	-0.138*	-0.159*
$\kappa_2 = 1.5$	CO1	EPD	-0.047*	-0.025*	-0.014*	-0.007*	-0.006*	-0.007*	-0.005*	-0.004*
		EPP	-0.153*	-0.095*	-0.056*	-0.054*	-0.044*	-0.034*	-0.031*	-0.031*
	CO2	EPD	-0.052*	-0.025*	-0.014*	-0.007*	-0.011*	-0.006*	-0.007*	-0.006*
		EPP	-0.141*	-0.094*	-0.047*	-0.047*	-0.036*	-0.039*	-0.030*	-0.028*
	CO3	EPD	-0.051*	-0.017*	-0.009*	-0.010*	-0.011*	-0.007*	-0.008*	-0.009*
		EPP	-0.188*	-0.089*	-0.053*	-0.047*	-0.040*	-0.032*	-0.039*	-0.050*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, λ = .3, p = 7

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.074*	0.067*	0.060*	0.053*	0.057*	0.063*	0.073*	0.052*
		ET2	6.749*	6.952*	5.932*	5.725*	5.636*	5.767*	6.015*	5.950*
	CO2	ET1	0.066*	0.071*	0.067*	0.066*	0.049*	0.063*	0.049*	0.046*
		ET2	6.493*	6.145*	5.845*	5.715*	5.377*	5.705*	5.421*	5.508*
	CO3	ET1	0.086*	0.059*	0.053*	0.058*	0.056*	0.056*	0.052*	0.054*
		ET2	7.070*	5.753*	5.403*	5.875*	5.758*	5.522*	5.747*	5.617*
$\kappa_2 = 0.3$	CO1	EPD	0.076*	0.078*	0.061*	0.077*	0.073*	0.056*	0.057*	0.069*
		EPP	-0.059*	-0.051*	-0.030*	-0.020*	-0.027*	-0.039*	-0.051*	-0.029*
	CO2	EPD	0.062*	0.069*	0.053*	0.071*	0.058*	0.073*	0.082*	0.069*
		EPP	-0.060*	-0.045*	-0.036*	-0.030*	-0.024*	-0.021*	-0.014*	-0.017*
	CO3	EPD	0.062*	0.083*	0.063*	0.074*	0.075*	0.082*	0.069*	0.053*
		EPP	-0.074*	-0.023*	-0.010*	-0.036*	-0.026*	-0.018*	-0.027*	-0.027*
$\kappa_2 = 0.7$	CO1	EPD	-0.061*	-0.011*	0.003*	0.002*	0.014*	0.021*	0.029*	0.030*
		EPP	-0.274*	-0.241*	-0.166*	-0.138*	-0.120*	-0.123*	-0.130*	-0.140*
	CO2	EPD	-0.063*	-0.019*	-0.003*	0.011*	0.015*	0.011*	0.018*	0.023*
		EPP	-0.268*	-0.188*	-0.164*	-0.130*	-0.123*	-0.145*	-0.105*	-0.116*
	CO3	EPD	-0.055*	-0.001*	0.013*	-0.002*	0.020*	0.000*	0.013*	0.028*
		EPP	-0.287*	-0.155*	-0.117*	-0.156*	-0.121*	-0.133*	-0.128*	-0.116*
$\kappa_2 = 1.5$	CO1	EPD	-0.032*	-0.010*	-0.006*	-0.007*	-0.001*	-0.004*	-0.001*	-0.004*
		EPP	-0.085*	-0.054*	-0.022*	-0.024*	-0.010*	-0.013*	-0.014*	-0.013*
	CO2	EPD	-0.029*	-0.012*	-0.004*	-0.004*	-0.007*	-0.003*	-0.003*	-0.004*
		EPP	-0.088*	-0.034*	-0.017*	-0.016*	-0.015*	-0.015*	-0.010*	-0.016*
	CO3	EPD	-0.025*	-0.013*	-0.005*	-0.005*	-0.007*	-0.003*	-0.003*	-0.004*
		EPP	-0.089*	-0.032*	-0.014*	-0.020*	-0.019*	-0.012*	-0.016*	-0.012*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.070*	0.051*	0.037*	0.027*	0.048*	0.046*	0.046*	0.035*
		ET2	6.091*	5.509*	5.075*	4.714*	5.075*	5.354*	5.513*	4.939*
	CO2	ET1	0.063*	0.052*	0.050*	0.055*	0.041*	0.043*	0.034*	0.036*
		ET2	5.740*	5.392*	5.288*	5.456*	4.973*	5.186*	4.974*	4.884*
	CO3	ET1	0.064*	0.040*	0.038*	0.044*	0.035*	0.032*	0.043*	0.035*
		ET2	5.754*	5.311*	5.021*	5.151*	5.333*	5.157*	5.006*	5.240*
$\kappa_2 = 0.3$	CO1	EPD	0.042*	0.065*	0.068*	0.056*	0.073*	0.064*	0.060*	0.076*
		EPP	-0.078*	-0.038*	-0.009*	-0.006*	-0.008*	-0.035*	-0.036*	0.004*
	CO2	EPD	0.043*	0.044*	0.055*	0.050*	0.048*	0.062*	0.051*	0.054*
		EPP	-0.061*	-0.036*	-0.037*	-0.044*	-0.021*	-0.024*	-0.023*	-0.011*
	CO3	EPD	0.065*	0.054*	0.045*	0.048*	0.048*	0.050*	0.059*	0.052*
		EPP	-0.043*	-0.035*	-0.021*	-0.028*	-0.044*	-0.018*	-0.009*	-0.031*
$\kappa_2 = 0.7$	CO1	EPD	-0.046*	-0.014*	0.007*	0.020*	0.016*	0.033*	0.026*	0.028*
		EPP	-0.236*	-0.167*	-0.085*	-0.052*	-0.093*	-0.076*	-0.108*	-0.057*
	CO2	EPD	-0.045*	-0.012*	0.008*	0.009*	0.020*	0.020*	0.006*	0.027*
		EPP	-0.225*	-0.151*	-0.109*	-0.126*	-0.072*	-0.091*	-0.080*	-0.063*
	CO3	EPD	-0.034*	0.015*	0.032*	0.025*	0.013*	0.027*	0.010*	0.016*
		EPP	-0.210*	-0.112*	-0.073*	-0.087*	-0.108*	-0.079*	-0.079*	-0.105*
$\kappa_2 = 1.5$	CO1	EPD	-0.007*	-0.002*	-0.001*	0.000*	-0.001*	0.000*	-0.001*	0.000*
		EPP	-0.024*	-0.006*	-0.004*	-0.001*	-0.001*	-0.002*	-0.003*	0.000*
	CO2	EPD	-0.006*	-0.001*	-0.001*	0.000*	0.000*	0.000*	-0.001*	0.000*
		EPP	-0.019*	-0.005*	-0.003*	-0.002*	-0.001*	-0.001*	-0.003*	-0.001*
	CO3	EPD	-0.007*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	-0.002*
		EPP	-0.024*	-0.007*	-0.002*	-0.002*	-0.002*	-0.002*	-0.001*	-0.003*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, λ = .5, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.045*	0.024*	0.022*	0.012*	0.016*	0.014*	0.024*	0.015*
		ET2	5.475*	4.580*	4.636*	4.272*	4.376*	4.368*	4.720*	4.318*
	CO2	ET1	0.027*	0.014*	0.022*	0.027*	0.011*	0.020*	0.018*	0.012*
		ET2	4.965*	4.232*	4.448*	4.683*	4.236*	4.418*	4.396*	4.350*
	CO3	ET1	0.025*	0.029*	0.017*	0.014*	0.013*	0.019*	0.018*	0.008*
		ET2	4.878*	4.936*	4.294*	4.276*	4.279*	4.517*	4.507*	4.303*
$\kappa_2 = 0.3$	CO1	EPD	0.002*	0.014*	0.022*	0.012*	0.018*	0.026*	0.008*	0.020*
		EPP	-0.079*	-0.022*	-0.036*	-0.016*	-0.026*	-0.008*	-0.048*	-0.010*
	CO2	EPD	-0.006*	-0.003*	0.014*	0.001*	0.016*	0.020*	0.010*	0.016*
		EPP	-0.063*	-0.028*	-0.030*	-0.051*	-0.019*	-0.021*	-0.020*	-0.020*
	CO3	EPD	0.006*	0.010*	-0.005*	0.021*	0.007*	0.006*	0.019*	0.014*
		EPP	-0.062*	-0.052*	-0.034*	-0.007*	-0.018*	-0.035*	-0.027*	-0.017*
$\kappa_2 = 0.7$	CO1	EPD	-0.099*	-0.052*	-0.032*	-0.031*	-0.016*	-0.015*	0.015*	-0.003*
		EPP	-0.231*	-0.110*	-0.086*	-0.060*	-0.058*	-0.054*	-0.048*	-0.039*
	CO2	EPD	-0.093*	-0.037*	-0.038*	-0.029*	-0.011*	-0.008*	-0.011*	-0.003*
		EPP	-0.191*	-0.070*	-0.082*	-0.091*	-0.038*	-0.058*	-0.045*	-0.041*
	CO3	EPD	-0.103*	-0.050*	-0.019*	-0.007*	0.001*	-0.014*	-0.002*	-0.014*
		EPP	-0.177*	-0.137*	-0.054*	-0.036*	-0.034*	-0.060*	-0.050*	-0.048*
$\kappa_2 = 1.5$	CO1	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.001*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002*	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, λ = .5, *p* = 7

			m = 2	*m* = 3	*m* = 4	*m* = 5	*m* = 6	*m* = 7	*m* = 8	*m* = 9
$\kappa_2 = 0$	CO1	ET1	0.016*	0.016*	0.003*	0.005*	0.009*	0.008*	0.012*	0.005*
		ET2	4.443*	4.350*	4.037*	4.203*	4.183*	4.098*	4.248*	3.988*
	CO2	ET1	0.021*	0.020*	0.010*	0.011*	0.007*	0.010*	0.017*	0.011*
		ET2	4.451*	4.495*	4.167*	4.252*	4.071*	4.354*	4.379*	4.209*
	CO3	ET1	0.018*	0.019*	0.021*	0.018*	0.009*	0.010*	0.007*	0.019*
		ET2	4.362*	4.661*	4.513*	4.401*	4.178*	4.070*	4.093*	4.362*
$\kappa_2 = 0.3$	CO1	EPD	-0.014*	0.008*	0.013*	0.007*	-0.002*	0.019*	0.017*	0.016*
		EPP	-0.058*	-0.034*	-0.004*	-0.018*	-0.023*	-0.003*	-0.017*	0.002*
	CO2	EPD	-0.028*	-0.001*	-0.002*	0.007*	0.009*	0.007*	0.004*	0.018*
		EPP	-0.065*	-0.044*	-0.024*	-0.026*	-0.004*	-0.028*	-0.038*	-0.011*
	CO3	EPD	-0.025*	-0.012*	0.003*	0.003*	0.019*	0.010*	0.015*	0.004*
		EPP	-0.059*	-0.061*	-0.043*	-0.035*	-0.007*	-0.006*	-0.001*	-0.027*
$\kappa_2 = 0.7$	CO1	EPD	-0.072*	-0.041*	-0.040*	-0.014*	-0.001*	0.008*	-0.016*	0.006*
		EPP	-0.117*	-0.078*	-0.056*	-0.039*	-0.024*	-0.008*	-0.040*	-0.004*
	CO2	EPD	-0.085*	-0.046*	-0.026*	-0.017*	-0.002*	-0.020*	-0.016*	-0.011*
		EPP	-0.126*	-0.091*	-0.049*	-0.044*	-0.017*	-0.056*	-0.052*	-0.029*
	CO3	EPD	-0.087*	-0.034*	-0.031*	-0.012*	-0.012*	-0.006*	-0.024*	-0.009*
		EPP	-0.136*	-0.090*	-0.081*	-0.047*	-0.032*	-0.023*	-0.040*	-0.041*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, λ = .7, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.014*	0.013*	0.020*	0.016*	0.019*	0.014*	0.011*	0.005*
		ET2	4.196*	4.286*	4.593*	4.482*	4.414*	4.444*	4.169*	4.062*
	CO2	ET1	0.016*	0.016*	0.011*	0.013*	0.008*	0.023*	0.017*	0.013*
		ET2	4.438*	4.248*	4.138*	4.350*	4.110*	4.665*	4.485*	4.214*
	CO3	ET1	0.020*	0.004*	0.011*	0.012*	0.008*	0.008*	0.007*	0.013*
		ET2	4.636*	3.941*	4.221*	4.215*	4.102*	4.068*	4.120*	4.306*
$\kappa_2 = 0.3$	CO1	EPD	-0.012*	-0.002*	-0.010*	0.020*	0.030*	0.016*	0.034*	0.023*
		EPP	-0.038*	-0.035*	-0.060*	-0.029*	-0.015*	-0.029*	0.010*	0.007*
	CO2	EPD	-0.002*	-0.005*	0.006*	0.012*	0.006*	0.006*	0.023*	0.018*
		EPP	-0.043*	-0.032*	-0.022*	-0.020*	-0.019*	-0.053*	-0.024*	-0.010*
	CO3	EPD	-0.012*	-0.012*	0.007*	0.014*	0.002*	0.003*	0.003*	0.018*
		EPP	-0.066*	-0.018*	-0.022*	-0.016*	-0.021*	-0.015*	-0.014*	-0.019*
$\kappa_2 = 0.7$	CO1	EPD	-0.083*	-0.047*	-0.019*	-0.019*	-0.003*	-0.007*	-0.012*	-0.006*
		EPP	-0.116*	-0.075*	-0.071*	-0.056*	-0.038*	-0.050*	-0.029*	-0.020*
	CO2	EPD	-0.099*	-0.038*	-0.020*	-0.022*	-0.006*	-0.014*	0.002*	0.003*
		EPP	-0.145*	-0.062*	-0.038*	-0.060*	-0.024*	-0.063*	-0.036*	-0.018*
	CO3	EPD	-0.084*	-0.050*	-0.037*	-0.023*	-0.019*	-0.016*	-0.011*	-0.016*
		EPP	-0.141*	-0.059*	-0.064*	-0.043*	-0.036*	-0.031*	-0.027*	-0.042*
$\kappa_2 = 1.5$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	N/A	N/A	0.000	0.000	0.000	0.000*	0.000	0.000*
		EPP	N/A	N/A	0.000	0.000	0.000	0.000*	0.000	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.003*	0.014*	0.006*	0.011*	0.007*	0.008*	0.012*	0.014*
		ET2	3.988*	4.198*	4.054*	4.419*	4.016*	4.090*	4.145*	4.312*
	CO2	ET1	0.014*	-0.003*	0.006*	0.010*	0.008*	0.005*	0.007*	0.012*
		ET2	4.381*	3.758*	4.030*	4.144*	4.049*	3.944*	4.054*	4.253*
	CO3	ET1	0.007*	0.005*	0.000*	0.008*	0.008*	0.008*	0.004*	0.005*
		ET2	4.091*	4.033*	3.847*	4.134*	4.107*	4.120*	3.969*	4.080*
$\kappa_2 = 0.3$	CO1	EPD	-0.029*	-0.010*	0.003*	-0.016*	0.017*	0.005*	0.008*	0.011*
		EPP	-0.037*	-0.036*	-0.016*	-0.058*	0.000*	-0.015*	-0.016*	-0.031*
	CO2	EPD	-0.041*	-0.010*	-0.017*	-0.004*	0.008*	0.004*	0.000*	-0.003*
		EPP	-0.078*	-0.004*	-0.033*	-0.029*	-0.009*	-0.006*	-0.018*	-0.040*
	CO3	EPD	-0.030*	0.003*	0.003*	-0.013*	-0.004*	0.016*	0.018*	0.026*
		EPP	-0.049*	-0.016*	0.003*	-0.037*	-0.026*	-0.008*	0.007*	0.008*
$\kappa_2 = 0.7$	CO1	EPD	-0.078*	-0.033*	-0.014*	-0.017*	-0.010*	-0.003*	-0.002*	0.008*
		EPP	-0.089*	-0.058*	-0.026*	-0.049*	-0.019*	-0.017*	-0.016*	-0.019*
	CO2	EPD	-0.084*	-0.017*	-0.025*	-0.006*	-0.011*	-0.021*	0.000*	-0.007*
		EPP	-0.126*	-0.014*	-0.033*	-0.025*	-0.020*	-0.025*	-0.011*	-0.026*
	CO3	EPD	-0.068*	-0.042*	-0.011*	-0.011*	-0.013*	-0.017*	-0.019*	-0.011*
		EPP	-0.092*	-0.049*	-0.011*	-0.027*	-0.030*	-0.029*	-0.027*	-0.020*
$\kappa_2 = 1.5$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	N/A	0.000	0.000	0.000	0.000	0.000*	0.000	0.000
		EPP	N/A	0.000	0.000	0.000	0.000	0.000*	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 50, $\lambda = .7$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.008*	0.006*	0.008*	0.010*	0.008*	0.015*	-0.004*	0.003*
		ET2	4.100*	4.029*	4.073*	4.224*	4.047*	4.285*	3.717*	3.955*
	CO2	ET1	0.010*	0.008*	0.007*	0.007*	0.008*	0.003*	-0.002*	0.003*
		ET2	4.173*	4.062*	4.126*	4.116*	4.178*	3.908*	3.774*	3.963*
	CO3	ET1	0.011*	0.007*	0.008*	0.010*	0.006*	0.004*	0.001*	0.000*
		ET2	4.265*	3.980*	4.149*	4.103*	3.991*	4.110*	3.873*	3.827*
$\kappa_2 = 0.3$	CO1	EPD	-0.036*	-0.011*	-0.014*	0.001*	-0.002*	0.013*	0.009*	0.006*
		EPP	-0.052*	-0.026*	-0.032*	-0.030*	-0.016*	-0.026*	0.018*	-0.003*
	CO2	EPD	-0.044*	-0.006*	-0.002*	0.008*	0.008*	-0.009*	-0.006*	-0.001*
		EPP	-0.067*	-0.025*	-0.029*	-0.016*	-0.017*	-0.014*	-0.003*	-0.009*
	CO3	EPD	-0.029*	-0.023*	-0.004*	0.003*	0.004*	-0.007*	0.004*	-0.005*
		EPP	-0.063*	-0.033*	-0.032*	-0.018*	-0.007*	-0.029*	0.001*	-0.002*
$\kappa_2 = 0.7$	CO1	EPD	-0.066*	-0.015*	-0.012*	-0.020*	-0.006*	-0.002*	0.000*	-0.007*
		EPP	-0.080*	-0.027*	-0.022*	-0.037*	-0.014*	-0.018*	0.008*	-0.013*
	CO2	EPD	-0.064*	-0.033*	-0.015*	-0.015*	-0.002*	0.002*	-0.016*	-0.008*
		EPP	-0.083*	-0.044*	-0.030*	-0.026*	-0.016*	-0.001*	-0.011*	-0.013*
	CO3	EPD	-0.056	-0.030*	-0.010*	-0.016*	-0.007*	-0.006*	0.001*	0.000*
		EPP	-0.083	-0.039*	-0.030*	-0.032*	-0.013*	-0.022*	0.000*	0.001*
$\kappa_2 = 1.5$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	N/A	N/A	0.000	0.000	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	N/A	0.000	0.000	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, λ = .3, p = 3

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.127*	0.109*	0.123*	0.080*	0.091*	0.085*	0.087*	0.075*
		ET2	6.748*	6.648*	6.108*	5.615*	5.856*	6.354*	5.591*	6.189*
	CO2	ET1	0.134*	0.095*	0.113*	0.093*	0.104*	0.095*	0.084*	0.076*
		ET2	6.255*	5.756*	6.626*	6.082*	6.278*	6.857*	6.161*	5.321*
	CO3	ET1	0.129*	0.085*	0.110*	0.083*	0.079*	0.070*	0.078*	0.083*
		ET2	6.465*	5.859*	6.371*	6.394*	5.892*	5.873*	6.234*	6.255*
$\kappa_2 = 0.3$	CO1	EPD	0.122*	0.112*	0.123*	0.131*	0.099*	0.133*	0.112*	0.116*
		EPP	-0.067*	-0.048*	-0.033*	0.013*	-0.021*	-0.031*	-0.001*	-0.030*
	CO2	EPD	0.074*	0.137*	0.116*	0.112*	0.145*	0.107*	0.118*	0.108*
		EPP	-0.060*	-0.001*	-0.052*	-0.025*	-0.027*	-0.071*	-0.021*	0.007*
	CO3	EPD	0.106*	0.124*	0.150*	0.114*	0.103*	0.127*	0.133*	0.099*
		EPP	-0.054*	-0.010*	-0.027*	-0.045*	-0.030*	-0.018*	-0.024*	-0.036*
$\kappa_2 = 0.7$	CO1	EPD	0.001*	0.024*	0.048*	0.078*	0.050*	0.080*	0.076*	0.074*
		EPP	-0.272*	-0.252*	-0.177*	-0.071*	-0.112*	-0.123*	-0.080*	-0.112*
	CO2	EPD	-0.017*	0.030*	0.032*	0.055*	0.055*	0.063*	0.072*	0.085*
		EPP	-0.230*	-0.149*	-0.214*	-0.132*	-0.132*	-0.181*	-0.120*	-0.030*
	CO3	EPD	-0.055*	0.031*	0.062*	0.059*	0.069*	0.082*	0.091*	0.066*
		EPP	-0.273*	-0.145*	-0.168*	-0.161*	-0.099*	-0.086*	-0.126*	-0.125*
$\kappa_2 = 1.5$	CO1	EPD	-0.012*	-0.008*	0.000*	-0.001*	-0.001*	0.000*	0.000*	-0.001*
		EPP	-0.066*	-0.032*	-0.006*	-0.005*	-0.005*	-0.004*	-0.003*	-0.003*
	CO2	EPD	-0.012*	-0.006*	-0.003*	-0.002*	0.001*	0.000*	0.001*	-0.001*
		EPP	-0.037*	-0.017*	-0.015*	-0.011*	-0.010*	-0.011*	-0.005*	-0.001*
	CO3	EPD	-0.017*	-0.004*	-0.003*	-0.002*	-0.001*	0.000*	0.000*	-0.001*
		EPP	-0.045*	-0.013*	-0.014*	-0.008*	-0.006*	-0.007*	-0.004*	-0.006*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, λ = .3, p = 5

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.098*	0.073*	0.064*	0.053*	0.054*	0.054*	0.045*	0.065*
		ET2	6.744*	6.053*	5.925*	5.725*	5.801*	5.687*	5.307*	5.869*
	CO2	ET1	0.085*	0.062*	0.060*	0.046*	0.048*	0.057*	0.047*	0.045*
		ET2	6.596*	5.695*	5.615*	5.371*	5.422*	5.576*	5.660*	5.376*
	CO3	ET1	0.084*	0.066*	0.054*	0.046*	0.047*	0.064*	0.046*	0.047*
		ET2	6.464*	5.696*	5.664*	5.414*	5.555*	5.476*	5.721*	5.567*
$\kappa_2 = 0.3$	CO1	EPD	0.059*	0.074*	0.052*	0.063*	0.077*	0.072*	0.055*	0.099*
		EPP	-0.102*	-0.064*	-0.073*	-0.054*	-0.045*	-0.052*	-0.041*	-0.042*
	CO2	EPD	0.025*	0.043*	0.040*	0.041*	0.085*	0.041*	0.056*	0.073*
		EPP	-0.113*	-0.070*	-0.059*	-0.061*	-0.018*	-0.065*	-0.045*	-0.038*
	CO3	EPD	0.059*	0.077*	0.077*	0.059*	0.062*	0.055*	0.052*	0.052*
		EPP	-0.083*	-0.046*	-0.050*	-0.040*	-0.044*	-0.050*	-0.059*	-0.043*
$\kappa_2 = 0.7$	CO1	EPD	-0.069*	-0.062*	-0.033*	-0.030*	-0.008*	-0.015*	0.014*	0.010*
		EPP	-0.265*	-0.252*	-0.172*	-0.150*	-0.142*	-0.137*	-0.085*	-0.121*
	CO2	EPD	-0.091*	-0.054*	-0.022*	0.000*	-0.013*	-0.015*	0.003*	0.005*
		EPP	-0.290*	-0.176*	-0.133*	-0.105*	-0.115*	-0.136*	-0.133*	-0.103*
	CO3	EPD	-0.083*	-0.025*	-0.024*	-0.012*	-0.005*	0.013*	-0.009*	-0.003*
		EPP	-0.280*	-0.155*	-0.149*	-0.118*	-0.106*	-0.089*	-0.128*	-0.119*
$\kappa_2 = 1.5$	CO1	EPD	-0.004*	0.000*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.011*	-0.001*	-0.001*	-0.001*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.007*	-0.001*	-0.001*	-0.001*	0.000*	-0.001*	0.000*	0.000*
	CO3	EPD	-0.002*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.007*	-0.001*	0.000*	0.000*	-0.002*	0.000*	-0.001*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, $\lambda = .3$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.046*	0.035*	0.037*	0.042*	0.030*	0.028*	0.029*	0.024*
		ET2	5.583*	5.006*	5.235*	5.390*	5.403*	4.697*	4.853*	4.503*
	CO2	ET1	0.070*	0.059*	0.037*	0.041*	0.026*	0.032*	0.046*	0.034*
		ET2	6.022*	5.903*	5.054*	5.171*	4.772*	5.098*	5.226*	4.814*
	CO3	ET1	0.054*	0.042*	0.044*	0.038*	0.037*	0.041*	0.032*	0.039*
		ET2	5.583*	5.218*	5.166*	5.185*	4.899*	5.392*	4.910*	4.950*
$\kappa_2 = 0.3$	CO1	EPD	0.019*	0.037*	0.021*	0.043*	0.051*	0.029*	0.039*	0.024*
		EPP	-0.086*	-0.051*	-0.073*	-0.071*	-0.058*	-0.030*	-0.030*	-0.022*
	CO2	EPD	-0.010*	0.020*	0.021*	0.037*	0.037*	0.032*	0.037*	0.044*
		EPP	-0.131*	-0.099*	-0.049*	-0.046*	-0.026*	-0.055*	-0.060*	-0.028*
	CO3	EPD	0.009*	0.018*	0.033*	0.027*	0.054*	0.028*	0.041*	0.038*
		EPP	-0.083*	-0.075*	-0.061*	-0.058*	-0.025*	-0.061*	-0.033*	-0.036*
$\kappa_2 = 0.7$	CO1	EPD	-0.109*	-0.076*	-0.027*	-0.005*	-0.012*	-0.009*	0.000*	-0.008*
		EPP	-0.230*	-0.147*	-0.107*	-0.095*	-0.103*	-0.047*	-0.042*	-0.040*
	CO2	EPD	-0.125*	-0.063*	-0.032*	-0.026*	-0.020*	-0.020*	-0.025*	0.000*
		EPP	-0.270*	-0.181*	-0.109*	-0.101*	-0.066*	-0.077*	-0.104*	-0.060*
	CO3	EPD	-0.088*	-0.047*	-0.036*	-0.022*	-0.012*	-0.016*	-0.018*	-0.017*
		EPP	-0.200*	-0.138*	-0.117*	-0.092*	-0.062*	-0.109*	-0.082*	-0.064*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.037*	0.031*	0.024*	0.013*	0.019*	0.020*	0.024*	0.013*
		ET2	5.238*	4.765*	4.624*	4.200*	4.203*	4.723*	4.548*	4.464*
	CO2	ET1	0.047*	0.024*	0.019*	0.031*	0.034*	0.015*	0.022*	0.025*
		ET2	5.156*	4.498*	4.403*	4.966*	4.760*	4.406*	4.760*	4.832*
	CO3	ET1	0.040*	0.022*	0.027*	0.022*	0.019*	0.026*	0.022*	0.014*
		ET2	5.031*	4.450*	4.893*	4.658*	4.490*	4.733*	4.725*	4.170*
$\kappa_2 = 0.3$	CO1	EPD	-0.012*	-0.002*	0.006*	0.029*	0.048*	0.013*	0.040*	0.032*
		EPP	-0.108*	-0.075*	-0.059*	-0.005*	0.011*	-0.045*	-0.019*	-0.029*
	CO2	EPD	-0.012*	0.002*	0.001*	0.019*	0.008*	0.013*	0.015*	0.021*
		EPP	-0.099*	-0.045*	-0.040*	-0.074*	-0.069*	-0.034*	-0.053*	-0.047*
	CO3	EPD	-0.025*	-0.005*	0.021*	0.031*	0.016*	0.028*	0.034*	0.025*
		EPP	-0.115*	-0.053*	-0.055*	-0.031*	-0.041*	-0.044*	-0.041*	-0.008*
$\kappa_2 = 0.7$	CO1	EPD	-0.081*	-0.060*	-0.015*	-0.020*	-0.004*	-0.012*	0.002*	-0.003*
		EPP	-0.167*	-0.101*	-0.052*	-0.032*	-0.014*	-0.039*	-0.024*	-0.020*
	CO2	EPD	-0.076*	-0.028*	-0.019*	-0.021*	-0.023*	-0.006*	-0.011*	-0.015*
		EPP	-0.152*	-0.056*	-0.039*	-0.069*	-0.060*	-0.028*	-0.045*	-0.051*
	CO3	EPD	-0.066*	-0.037*	-0.016*	-0.026*	-0.016*	-0.006*	-0.024*	-0.019*
		EPP	-0.143*	-0.067*	-0.064*	-0.060*	-0.037*	-0.036*	-0.049*	-0.030*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, λ = .5, *p* = 5

			$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$	$m=8$	$m=9$
$\kappa_2 = 0$	CO1	ET1	0.017*	0.003*	0.013*	0.002*	0.009*	0.016*	0.006*	0.014*
		ET2	4.317*	3.906*	4.223*	3.919*	4.230*	4.383*	4.054*	4.402*
	CO2	ET1	0.028*	0.012*	0.004*	0.009*	0.007*	0.018*	0.007*	0.003*
		ET2	4.766*	4.277*	3.943*	4.177*	3.967*	4.290*	4.061*	3.963*
	CO3	ET1	0.013*	0.021*	0.005*	0.013*	0.010*	0.020*	0.009*	0.014*
		ET2	4.355*	4.503*	3.979*	4.149*	4.222*	4.292*	4.237*	4.345*
$\kappa_2 = 0.3$	CO1	EPD	-0.032*	-0.028*	0.001*	-0.006*	0.005*	0.002*	0.000*	0.004*
		EPP	-0.084*	-0.034*	-0.034*	-0.012*	-0.031*	-0.048*	-0.019*	-0.046*
	CO2	EPD	-0.071*	-0.033*	-0.033*	-0.005*	-0.001*	0.004*	-0.015*	-0.004*
		EPP	-0.145*	-0.080*	-0.037*	-0.033*	-0.013*	-0.038*	-0.035*	-0.017*
	CO3	EPD	-0.055*	-0.026*	-0.018*	-0.006*	-0.015*	-0.006*	-0.005*	0.013*
		EPP	-0.096*	-0.076*	-0.031*	-0.037*	-0.052*	-0.053*	-0.040*	-0.035*
$\kappa_2 = 0.7$	CO1	EPD	-0.044*	-0.019*	-0.004*	-0.011*	-0.007*	-0.004*	-0.001*	-0.004*
		EPP	-0.060*	-0.019*	-0.014*	-0.012*	-0.015*	-0.011*	-0.004*	-0.015*
	CO2	EPD	-0.050*	-0.016*	-0.019*	-0.023*	-0.004*	-0.010*	-0.008*	-0.004*
		EPP	-0.087*	-0.028*	-0.021*	-0.030*	-0.006*	-0.019*	-0.014*	-0.007*
	CO3	EPD	-0.049*	-0.029*	-0.011*	-0.014*	-0.009*	-0.006*	-0.002*	-0.004*
		EPP	-0.064*	-0.041*	-0.014*	-0.020*	-0.017*	-0.013*	-0.010*	-0.014*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, $\lambda = .5$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.011*	0.009*	0.005*	0.006*	0.009*	0.011*	0.009*	0.013*
		ET2	4.131*	4.096*	4.166*	4.019*	4.191*	4.185*	4.158*	4.342*
	CO2	ET1	0.013*	0.003*	0.004*	0.012*	0.005*	0.004*	0.012*	0.013*
		ET2	4.272*	3.879*	3.984*	4.185*	4.008*	3.930*	4.144*	4.123*
	CO3	ET1	0.012*	0.008*	0.007*	0.010*	0.004*	0.011*	0.019*	0.012*
		ET2	4.282*	4.186*	4.084*	4.146*	3.934*	4.228*	4.431*	4.334*
$\kappa_2 = 0.3$	CO1	EPD	-0.054*	-0.015*	-0.022*	0.001*	-0.010*	0.001*	-0.004*	-0.008*
		EPP	-0.078*	-0.040*	-0.052*	-0.017*	-0.046*	-0.033*	-0.032*	-0.055*
	CO2	EPD	-0.073*	-0.025*	-0.022*	-0.016*	-0.008*	-0.010*	0.008*	0.003*
		EPP	-0.105*	-0.030*	-0.042*	-0.048*	-0.025*	-0.018*	-0.021*	-0.030*
	CO3	EPD	-0.050*	-0.039*	-0.022*	-0.015*	0.012*	0.005*	0.001*	0.002*
		EPP	-0.089*	-0.074*	-0.042*	-0.048*	0.007*	-0.025*	-0.057*	-0.045*
$\kappa_2 = 0.7$	CO1	EPD	-0.031*	-0.018*	-0.008*	-0.002*	-0.005*	-0.004*	-0.002*	-0.006*
		EPP	-0.036*	-0.023*	-0.013*	-0.002*	-0.011*	-0.009*	-0.006*	-0.012*
	CO2	EPD	-0.030*	-0.014*	-0.010*	-0.004*	-0.004*	-0.005*	-0.002*	-0.003*
		EPP	-0.042*	-0.014*	-0.011*	-0.011*	-0.006*	-0.005*	-0.005*	-0.007*
	CO3	EPD	-0.023*	-0.015*	-0.013*	-0.007*	-0.002*	-0.001*	-0.004*	-0.003*
		EPP	-0.036*	-0.020*	-0.015*	-0.009*	-0.003*	-0.004*	-0.013*	-0.011*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, $\lambda = .7$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.005*	0.019*	0.003*	0.002*	0.003*	0.017*	0.003*	0.000*
		ET2	4.080*	4.406*	3.945*	3.968*	3.936*	4.357*	3.986*	3.832*
	CO2	ET1	0.006*	0.015*	0.005*	0.007*	0.004*	0.007*	0.014*	0.009*
		ET2	4.052*	4.336*	4.056*	4.077*	3.914*	4.025*	4.434*	4.158*
	CO3	ET1	0.004*	0.016*	0.006*	0.002*	0.009*	0.018*	0.005*	0.014*
		ET2	4.066*	4.410*	4.123*	3.879*	4.126*	4.514*	3.945*	4.212*
$\kappa_2 = 0.3$	CO1	EPD	-0.091*	-0.037*	-0.027*	0.001*	0.000*	-0.023*	0.010*	-0.004*
		EPP	-0.112*	-0.086*	-0.032*	-0.010*	-0.011*	-0.079*	-0.004*	-0.004*
	CO2	EPD	-0.084*	-0.045*	-0.007*	-0.015*	-0.023*	-0.034*	-0.007*	-0.001*
		EPP	-0.107*	-0.095*	-0.027*	-0.040*	-0.031*	-0.054*	-0.059*	-0.031*
	CO3	EPD	-0.059*	-0.047*	-0.015*	-0.018*	-0.020*	-0.014*	-0.009*	0.003*
		EPP	-0.076*	-0.097*	-0.040*	-0.020*	-0.041*	-0.083*	-0.021*	-0.031*
$\kappa_2 = 0.7$	CO1	EPD	-0.024*	-0.018*	-0.009*	-0.003*	-0.001*	0.001*	0.001*	0.001*
		EPP	-0.029*	-0.027*	-0.009*	-0.003*	-0.001*	-0.002*	0.000*	0.001*
	CO2	EPD	-0.031*	-0.006*	-0.008*	-0.005*	-0.009*	0.000*	-0.001*	-0.001*
		EPP	-0.039*	-0.013*	-0.009*	-0.010*	-0.010*	-0.002*	-0.006*	-0.005*
	CO3	EPD	-0.030*	-0.012*	-0.010*	-0.006*	-0.001*	-0.003*	-0.007*	-0.004*
		EPP	-0.036*	-0.023*	-0.014*	-0.006*	-0.003*	-0.009*	-0.008*	-0.008*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, λ = .7, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.003*	0.005*	-0.003*	-0.001*	0.011*	0.005*	0.005*	0.008*
		ET2	3.957*	4.088*	3.780*	3.807*	4.138*	4.142*	4.112*	4.171*
	CO2	ET1	0.001*	0.002*	0.002*	0.008*	0.001*	0.010*	0.009*	-0.004*
		ET2	3.860*	3.872*	3.947*	4.141*	3.870*	4.165*	4.071*	3.661*
	CO3	ET1	0.007*	0.009*	0.002*	0.001*	0.007*	0.003*	0.004*	0.002*
		ET2	4.138*	4.081*	3.946*	3.897*	4.033*	3.977*	3.973*	3.930*
$\kappa_2 = 0.3$	CO1	EPD	-0.062*	-0.049*	-0.024*	-0.003*	-0.012*	-0.013*	0.013*	0.021*
		EPP	-0.074*	-0.073*	-0.017*	0.000*	-0.043*	-0.047*	-0.019*	-0.008*
	CO2	EPD	-0.100*	-0.036*	-0.008*	-0.035*	-0.004*	-0.021*	-0.001*	-0.034*
		EPP	-0.100*	-0.040*	-0.020*	-0.063*	-0.005*	-0.049*	-0.025*	-0.014*
	CO3	EPD	-0.065*	-0.040*	-0.034*	-0.017*	0.013*	0.005*	-0.024*	-0.012*
		EPP	-0.099*	-0.059*	-0.047*	-0.022*	-0.008*	-0.012*	-0.036*	-0.028*
$\kappa_2 = 0.7$	CO1	EPD	-0.018*	-0.008*	-0.005*	0.001*	-0.002*	0.000*	-0.004*	0.000*
		EPP	-0.018*	-0.009*	-0.005*	0.001*	-0.003*	-0.001*	-0.005*	-0.004*
	CO2	EPD	-0.013*	-0.002*	-0.001*	-0.002*	-0.002*	0.000*	-0.006*	0.002*
		EPP	-0.014*	-0.003*	-0.002*	-0.004*	-0.002*	-0.004*	-0.008*	0.002*
	CO3	EPD	-0.013*	-0.007*	-0.002*	-0.006*	-0.004*	-0.002*	-0.003*	0.001*
		EPP	-0.017*	-0.010*	-0.002*	-0.006*	-0.004*	-0.002*	-0.004*	0.001*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	N/A	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 100, λ = .7, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	-0.006*	-0.014*	0.004*	-0.005*	0.013*	-0.005*	0.000*	0.004*
		ET2	3.633*	3.432*	4.005*	3.629*	4.252*	3.718*	3.788*	3.967*
	CO2	ET1	0.013*	-0.004*	0.004*	-0.002*	-0.007*	0.001*	0.001*	-0.007*
		ET2	4.335*	3.720*	3.924*	3.709*	3.675*	3.884*	3.859*	3.478*
	CO3	ET1	0.010*	-0.006*	0.009*	0.003*	-0.006*	0.007*	0.002*	0.013*
		ET2	4.095*	3.675*	4.280*	3.912*	3.620*	4.130*	3.874*	4.233*
$\kappa_2 = 0.3$	CO1	EPD	-0.078*	-0.021*	0.001*	-0.008*	-0.011*	0.011*	0.009*	-0.008*
		EPP	-0.055*	0.020*	-0.011*	0.019*	-0.048*	0.022*	0.017*	-0.018*
	CO2	EPD	-0.075*	-0.054*	-0.035*	-0.013*	-0.023*	-0.016*	0.011*	-0.009*
		EPP	-0.120*	-0.045*	-0.040*	0.001*	-0.004*	-0.020*	0.008*	0.031*
	CO3	EPD	-0.049*	-0.033*	-0.007*	-0.017*	-0.023*	0.000*	0.019*	-0.011*
		EPP	-0.075*	-0.016*	-0.043*	-0.024*	0.002*	-0.031*	0.018*	-0.050*
$\kappa_2 = 0.7$	CO1	EPD	-0.010*	-0.002*	0.001*	0.001*	-0.001*	0.001*	0.002*	-0.002*
		EPP	-0.007*	-0.001*	0.001*	0.001*	-0.003*	0.001*	0.002*	-0.003*
	CO2	EPD	-0.008*	-0.001*	-0.003*	-0.003*	-0.001*	0.000*	-0.001*	-0.004*
		EPP	-0.011*	-0.001*	-0.003*	-0.002*	0.000*	0.000*	-0.001*	-0.002*
	CO3	EPD	-0.005*	-0.002*	-0.003*	-0.002*	-0.005*	-0.001*	0.001*	0.001*
		EPP	-0.007*	-0.002*	-0.005*	-0.002*	-0.004*	-0.003*	0.001*	-0.002*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	N/A	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	N/A	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, $\lambda = .3$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.050*	0.026*	0.034*	0.020*	0.032*	0.021*	0.038*	0.024*
		ET2	5.169*	4.769*	5.085*	4.553*	4.628*	4.350*	4.974*	5.014*
	CO2	ET1	0.057*	0.032*	0.032*	0.041*	0.026*	0.022*	0.033*	0.040*
		ET2	5.724*	5.316*	4.698*	4.964*	4.959*	4.392*	4.947*	5.042*
	CO3	ET1	0.082*	0.043*	0.039*	0.034*	0.022*	0.021*	0.024*	0.054*
		ET2	5.947*	4.910*	5.259*	4.815*	4.396*	4.637*	4.787*	5.080*
$\kappa_2 = 0.3$	CO1	EPD	-0.055*	-0.026*	0.001*	0.019*	0.007*	-0.003*	0.005*	0.021*
		EPP	-0.181*	-0.109*	-0.119*	-0.038*	-0.063*	-0.049*	-0.097*	-0.074*
	CO2	EPD	-0.045*	-0.026*	0.001*	-0.054*	-0.001*	0.015*	-0.047*	0.014*
		EPP	-0.213*	-0.166*	-0.073*	-0.151*	-0.095*	-0.046*	-0.129*	-0.086*
	CO3	EPD	-0.083*	0.010*	0.007*	-0.004*	0.000*	0.027*	0.022*	-0.023*
		EPP	-0.277*	-0.101*	-0.109*	-0.077*	-0.053*	-0.031*	-0.063*	-0.122*
$\kappa_2 = 0.7$	CO1	EPD	-0.011*	-0.001*	-0.001*	0.000*	-0.001*	-0.002*	0.000*	-0.001*
		EPP	-0.019*	-0.006*	-0.002*	0.000*	-0.001*	-0.002*	0.000*	-0.003*
	CO2	EPD	-0.002*	-0.003*	-0.002*	0.000*	0.000*	-0.002*	0.000*	-0.002*
		EPP	-0.024*	-0.006*	-0.006*	0.000*	-0.002*	-0.003*	0.000*	-0.002*
	CO3	EPD	-0.005*	0.000*	-0.003*	0.000*	-0.001*	0.000*	-0.001*	0.000*
		EPP	-0.020*	-0.004*	-0.003*	-0.002*	-0.001*	-0.003*	-0.001*	-0.002*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, λ = .3, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.013*	0.020*	0.015*	0.009*	0.011*	0.003*	0.005*	-0.001*
		ET2	4.208*	4.755*	4.416*	4.035*	4.111*	3.986*	4.097*	3.802*
	CO2	ET1	0.041*	0.008*	0.030*	0.009*	0.009*	0.022*	0.017*	0.001*
		ET2	4.968*	4.128*	4.571*	4.251*	4.311*	4.637*	4.483*	3.935*
	CO3	ET1	0.031*	0.021*	0.008*	0.002*	0.003*	0.012*	0.013*	0.011*
		ET2	4.822*	4.550*	4.129*	3.960*	4.004*	4.281*	4.414*	4.257*
$\kappa_2 = 0.3$	CO1	EPD	-0.127*	-0.067*	-0.045*	-0.028*	-0.025*	-0.016*	0.004*	-0.014*
		EPP	-0.159*	-0.151*	-0.095*	-0.040*	-0.047*	-0.024*	-0.007*	-0.010*
	CO2	EPD	-0.150*	-0.078*	-0.061*	-0.008*	-0.020*	-0.008*	-0.021*	-0.039*
		EPP	-0.234*	-0.107*	-0.122*	-0.053*	-0.057*	-0.061*	-0.073*	-0.043*
	CO3	EPD	-0.123*	-0.069*	-0.042*	0.001*	-0.033*	-0.026*	0.008*	-0.027*
		EPP	-0.207*	-0.130*	-0.072*	-0.013*	-0.050*	-0.065*	-0.052*	-0.063*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002*	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, λ = .3, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.006*	0.005*	0.004*	0.007*	-0.003*	0.009*	0.004*	0.018*
		ET2	4.093*	4.123*	4.097*	4.179*	3.734*	4.049*	3.999*	4.467*
	CO2	ET1	0.005*	0.009*	0.013*	0.010*	0.003*	0.005*	0.017*	0.009*
		ET2	4.010*	4.321*	4.316*	4.198*	4.015*	3.985*	4.290*	4.222*
	CO3	ET1	0.008*	0.000*	0.016*	0.017*	0.010*	-0.007*	0.014*	0.002*
		ET2	4.212*	3.803*	4.281*	4.370*	4.315*	3.661*	4.678*	3.884*
$\kappa_2 = 0.3$	CO1	EPD	-0.118*	-0.046*	-0.044*	-0.024*	-0.024*	-0.023*	-0.025*	-0.006*
		EPP	-0.138*	-0.070*	-0.060*	-0.046*	-0.018*	-0.034*	-0.031*	-0.037*
	CO2	EPD	-0.115*	-0.058*	-0.035*	-0.029*	-0.026*	-0.027*	-0.021*	-0.015*
		EPP	-0.128*	-0.098*	-0.069*	-0.056*	-0.037*	-0.035*	-0.047*	-0.045*
	CO3	EPD	-0.109*	-0.071*	-0.039*	-0.039*	-0.037*	-0.022*	-0.020*	-0.013*
		EPP	-0.136*	-0.066*	-0.066*	-0.066*	-0.067*	-0.011*	-0.073*	-0.019*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.027*	0.009*	0.004*	-0.002*	-0.007*	0.010*	0.010*	-0.009*
		ET2	4.909*	4.172*	3.920*	3.820*	3.574*	4.156*	4.184*	3.464*
	CO2	ET1	0.007*	0.010*	0.016*	-0.008*	0.009*	0.004*	0.010*	-0.006*
		ET2	4.068*	4.124*	4.641*	3.627*	4.103*	3.966*	4.064*	3.701*
	CO3	ET1	0.023*	0.002*	-0.003*	0.008*	-0.003*	-0.013*	0.011*	0.006*
		ET2	4.423*	3.932*	3.740*	4.192*	3.692*	3.589*	4.247*	3.959*
$\kappa_2 = 0.3$	CO1	EPD	-0.097*	-0.064*	-0.035*	-0.033*	-0.012*	-0.023*	-0.006*	0.003*
		EPP	-0.160*	-0.088*	-0.038*	-0.033*	-0.002*	-0.042*	-0.017*	0.020*
	CO2	EPD	-0.100*	-0.073*	-0.029*	-0.019*	-0.029*	-0.017*	0.000*	-0.002*
		EPP	-0.112*	-0.088*	-0.062*	-0.012*	-0.045*	-0.021*	-0.005*	0.003*
	CO3	EPD	-0.097*	-0.034*	-0.030*	-0.030*	-0.014*	-0.006*	-0.007*	-0.027*
		EPP	-0.139*	-0.039*	-0.027*	-0.057*	-0.007*	0.007*	-0.020*	-0.033*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, λ = .5, p = 5

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.010*	-0.003*	0.001*	0.001*	0.010*	0.000*	0.005*	-0.003*
		ET2	4.253*	3.683*	3.893*	3.865*	4.181*	3.820*	3.959*	3.757*
	CO2	ET1	-0.005*	-0.002*	-0.002*	0.004*	0.002*	-0.003*	0.011*	0.007*
		ET2	3.693*	3.813*	3.717*	4.036*	3.901*	3.752*	4.384*	3.983*
	CO3	ET1	0.008*	0.000*	0.001*	-0.004*	0.003*	0.006*	-0.003*	0.010*
		ET2	4.213*	3.841*	3.926*	3.749*	3.918*	3.982*	3.670*	4.165*
$\kappa_2 = 0.3$	CO1	EPD	-0.039*	-0.033*	-0.028*	-0.002*	-0.005*	0.001*	0.001*	0.005*
		EPP	-0.050*	-0.029*	-0.029*	-0.003*	-0.014*	0.002*	-0.002*	0.008*
	CO2	EPD	-0.078*	-0.030*	-0.011*	-0.010*	-0.002*	-0.010*	-0.013*	-0.015*
		EPP	-0.067*	-0.029*	-0.011*	-0.018*	-0.003*	-0.007*	-0.030*	-0.018*
	CO3	EPD	-0.056*	-0.025*	-0.025*	-0.017*	-0.003*	-0.008*	-0.008*	0.005*
		EPP	-0.076*	-0.025*	-0.029*	-0.015*	-0.003*	-0.011*	-0.005*	-0.006*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, λ = .5, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.009*	0.001*	0.006*	0.002*	-0.011*	0.003*	0.005*	0.001*
		ET2	4.057*	3.849*	4.125*	3.888*	3.465*	4.037*	4.035*	3.881*
	CO2	ET1	0.009*	-0.003*	0.014*	0.004*	-0.001*	0.003*	0.000*	-0.006*
		ET2	4.181*	3.704*	4.323*	4.003*	3.761*	3.986*	3.843*	3.341*
	CO3	ET1	0.004*	-0.013*	-0.008*	0.005*	-0.007*	-0.002*	-0.005*	0.001*
		ET2	3.936*	3.436*	3.566*	3.942*	3.474*	3.709*	3.705*	3.859*
$\kappa_2 = 0.3$	CO1	EPD	-0.017*	-0.020*	-0.009*	0.000*	-0.005*	-0.006*	-0.003*	-0.003*
		EPP	-0.022*	-0.020*	-0.014*	-0.001*	-0.001*	-0.011*	-0.007*	-0.003*
	CO2	EPD	-0.038*	-0.017*	-0.017*	-0.011*	-0.003*	-0.006*	-0.012*	0.000*
		EPP	-0.045*	-0.015*	-0.024*	-0.014*	-0.001*	-0.008*	-0.012*	0.006*
	CO3	EPD	-0.029*	0.001*	0.000*	-0.003*	-0.003*	-0.003*	0.010*	0.003*
		EPP	-0.034*	0.006*	0.005*	-0.004*	0.001*	-0.002*	0.013*	0.003*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, $\lambda = .7$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.009*	0.003*	-0.009*	-0.001*	-0.005*	0.006*	-0.004*	0.012*
		ET2	4.023*	4.012*	3.599*	3.783*	3.735*	4.256*	3.554*	4.116*
	CO2	ET1	0.001*	0.007*	-0.003*	-0.004*	0.006*	0.003*	-0.012*	0.006*
		ET2	3.865*	4.076*	3.607*	3.634*	4.006*	3.981*	3.518*	3.923*
	CO3	ET1	0.005*	-0.006*	0.017*	0.002*	-0.006*	0.002*	-0.007*	0.018*
		ET2	4.062*	3.693*	4.378*	3.955*	3.558*	3.945*	3.527*	4.588*
$\kappa_2 = 0.3$	CO1	EPD	-0.039*	-0.016*	-0.007*	-0.002*	-0.004*	-0.009*	-0.003*	-0.003*
		EPP	-0.043*	-0.022*	0.000*	-0.002*	-0.003*	-0.014*	0.000*	-0.007*
	CO2	EPD	-0.047*	-0.025*	-0.012*	-0.009*	-0.007*	-0.003*	-0.010*	-0.006*
		EPP	-0.047*	-0.030*	-0.009*	-0.005*	-0.009*	-0.005*	-0.004*	-0.008*
	CO3	EPD	-0.039*	-0.008*	-0.005*	-0.014*	-0.003*	-0.006*	-0.008*	-0.005*
		EPP	-0.049*	-0.006*	-0.017*	-0.020*	0.003*	-0.008*	0.001*	-0.018*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.001*	-0.002*	-0.003*	0.003*	0.014*	0.000*	0.004*	0.001*
		ET2	3.940*	3.725*	3.608*	3.913*	4.203*	3.819*	4.059*	3.848*
	CO2	ET1	0.010*	0.008*	-0.005*	0.001*	0.003*	-0.005*	-0.007*	-0.002*
		ET2	4.332*	4.436*	3.705*	3.914*	3.911*	3.764*	3.617*	3.777*
	CO3	ET1	0.002*	0.011*	-0.002*	-0.003*	0.005*	-0.003*	-0.014*	0.010*
		ET2	3.954*	4.369*	3.729*	3.766*	4.016*	3.802*	3.529*	4.231*
$\kappa_2 = 0.3$	CO1	EPD	-0.013*	-0.012*	0.001*	-0.008*	-0.007*	0.001*	0.003*	-0.006*
		EPP	-0.015*	-0.011*	0.002*	-0.008*	-0.008*	0.001*	0.002*	-0.006*
	CO2	EPD	-0.019*	-0.012*	-0.006*	0.000*	-0.005*	-0.004*	0.002*	-0.008*
		EPP	-0.028*	-0.020*	-0.003*	-0.002*	-0.007*	-0.004*	0.004*	-0.008*
	CO3	EPD	-0.021*	-0.004*	-0.003*	-0.003*	-0.001*	-0.007*	-0.001*	-0.006*
		EPP	-0.022*	-0.010*	0.000*	-0.003*	-0.001*	-0.005*	0.001*	-0.009*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 500, $\lambda = .7$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.003*	-0.005*	-0.013*	0.003*	0.005*	0.003*	0.000*	-0.012*
		ET2	3.862*	3.711*	3.454*	3.907*	3.968*	3.917*	3.837*	3.544*
	CO2	ET1	0.007*	0.003*	-0.009*	0.002*	0.014*	0.005*	0.001*	-0.001*
		ET2	4.112*	3.911*	3.582*	4.106*	4.087*	3.961*	3.891*	3.731*
	CO3	ET1	-0.004*	-0.003*	0.010*	-0.002*	-0.005*	-0.011*	0.001*	0.005*
		ET2	3.759*	3.720*	4.087*	3.775*	3.704*	3.396*	3.868*	4.012*
$\kappa_2 = 0.3$	CO1	EPD	-0.013*	-0.001*	-0.001*	0.003*	-0.003*	0.001*	0.004*	0.001*
		EPP	-0.014*	-0.001*	0.001*	0.003*	-0.005*	0.001*	0.004*	0.002*
	CO2	EPD	-0.011*	-0.006*	-0.006*	-0.004*	-0.007*	-0.002*	0.000*	-0.001*
		EPP	-0.015*	-0.006*	-0.002*	-0.005*	-0.009*	-0.002*	-0.001*	0.000*
	CO3	EPD	-0.006*	-0.004*	-0.002*	0.002*	0.000*	0.000*	0.002*	-0.005*
		EPP	-0.004*	-0.002*	-0.005*	0.003*	0.001*	0.003*	0.002*	-0.006*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .3, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.039*	0.023*	0.015*	0.017*	0.010*	0.013*	0.004*	0.008*
		ET2	5.134*	4.713*	4.285*	4.247*	4.156*	4.397*	3.935*	4.247*
	CO2	ET1	0.028*	0.020*	0.015*	0.019*	0.011*	0.020*	0.016*	0.023*
		ET2	4.981*	4.506*	4.170*	4.432*	4.286*	4.584*	4.292*	4.582*
	CO3	ET1	0.036*	0.015*	0.002*	0.028*	0.009*	0.018*	0.007*	0.014*
		ET2	4.882*	4.313*	3.857*	4.589*	4.261*	4.547*	4.071*	4.303*
$\kappa_2 = 0.3$	CO1	EPD	-0.125*	-0.057*	-0.035*	-0.043*	-0.015*	-0.004*	-0.007*	-0.005*
		EPP	-0.224*	-0.112*	-0.061*	-0.066*	-0.034*	-0.036*	-0.010*	-0.026*
	CO2	EPD	-0.152*	-0.066*	-0.046*	-0.040*	-0.041*	-0.038*	-0.012*	-0.019*
		EPP	-0.248*	-0.114*	-0.066*	-0.063*	-0.059*	-0.079*	-0.027*	-0.062*
	CO3	EPD	-0.131*	-0.047*	-0.054*	-0.006*	-0.023*	-0.023*	-0.023*	-0.015*
		EPP	-0.203*	-0.089*	-0.054*	-0.051*	-0.044*	-0.066*	-0.035*	-0.038*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .3, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.024*	0.013*	0.005*	0.005*	0.015*	0.002*	0.019*	0.008*
		ET2	4.272*	4.266*	3.959*	4.052*	4.487*	3.878*	4.505*	4.137*
	CO2	ET1	0.004*	0.006*	-0.006*	-0.004*	0.009*	0.006*	0.010*	0.006*
		ET2	3.935*	3.972*	3.722*	3.701*	4.153*	4.119*	4.207*	4.194*
	CO3	ET1	0.009*	-0.003*	0.004*	0.012*	0.006*	0.007*	0.002*	-0.002*
		ET2	4.178*	3.729*	3.953*	4.242*	4.043*	4.136*	3.962*	3.763*
$\kappa_2 = 0.3$	CO1	EPD	-0.088*	-0.041*	-0.019*	-0.001*	-0.010*	-0.008*	-0.012*	-0.006*
		EPP	-0.109*	-0.056*	-0.023*	-0.008*	-0.024*	-0.010*	-0.021*	-0.014*
	CO2	EPD	-0.113*	-0.037*	-0.018*	-0.007*	-0.006*	-0.007*	-0.006*	-0.014*
		EPP	-0.116*	-0.040*	-0.016*	-0.003*	-0.012*	-0.013*	-0.012*	-0.024*
	CO3	EPD	-0.058*	-0.030*	-0.020*	-0.015*	-0.002*	-0.001*	-0.011*	0.006*
		EPP	-0.071*	-0.030*	-0.023*	-0.026*	-0.009*	-0.011*	-0.013*	0.007*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .3, p = 7

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.015*	0.012*	0.007*	0.003*	-0.005*	0.005*	0.014*	0.005*
		ET2	4.209*	4.216*	3.979*	3.855*	3.706*	3.976*	4.333*	3.951*
	CO2	ET1	0.004*	-0.001*	-0.007*	0.007*	0.012*	0.007*	0.006*	-0.001*
		ET2	4.021*	3.830*	3.641*	4.151*	4.330*	4.233*	3.992*	3.788*
	CO3	ET1	0.004*	0.013*	0.008*	0.004*	0.006*	0.004*	0.003*	-0.004*
		ET2	3.959*	4.262*	4.110*	3.984*	4.009*	3.978*	3.956*	3.646*
$\kappa_2 = 0.3$	CO1	EPD	-0.032*	-0.019*	-0.007*	-0.002*	-0.002*	0.002*	-0.002*	-0.002*
		EPP	-0.048*	-0.027*	-0.008*	-0.002*	-0.002*	0.002*	-0.004*	-0.002*
	CO2	EPD	-0.053*	-0.013*	-0.013*	-0.006*	-0.010*	-0.001*	-0.004*	-0.002*
		EPP	-0.058*	-0.013*	-0.009*	-0.006*	-0.014*	-0.005*	-0.005*	-0.002*
	CO3	EPD	-0.045*	-0.009*	-0.011*	-0.006*	0.000*	0.002*	-0.005*	-0.002*
		EPP	-0.049*	-0.017*	-0.013*	-0.006*	-0.002*	0.001*	-0.005*	-0.001*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	-0.001*	-0.005*	0.011*	0.015*	0.001*	0.009*	0.006*	0.004*
		ET2	3.744*	3.645*	4.199*	4.340*	3.866*	4.016*	3.990*	3.978*
	CO2	ET1	-0.011*	-0.003*	-0.006*	-0.004*	-0.010*	0.006*	-0.015*	0.004*
		ET2	3.398*	3.750*	3.701*	3.707*	3.629*	4.053*	3.301*	4.030*
	CO3	ET1	0.009*	0.004*	0.003*	0.010*	0.000*	-0.001*	-0.008*	0.009*
		ET2	4.080*	3.984*	3.894*	4.214*	3.849*	3.824*	3.534*	4.176*
$\kappa_2 = 0.3$	CO1	EPD	-0.010*	-0.010*	-0.002*	-0.006*	0.001*	-0.001*	0.001*	-0.004*
		EPP	-0.009*	-0.010*	-0.003*	-0.009*	0.000*	-0.001*	0.001*	-0.004*
	CO2	EPD	-0.025*	-0.006*	-0.003*	-0.001*	0.000*	-0.002*	0.001*	-0.002*
		EPP	-0.019*	-0.005*	-0.003*	-0.001*	0.001*	-0.002*	0.002*	-0.003*
	CO3	EPD	-0.014*	-0.006*	-0.005*	-0.002*	-0.002*	-0.001*	0.001*	-0.002*
		EPP	-0.014*	-0.006*	-0.006*	-0.005*	-0.002*	0.000*	0.002*	-0.002*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .5, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.005*	-0.002*	0.002*	-0.006*	0.014*	-0.007*	0.000*	0.000*
		ET2	4.096*	3.774*	3.937*	3.655*	4.321*	3.675*	3.820*	3.855*
	CO2	ET1	0.001*	0.008*	0.002*	0.001*	-0.010*	0.003*	-0.007*	0.002*
		ET2	3.905*	4.156*	3.913*	3.922*	3.560*	3.892*	3.660*	3.870*
	CO3	ET1	0.006*	0.002*	-0.012*	0.002*	-0.012*	0.008*	0.011*	0.004*
		ET2	4.132*	3.909*	3.355*	3.898*	3.582*	4.224*	4.180*	3.984*
$\kappa_2 = 0.3$	CO1	EPD	-0.003*	-0.004*	-0.001*	0.000*	-0.001*	-0.001*	0.000*	-0.001*
		EPP	-0.003*	-0.004*	-0.001*	0.000*	-0.001*	-0.001*	0.000*	-0.001*
	CO2	EPD	-0.006*	-0.003*	-0.001*	-0.003*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.006*	-0.003*	-0.001*	-0.003*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.003*	-0.001*	-0.001*	-0.003*	-0.003*	-0.001*	-0.002*	-0.001*
		EPP	-0.003*	-0.001*	-0.001*	-0.003*	-0.003*	-0.001*	-0.002*	-0.001*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, $\lambda = .5$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	-0.010*	0.005*	0.004*	-0.003*	-0.001*	0.000*	0.011*	0.004*
		ET2	3.479*	3.941*	3.988*	3.696*	3.724*	3.896*	4.319*	3.909*
	CO2	ET1	-0.001*	0.002*	-0.012*	0.012*	0.010*	0.001*	0.002*	-0.001*
		ET2	3.803*	3.926*	3.348*	4.125*	4.119*	3.971*	3.925*	3.688*
	CO3	ET1	0.001*	-0.005*	-0.001*	0.012*	-0.003*	0.002*	0.003*	-0.006*
		ET2	3.908*	3.732*	3.808*	4.188*	3.727*	3.884*	3.952*	3.672*
$\kappa_2 = 0.3$	CO1	EPD	-0.002*	0.000*	-0.001*	0.000*	0.000*	-0.001*	0.000*	0.000*
		EPP	-0.002*	0.000*	-0.001*	0.000*	0.000*	-0.001*	0.000*	0.000*
	CO2	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .7, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.003*	0.010*	0.001*	-0.005*	-0.002*	0.005*	-0.010*	-0.001*
		ET2	3.921*	4.086*	3.946*	3.710*	3.785*	3.956*	3.326*	3.822*
	CO2	ET1	-0.006*	0.012*	-0.006*	-0.011*	0.007*	-0.011*	0.005*	-0.001*
		ET2	3.714*	4.247*	3.659*	3.428*	4.038*	3.448*	4.036*	3.736*
	CO3	ET1	0.008*	0.001*	0.011*	-0.003*	0.003*	0.008*	-0.006*	-0.006*
		ET2	4.088*	3.889*	4.113*	3.741*	4.008*	4.291*	3.470*	3.634*
$\kappa_2 = 0.3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	-0.001*	0.000*	0.000*
	CO3	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.003*	-0.008*	-0.001*	0.006*	0.013*	-0.013*	0.002*	0.000*
		ET2	4.031*	3.523*	3.811*	4.044*	4.221*	3.394*	3.966*	3.814*
	CO2	ET1	0.002*	-0.005*	0.003*	-0.008*	0.002*	0.003*	0.002*	0.000*
		ET2	3.910*	3.703*	3.922*	3.406*	3.901*	3.994*	3.974*	3.845*
	CO3	ET1	-0.003*	0.004*	0.000*	0.000*	-0.010*	-0.002*	0.006*	-0.002*
		ET2	3.762*	4.014*	3.811*	3.885*	3.382*	3.793*	4.098*	3.746*
$\kappa_2 = 0.3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

IM Option Results when n = 1000, λ = .7, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	-0.014*	0.002*	-0.004*	0.004*	-0.003*	0.002*	-0.003*	0.012*
		ET2	3.318*	3.876*	3.716*	3.989*	3.687*	3.850*	3.676*	4.330*
	CO2	ET1	-0.004*	-0.002*	0.003*	-0.004*	-0.014*	0.005*	0.005*	-0.001*
		ET2	3.663*	3.769*	3.926*	3.664*	3.586*	3.950*	4.039*	3.802*
	CO3	ET1	-0.010*	-0.003*	0.000*	0.009*	0.016*	-0.001*	0.004*	0.002*
		ET2	3.549*	3.669*	3.891*	4.181*	4.065*	3.798*	3.931*	3.867*
$\kappa_2 = 0.3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, λ = .3, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.062	0.107*	0.059*	-0.013	0.104	0.150	-0.050	N/A
		ET2	6.055	7.531*	5.674*	3.632	9.407	4.211	0.488	N/A
	CO2	ET1	0.203	0.159*	0.114*	0.099*	0.100*	0.102	0.071	0.050
		ET2	13.715	7.507*	7.140*	6.695*	5.975*	6.476	7.273	5.165
	CO3	ET1	0.118	0.130*	0.096*	0.102*	0.116*	0.116*	0.091*	0.110*
		ET2	9.535	7.761*	6.283*	6.712*	7.251*	7.188*	6.335*	6.432*
$\kappa_2 = 0.3$	CO1	EPD	0.090	0.122*	0.092*	0.029	0.140	N/A	N/A	N/A
		EPP	-0.019	-0.029*	-0.008*	0.045	-0.110	N/A	N/A	N/A
	CO2	EPD	0.217	0.155*	0.113*	0.120*	0.127*	0.057*	0.142	0.103
		EPP	-0.010	-0.016*	-0.031*	-0.013*	-0.003*	-0.061*	-0.030	0.029
	CO3	EPD	0.122	0.148*	0.131*	0.130*	0.145*	0.143*	0.138*	0.100*
		EPP	-0.022	-0.028*	0.010*	-0.014*	-0.024*	-0.024*	-0.008*	-0.036*
$\kappa_2 = 0.7$	CO1	EPD	-0.076	0.072*	0.062*	-0.074	-0.242	-0.384	N/A	N/A
		EPP	-0.173	-0.152*	-0.090*	-0.040	-0.384	-0.384	N/A	N/A
	CO2	EPD	-0.035	0.105*	0.128*	0.121*	0.099*	0.126*	0.057	0.072
		EPP	-0.257	-0.116*	-0.118*	-0.106*	-0.085*	-0.095*	-0.181	-0.022
	CO3	EPD	-0.018	0.139*	0.115*	0.128*	0.145*	0.124*	0.155*	0.138*
		EPP	-0.268	-0.134*	-0.075*	-0.103*	-0.111*	-0.138*	-0.047*	-0.081*
$\kappa_2 = 1.5$	CO1	EPD	-0.241	-0.043*	-0.045*	-0.010	0.054	N/A	N/A	N/A
		EPP	-0.326	-0.196*	-0.128*	-0.010	-0.946	N/A	N/A	N/A
	CO2	EPD	-0.079	-0.036*	-0.014*	-0.007*	-0.008*	-0.005*	-0.005*	0.002
		EPP	-0.389	-0.165*	-0.131*	-0.103*	-0.067*	-0.110*	-0.148*	-0.045
	CO3	EPD	-0.275	-0.029*	-0.010*	0.010*	0.006*	0.001*	0.005*	0.004*
		EPP	-0.527	-0.173*	-0.086*	-0.086*	-0.122*	-0.124*	-0.078*	-0.084*
$\kappa_2 = 3$	CO1	EPD	-0.114	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.127	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.081	-0.003*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.168	-0.005*	-0.001*	0.000*	0.000*	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, $\lambda = .3$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.140	0.093	0.034*	-0.032	-0.050	N/A	N/A	N/A
		ET2	6.913	6.185	4.787*	3.209	0.140	N/A	N/A	N/A
	CO2	ET1	0.307	0.100*	0.080*	0.073*	0.085*	0.089	0.112	0.200
		ET2	25.141	7.815*	6.860*	6.472*	6.472*	6.465	7.345	9.663
	CO3	ET1	0.211	0.102*	0.092*	0.109*	0.104*	0.116*	0.126*	0.110*
		ET2	8.289	6.696*	7.208*	6.670*	7.356*	7.058*	7.328*	7.132*
$\kappa_2 = 0.3$	CO1	EPD	0.040	0.044*	0.007*	-0.011	0.362	N/A	N/A	N/A
		EPP	-0.071	-0.048*	-0.035*	0.005	0.862	N/A	N/A	N/A
	CO2	EPD	0.272	0.087*	0.093*	0.071*	0.137*	0.061	0.141	0.112
		EPP	-0.078	-0.054*	-0.042*	-0.033*	-0.011*	-0.054	-0.025	-0.107
	CO3	EPD	0.133	0.086*	0.111*	0.132*	0.128*	0.157*	0.144*	0.160*
		EPP	-0.111	-0.037*	-0.029*	-0.026*	-0.043*	-0.024*	-0.031*	-0.016*
$\kappa_2 = 0.7$	CO1	EPD	-0.197	-0.019*	-0.060*	-0.162	-0.517	N/A	N/A	N/A
		EPP	-0.286	-0.181*	-0.150*	-0.095	0.483	N/A	N/A	N/A
	CO2	EPD	0.092	-0.004*	0.033*	0.057*	0.038*	0.030*	0.057	0.091
		EPP	-0.424	-0.241*	-0.170*	-0.140*	-0.152*	-0.164*	-0.210	-0.300
	CO3	EPD	-0.184	0.050*	0.085*	0.089*	0.105*	0.131*	0.139*	0.127*
		EPP	-0.378	-0.142*	-0.164*	-0.113*	-0.149*	-0.113*	-0.120*	-0.138*
$\kappa_2 = 1.5$	CO1	EPD	-0.198	-0.038*	-0.049	0.010	N/A	N/A	N/A	N/A
		EPP	-0.276	-0.082*	-0.078	0.010	N/A	N/A	N/A	N/A
	CO2	EPD	-0.009	-0.019*	-0.011*	-0.007*	0.001*	-0.005*	-0.011	-0.027
		EPP	-0.452	-0.098*	-0.049*	-0.038*	-0.037*	-0.042*	-0.052	-0.151
	CO3	EPD	-0.229	-0.018*	-0.006*	-0.005*	0.000*	0.000*	-0.002*	-0.002*
		EPP	-0.431	-0.061*	-0.048*	-0.040*	-0.035*	-0.042*	-0.042*	-0.050*
$\kappa_2 = 3$	CO1	EPD	-0.049	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.118	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.057	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.031	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.108	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, $\lambda = .3$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.111	0.083	0.015*	0.068	N/A	N/A	N/A	N/A
		ET2	7.763	8.766	4.357*	6.103	N/A	N/A	N/A	N/A
	CO2	ET1	0.392	0.087*	0.062*	0.065*	0.047*	0.065	0.088	0.283
		ET2	21.986	6.872*	5.872*	6.097*	6.188*	5.033	4.904	5.102
	CO3	ET1	0.009	0.076*	0.077*	0.086*	0.095*	0.104*	0.108*	0.129*
		ET2	5.381	6.171*	6.349*	6.900*	7.143*	6.992*	6.926*	7.981*
$\kappa_2 = 0.3$	CO1	EPD	0.023	0.035	-0.033*	0.119	N/A	N/A	N/A	N/A
		EPP	-0.068	-0.131	-0.051*	-0.104	N/A	N/A	N/A	N/A
	CO2	EPD	0.312	0.057*	0.055*	0.045*	0.031*	0.111	0.237	0.008
		EPP	-0.066	-0.065*	-0.037*	-0.052*	-0.082*	0.024	0.105	-0.159
	CO3	EPD	-0.048	0.053*	0.090*	0.107*	0.117*	0.132*	0.132*	0.127*
		EPP	-0.048	-0.040*	-0.033*	-0.049*	-0.043*	-0.038*	-0.027*	-0.057*
$\kappa_2 = 0.7$	CO1	EPD	-0.118	-0.065*	-0.137*	-0.333	N/A	N/A	N/A	N/A
		EPP	-0.349	-0.351*	-0.199*	-0.605	N/A	N/A	N/A	N/A
	CO2	EPD	0.010	-0.051*	-0.015*	-0.012*	0.001*	0.005	-0.071	-0.026
		EPP	-0.452	-0.250*	-0.158*	-0.187*	-0.180*	-0.091	-0.149	-0.026
	CO3	EPD	-0.094	-0.017*	0.027*	0.050*	0.061*	0.104*	0.099*	0.118*
		EPP	-0.187	-0.193*	-0.151*	-0.170*	-0.170*	-0.117*	-0.144*	-0.185*
$\kappa_2 = 1.5$	CO1	EPD	-0.306	-0.021*	-0.029	N/A	N/A	N/A	N/A	N/A
		EPP	-0.409	-0.101*	-0.050	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.002	-0.009*	-0.005*	0.000*	-0.003*	-0.002*	-0.002	0.002
		EPP	-0.403	-0.038*	-0.015*	-0.014*	-0.015*	-0.005*	-0.007	0.002
	CO3	EPD	-0.189	-0.017*	-0.007*	-0.003*	-0.002*	-0.001*	0.001*	0.000*
		EPP	-0.248	-0.038*	-0.022*	-0.021*	-0.018*	-0.019*	-0.012*	-0.018*
$\kappa_2 = 3$	CO1	EPD	-0.093	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.130	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO3	EPD	-0.057	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.057	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, λ = .5, p = 3

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.101	0.076*	0.020*	-0.013	0.003	-0.050	N/A	N/A
		ET2	8.098	6.011*	4.450*	3.442	4.014	2.707	N/A	N/A
	CO2	ET1	0.240*	0.088*	0.050*	0.041*	0.047*	0.035*	0.025	0.020
		ET2	15.550*	6.787*	5.541*	5.117*	5.246*	5.029*	4.616	4.307
	CO3	ET1	0.093	0.057*	0.047*	0.061*	0.042*	0.046*	0.044*	0.052*
		ET2	8.168	5.685*	5.238*	5.582*	5.221*	5.137*	5.124*	5.182*
$\kappa_2 = 0.3$	CO1	EPD	0.072	0.055*	-0.001*	-0.066	-0.038	0.316	N/A	N/A
		EPP	-0.074	-0.045*	-0.028*	-0.031	-0.038	0.316	N/A	N/A
	CO2	EPD	0.245*	0.087*	0.073*	0.043*	0.049*	0.015*	0.011*	-0.008
		EPP	-0.089*	-0.057*	-0.019*	-0.031*	-0.037*	-0.048*	-0.033*	-0.027
	CO3	EPD	0.027	0.065*	0.075*	0.076*	0.073*	0.064*	0.067*	0.064*
		EPP	-0.105	-0.037*	-0.011*	-0.027*	-0.016*	-0.013*	-0.009*	-0.023*
$\kappa_2 = 0.7$	CO1	EPD	-0.220	0.009*	-0.054*	-0.151	0.014	-0.692	N/A	N/A
		EPP	-0.395	-0.148*	-0.103*	-0.103	-0.045	-0.692	N/A	N/A
	CO2	EPD	0.047	0.003*	0.029*	0.025*	-0.002*	-0.011*	-0.031*	-0.044
		EPP	-0.418	-0.197*	-0.098*	-0.081*	-0.111*	-0.110*	-0.113*	-0.081
	CO3	EPD	-0.199	0.010*	0.018*	0.043*	0.038*	0.036*	0.030*	0.017*
		EPP	-0.403	-0.131*	-0.090*	-0.105*	-0.071*	-0.066*	-0.068*	-0.101*
$\kappa_2 = 1.5$	CO1	EPD	-0.194	-0.002*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	-0.295	-0.008*	0.000	0.000	0.000	N/A	N/A	N/A
	CO2	EPD	-0.005	0.000*	-0.001*	0.000*	0.000*	0.000*	-0.001*	0.000*
		EPP	-0.124	-0.006*	-0.003*	-0.001*	0.000*	-0.001*	-0.003*	-0.002*
	CO3	EPD	-0.189	-0.004*	0.000*	0.000*	-0.001*	-0.001*	-0.001*	0.000
		EPP	-0.309	-0.008*	-0.003*	-0.002*	-0.005*	-0.003*	-0.002*	-0.006
$\kappa_2 = 3$	CO1	EPD	-0.070*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.121*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.018	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO3	EPD	-0.070*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A
		EPP	-0.132*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, $\lambda = .5$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.045*	0.064	-0.003*	-0.041	-0.050	N/A	N/A	N/A
		ET2	5.713*	5.603	3.708*	2.021	1.157	N/A	N/A	N/A
	CO2	ET1	0.371*	0.041*	0.034*	0.020*	0.008*	0.008*	-0.001	-0.023
		ET2	21.328*	5.342*	4.817*	4.621*	4.230*	4.036*	3.920	1.839
	CO3	ET1	0.044*	0.037*	0.033*	0.028*	0.030*	0.021*	0.019*	0.019*
		ET2	5.939*	5.163*	4.891*	4.776*	4.853*	4.641*	4.554*	4.420*
$\kappa_2 = 0.3$	CO1	EPD	-0.001*	0.038*	-0.025*	-0.103	-0.219	N/A	N/A	N/A
		EPP	-0.108*	-0.060*	-0.014*	0.150	0.281	N/A	N/A	N/A
	CO2	EPD	0.316*	0.051*	0.030*	0.025*	-0.004*	-0.003*	-0.011	-0.042
		EPP	-0.129*	-0.034*	-0.038*	-0.028*	-0.032*	-0.020*	-0.014	0.264
	CO3	EPD	-0.010*	0.046*	0.033*	0.039*	0.036*	0.040*	0.036*	0.028*
		EPP	-0.104*	-0.039*	-0.037*	-0.028*	-0.032*	-0.011*	-0.022*	-0.018*
$\kappa_2 = 0.7$	CO1	EPD	-0.292*	-0.027*	-0.125*	-0.241	0.214	N/A	N/A	N/A
		EPP	-0.385*	-0.146*	-0.100*	-0.029	0.214	N/A	N/A	N/A
	CO2	EPD	0.047	-0.016*	-0.014*	-0.009*	-0.029*	-0.042*	-0.067*	-0.109
		EPP	-0.563	-0.122*	-0.083*	-0.064*	-0.064*	-0.057*	-0.073*	0.072
	CO3	EPD	-0.267*	-0.003*	0.012*	0.020*	0.012*	-0.011*	-0.006*	-0.003*
		EPP	-0.378*	-0.090*	-0.065*	-0.047*	-0.059*	-0.057*	-0.058*	-0.048*
$\kappa_2 = 1.5$	CO1	EPD	-0.229*	-0.001*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.274*	-0.002*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.176*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.249*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.302*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.080*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.111*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000	0.000	0.000	N/A
		EPP	-0.022	0.000*	0.000*	0.000*	0.000	0.000	0.000	N/A
	CO3	EPD	-0.075*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.111*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, λ = .5, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.047*	0.034	-0.014*	-0.007	N/A	N/A	N/A	N/A
		ET2	4.933*	5.570	3.336*	4.386	N/A	N/A	N/A	N/A
	CO2	ET1	0.403*	0.038*	0.032*	0.009*	0.013*	-0.020	-0.029	-0.050
		ET2	20.773*	5.295*	4.783*	3.993*	4.367*	3.193	3.128	1.116
	CO3	ET1	0.048*	0.023*	0.010*	0.012*	0.010*	0.011*	0.013*	0.016*
		ET2	5.414*	4.577*	4.203*	4.212*	4.163*	4.274*	4.290*	4.417*
$\kappa_2 = 0.3$	CO1	EPD	-0.041*	-0.008*	-0.071*	-0.196	-0.239	N/A	N/A	N/A
		EPP	-0.092*	-0.098*	-0.033*	-0.196	-0.239	N/A	N/A	N/A
	CO2	EPD	0.326*	0.026*	0.002*	-0.005*	-0.029*	-0.053	-0.064	-0.134
		EPP	-0.144*	-0.064*	-0.061*	-0.018*	-0.075*	0.003	0.008	0.340
	CO3	EPD	-0.012*	0.018*	0.015*	0.016*	0.026*	0.008*	-0.009*	-0.018*
		EPP	-0.098*	-0.030*	-0.011*	-0.009*	-0.003*	-0.026*	-0.044*	-0.058*
$\kappa_2 = 0.7$	CO1	EPD	-0.323*	-0.044*	-0.138	0.027	N/A	N/A	N/A	N/A
		EPP	-0.388*	-0.180*	-0.069	0.027	N/A	N/A	N/A	N/A
	CO2	EPD	0.010	-0.038*	-0.006*	-0.033*	-0.066*	-0.103*	-0.170	-0.274
		EPP	-0.587	-0.135*	-0.075*	-0.044*	-0.115*	-0.033*	-0.089	0.045
	CO3	EPD	-0.296*	-0.021*	-0.018*	-0.013*	-0.006*	-0.010*	-0.027*	-0.029*
		EPP	-0.388*	-0.062*	-0.040*	-0.041*	-0.031*	-0.043*	-0.060*	-0.066*
$\kappa_2 = 1.5$	CO1	EPD	-0.226*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.260*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.103*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.232*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.286*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.081*	N/A	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.097*	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
		EPP	-0.009*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
	CO3	EPD	-0.074*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.101*	0.000	0.000	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, λ = .7, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.036*	0.031*	-0.004*	-0.014	0.018	-0.050	N/A	N/A
		ET2	5.258*	4.756*	3.629*	3.262	5.482	2.188	N/A	N/A
	CO2	ET1	0.261*	0.051*	0.032*	0.006*	0.003*	-0.002*	-0.017*	0.006
		ET2	14.206*	5.429*	4.813*	4.022*	3.922*	3.712*	3.446*	3.990
	CO3	ET1	0.056*	0.024*	0.010*	0.017*	0.003*	0.020*	0.009*	0.014*
		ET2	5.693*	4.642*	4.122*	4.291*	3.962*	4.531*	4.080*	4.278*
$\kappa_2 = 0.3$	CO1	EPD	-0.021*	0.009*	-0.048*	-0.069	-0.071	-0.251	N/A	N/A
		EPP	-0.097*	-0.049*	-0.029*	-0.020	-0.148	-0.251	N/A	N/A
	CO2	EPD	0.179*	0.039*	0.035*	0.015*	-0.020*	-0.045*	-0.034*	-0.064
		EPP	-0.177*	-0.059*	-0.035*	0.003*	-0.026*	-0.038*	0.001*	-0.077
	CO3	EPD	-0.008*	0.026*	0.029*	0.030*	0.027*	0.026*	0.003*	0.020*
		EPP	-0.109*	-0.028*	0.011*	-0.007*	0.022*	-0.021*	-0.016*	-0.015*
$\kappa_2 = 0.7$	CO1	EPD	-0.312*	-0.037*	-0.106*	-0.179	-0.280	0.149	N/A	N/A
		EPP	-0.386*	-0.096*	-0.092*	-0.123	-0.708	0.149	N/A	N/A
	CO2	EPD	-0.051*	-0.022*	-0.012*	-0.001*	-0.029*	-0.047*	-0.063*	-0.093*
		EPP	-0.562*	-0.121*	-0.071*	-0.011*	-0.034*	-0.039*	-0.027*	-0.109*
	CO3	EPD	-0.281*	-0.020*	0.001*	0.010*	0.004*	-0.011*	-0.016*	-0.038*
		EPP	-0.391*	-0.061*	-0.013*	-0.012*	-0.003*	-0.057*	-0.032*	-0.060*
$\kappa_2 = 1.5$	CO1	EPD	-0.220*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.264*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	-0.005*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	-0.094*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
	CO3	EPD	-0.244*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.306*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.027	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.031	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	-0.001*	0.000*	0.000	0.000	0.000	N/A	0.000	N/A
		EPP	-0.017*	0.000*	0.000	0.000	0.000	N/A	0.000	N/A
	CO3	EPD	-0.027	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.040	0.000	0.000	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.045*	0.013*	-0.013*	-0.012	-0.050	N/A	N/A	N/A
		ET2	5.186*	4.287*	3.276*	3.230	1.501	N/A	N/A	N/A
	CO2	ET1	0.312*	0.022*	0.019*	0.008*	-0.001*	-0.011*	-0.009	-0.050
		ET2	16.290*	4.723*	4.401*	4.223*	3.792*	3.423*	3.731	2.930
	CO3	ET1	0.047*	0.011*	0.017*	0.011*	0.011*	0.006*	0.007*	-0.002*
		ET2	5.593*	4.139*	4.389*	4.153*	4.292*	4.071*	4.039*	3.816*
$\kappa_2 = 0.3$	CO1	EPD	-0.038*	0.000*	-0.087*	-0.141	N/A	N/A	N/A	N/A
		EPP	-0.110*	-0.027*	-0.040*	-0.074	N/A	N/A	N/A	N/A
	CO2	EPD	0.161*	0.010*	-0.002*	-0.007*	-0.030*	-0.043*	-0.099	-0.061
		EPP	-0.189*	-0.051*	-0.043*	-0.035*	-0.026*	-0.008*	-0.094	0.013
	CO3	EPD	-0.019*	0.015*	0.035*	0.008*	0.011*	0.001*	0.003*	-0.041*
		EPP	-0.114*	-0.009*	-0.012*	-0.013*	-0.028*	-0.017*	-0.017*	-0.040*
$\kappa_2 = 0.7$	CO1	EPD	-0.286*	-0.031*	-0.143	-0.128	N/A	N/A	N/A	N/A
		EPP	-0.370*	-0.051*	-0.086	-0.093	N/A	N/A	N/A	N/A
	CO2	EPD	-0.040*	-0.028*	-0.015*	-0.021*	-0.041*	-0.053*	-0.076*	-0.167
		EPP	-0.579*	-0.072*	-0.045*	-0.044*	-0.038*	-0.028*	-0.073*	-0.082
	CO3	EPD	-0.293*	-0.021*	-0.014*	-0.015*	-0.011*	-0.026*	-0.038*	-0.066*
		EPP	-0.382*	-0.036*	-0.042*	-0.027*	-0.031*	-0.038*	-0.053*	-0.064*
$\kappa_2 = 1.5$	CO1	EPD	-0.229*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.269*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.080*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.237*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.297*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.103	N/A	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.115	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	-0.019*	0.000	0.000	0.000	0.000	N/A	N/A	N/A
	CO3	EPD	-0.040	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.070	0.000	N/A	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 50, λ = .7, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.031*	0.008*	-0.021*	-0.050	N/A	N/A	N/A	N/A
		ET2	4.817*	4.037*	3.102*	2.106	N/A	N/A	N/A	N/A
	CO2	ET1	0.311*	0.027*	0.007*	0.009*	-0.007*	-0.018	-0.024	-0.050
		ET2	14.992*	4.786*	4.052*	4.082*	3.421*	3.304	2.562	0.888
	CO3	ET1	0.037*	0.016*	0.007*	0.006*	0.006*	-0.001*	-0.004*	-0.004*
		ET2	4.849*	4.327*	4.055*	4.030*	4.098*	3.816*	3.705*	3.743*
$\kappa_2 = 0.3$	CO1	EPD	-0.032*	-0.015*	-0.110*	-0.170	N/A	N/A	N/A	N/A
		EPP	-0.090*	-0.034*	-0.067*	-0.093	N/A	N/A	N/A	N/A
	CO2	EPD	0.173*	0.005*	-0.029*	-0.026*	-0.045*	-0.093*	-0.138	-0.164
		EPP	-0.190*	-0.059*	-0.044*	-0.044*	-0.008*	-0.046*	0.006	0.228
	CO3	EPD	-0.068*	0.010*	-0.003*	0.018*	0.004*	-0.010*	-0.006*	-0.052*
		EPP	-0.115*	-0.029*	-0.022*	0.000*	-0.019*	-0.006*	0.005*	-0.042*
$\kappa_2 = 0.7$	CO1	EPD	-0.296*	-0.047*	-0.175	-0.235	N/A	N/A	N/A	N/A
		EPP	-0.349*	-0.059*	-0.083	-0.124	N/A	N/A	N/A	N/A
	CO2	EPD	-0.023*	-0.009*	-0.025*	-0.022*	-0.041*	-0.079*	-0.106	-0.084
		EPP	-0.548*	-0.053*	-0.033*	-0.032*	-0.015*	-0.041*	-0.004	0.073
	CO3	EPD	-0.285*	-0.010*	-0.003*	-0.016*	-0.019*	-0.022*	-0.042*	-0.070*
		EPP	-0.339*	-0.033*	-0.013*	-0.024*	-0.033*	-0.021*	-0.029*	-0.060*
$\kappa_2 = 1.5$	CO1	EPD	-0.253*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.291*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.047*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO3	EPD	-0.256*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.288*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.052	N/A	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.052	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.002*	0.000	0.000	0.000	N/A	N/A	N/A	N/A
	CO3	EPD	-0.018	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.036	0.000	N/A	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, λ = .3, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.069	0.137*	0.097*	0.074*	0.100	0.139	-0.013	0.236
		ET2	5.010	7.543*	6.486*	5.547*	6.346	7.720	3.826	18.369
	CO2	ET1	0.203	0.155*	0.103*	0.121*	0.098*	0.113*	0.109*	0.128
		ET2	25.274	8.454*	6.720*	6.835*	6.797*	6.808*	6.330*	7.822
	CO3	ET1	0.171	0.122*	0.121*	0.132*	0.106*	0.113*	0.112*	0.108*
		ET2	8.893	7.003*	6.761*	7.189*	6.704*	6.756*	6.586*	6.642*
$\kappa_2 = 0.3$	CO1	EPD	0.077	0.150*	0.122*	0.093*	0.101	0.160	0.187	-0.006
		EPP	0.025	-0.032*	-0.029*	-0.007*	-0.040	-0.046	0.187	-0.173
	CO2	EPD	0.176	0.133*	0.136*	0.159*	0.172*	0.171*	0.146*	0.178*
		EPP	-0.119	-0.057*	-0.025*	-0.028*	-0.032*	-0.028*	-0.017*	-0.064*
	CO3	EPD	0.086	0.151*	0.126*	0.145*	0.162*	0.156*	0.144*	0.176*
		EPP	-0.089	-0.021*	-0.036*	-0.061*	-0.037*	-0.024*	-0.037*	-0.021*
$\kappa_2 = 0.7$	CO1	EPD	-0.132	0.054*	0.054*	0.040*	-0.015	0.087	-0.068	-0.656
		EPP	-0.200	-0.195*	-0.148*	-0.101*	-0.199	-0.299	-0.068	-0.656
	CO2	EPD	-0.137	0.041*	0.074*	0.060*	0.078*	0.083*	0.102*	0.103*
		EPP	-0.586	-0.257*	-0.139*	-0.170*	-0.145*	-0.136*	-0.093*	-0.223*
	CO3	EPD	-0.133	0.060*	0.086*	0.087*	0.091*	0.123*	0.096*	0.131*
		EPP	-0.381	-0.165*	-0.123*	-0.164*	-0.124*	-0.108*	-0.117*	-0.089*
$\kappa_2 = 1.5$	CO1	EPD	-0.160	0.000*	-0.003*	-0.003	0.001	0.001	0.001	0.001
		EPP	-0.190	-0.017*	-0.008*	-0.005	-0.007	0.001	0.001	0.001
	CO2	EPD	-0.006	-0.001*	-0.003*	0.000*	0.000*	0.001*	0.000*	0.000*
		EPP	-0.337	-0.025*	-0.011*	-0.007*	-0.004*	-0.005*	-0.005*	-0.013*
	CO3	EPD	-0.136	-0.002*	0.000*	-0.002*	0.000*	0.001*	0.001*	0.000*
		EPP	-0.212	-0.019*	-0.008*	-0.006*	-0.002*	-0.003*	-0.004*	-0.005*
$\kappa_2 = 3$	CO1	EPD	-0.033	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	-0.033	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.034	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.078	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, λ = .3, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.133	0.087*	0.060*	0.041*	0.022	0.129	-0.050	N/A
		ET2	8.863	7.142*	5.515*	4.989*	5.472	7.672	0.179	N/A
	CO2	ET1	0.419	0.099*	0.101*	0.099*	0.108*	0.128*	0.159*	0.106
		ET2	40.461	7.606*	6.757*	7.147*	6.899*	7.291*	8.031*	7.119
	CO3	ET1	0.133	0.094*	0.091*	0.102*	0.093*	0.109*	0.133*	0.121*
		ET2	11.534	7.198*	6.541*	7.028*	6.420*	7.267*	7.544*	7.826*
$\kappa_2 = 0.3$	CO1	EPD	0.155	0.091*	0.060*	0.058*	0.024	0.004	-0.230	N/A
		EPP	-0.114	-0.080*	-0.051*	-0.021*	-0.084	-0.130	0.770	N/A
	CO2	EPD	0.287	0.074*	0.117*	0.108*	0.125*	0.144*	0.140*	0.180*
		EPP	-0.187	-0.096*	-0.059*	-0.067*	-0.057*	-0.073*	-0.088*	-0.030*
	CO3	EPD	0.042	0.096*	0.148*	0.139*	0.159*	0.140*	0.174*	0.182*
		EPP	-0.106	-0.067*	-0.037*	-0.047*	-0.017*	-0.059*	-0.055*	-0.064*
$\kappa_2 = 0.7$	CO1	EPD	-0.152	-0.025*	-0.020*	-0.022*	-0.009	-0.211	-0.144	N/A
		EPP	-0.433	-0.231*	-0.120*	-0.121*	-0.124	-0.411	-0.144	N/A
	CO2	EPD	-0.092	-0.008*	0.018*	0.027*	0.045*	0.044*	0.036*	0.060*
		EPP	-0.679	-0.216*	-0.159*	-0.159*	-0.133*	-0.168*	-0.213*	-0.128*
	CO3	EPD	-0.246	-0.014*	0.026*	0.051*	0.050*	0.066*	0.077*	0.083*
		EPP	-0.520	-0.200*	-0.122*	-0.128*	-0.086*	-0.119*	-0.121*	-0.140*
$\kappa_2 = 1.5$	CO1	EPD	-0.116	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
		EPP	-0.203	-0.002*	0.000*	0.000	0.000	0.000	N/A	N/A
	CO2	EPD	0.000	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.261	-0.002*	0.000*	-0.001*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.092	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.275	-0.001*	-0.002*	0.000*	-0.001*	0.000*	0.000*	-0.001*
$\kappa_2 = 3$	CO1	EPD	-0.023	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.077	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.008	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.076	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, λ = .3, p = 7

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.200	0.062*	0.046*	0.008*	0.044	0.050	-0.050	N/A
		ET2	11.413	5.928*	5.446*	4.268*	5.080	6.300	3.194	N/A
	CO2	ET1	0.477	0.085*	0.063*	0.060*	0.074*	0.073*	0.082*	0.139
		ET2	57.281	7.038*	5.756*	5.666*	6.700*	6.786*	6.541*	8.069
	CO3	ET1	0.130	0.067*	0.070*	0.077*	0.090*	0.097*	0.103*	0.118*
		ET2	9.716	5.890*	6.317*	6.093*	6.459*	6.513*	6.766*	7.567*
$\kappa_2 = 0.3$	CO1	EPD	-0.026	0.033*	0.044*	0.039*	0.054	0.299	N/A	N/A
		EPP	-0.215	-0.094*	-0.068*	-0.005*	-0.007	0.299	N/A	N/A
	CO2	EPD	0.357	0.048*	0.066*	0.072*	0.106*	0.108*	0.151*	0.152*
		EPP	-0.196	-0.119*	-0.059*	-0.043*	-0.078*	-0.075*	-0.038*	-0.128*
	CO3	EPD	0.037	0.073*	0.075*	0.077*	0.125*	0.128*	0.144*	0.152*
		EPP	-0.091	-0.051*	-0.081*	-0.059*	-0.052*	-0.046*	-0.044*	-0.068*
$\kappa_2 = 0.7$	CO1	EPD	-0.235	-0.041*	-0.027*	-0.059*	-0.048	-0.885	N/A	N/A
		EPP	-0.573	-0.160*	-0.110*	-0.084*	-0.157	-0.885	N/A	N/A
	CO2	EPD	-0.063	-0.049*	-0.004*	0.004*	0.019*	0.018*	0.013*	0.005*
		EPP	-0.779	-0.213*	-0.110*	-0.080*	-0.117*	-0.107*	-0.120*	-0.197*
	CO3	EPD	-0.218	-0.006*	0.001*	0.006*	0.040*	0.034*	0.044*	0.041*
		EPP	-0.507	-0.105*	-0.111*	-0.093*	-0.073*	-0.071*	-0.071*	-0.120*
$\kappa_2 = 1.5$	CO1	EPD	-0.083	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A
		EPP	-0.267	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A
	CO2	EPD	0.000	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.333	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.102	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.219	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.027	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.081	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.034	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	-0.068	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.098	0.056*	0.027*	0.011*	0.005*	0.029	-0.025	0.017
		ET2	8.750	5.622*	4.705*	4.228*	3.990*	4.735	2.924	4.589
	CO2	ET1	0.391*	0.080*	0.047*	0.052*	0.039*	0.036*	0.029*	0.031*
		ET2	28.207*	6.600*	5.300*	5.584*	4.923*	4.967*	4.587*	4.820*
	CO3	ET1	0.078	0.051*	0.044*	0.038*	0.037*	0.029*	0.026*	0.045*
		ET2	7.086	5.551*	5.080*	5.094*	4.686*	4.565*	4.658*	5.250*
$\kappa_2 = 0.3$	CO1	EPD	0.028	0.058*	0.041*	-0.002*	-0.023	0.008	-0.162	-0.072
		EPP	-0.197	-0.072*	-0.028*	-0.032*	-0.036	-0.063	-0.002	-0.072
	CO2	EPD	0.238*	0.053*	0.053*	0.035*	0.034*	0.052*	0.029*	0.032*
		EPP	-0.234*	-0.115*	-0.048*	-0.085*	-0.046*	-0.049*	-0.032*	-0.039*
	CO3	EPD	0.023	0.049*	0.067*	0.058*	0.044*	0.058*	0.065*	0.086*
		EPP	-0.123	-0.074*	-0.028*	-0.050*	-0.026*	0.004*	-0.002*	-0.028*
$\kappa_2 = 0.7$	CO1	EPD	-0.205*	-0.017*	-0.021*	-0.004*	-0.016	-0.048	-0.062	N/A
		EPP	-0.423*	-0.082*	-0.049*	-0.020*	-0.027	-0.112	0.063	N/A
	CO2	EPD	-0.044	-0.017*	0.006*	0.009*	-0.003*	-0.005*	0.006*	-0.003*
		EPP	-0.699	-0.122*	-0.050*	-0.049*	-0.039*	-0.032*	-0.013*	-0.046*
	CO3	EPD	-0.243*	-0.006*	0.006*	0.000*	0.006*	0.012*	0.005*	0.010*
		EPP	-0.412*	-0.065*	-0.041*	-0.040*	-0.016*	-0.011*	-0.019*	-0.032*
$\kappa_2 = 1.5$	CO1	EPD	-0.122*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
		EPP	-0.205*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.032	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.095*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.137*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.030*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.060*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	-0.038*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
		EPP	-0.057*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, $\lambda = .5$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.067*	0.038*	0.019*	-0.003*	0.003	0.028	-0.050	N/A
		ET2	6.234*	4.783*	4.383*	3.731*	3.930	4.335	0.973	N/A
	CO2	ET1	0.550*	0.050*	0.032*	0.023*	0.009*	0.013*	0.012*	-0.003*
		ET2	40.391*	5.351*	4.833*	4.595*	4.023*	4.279*	4.307*	3.772*
	CO3	ET1	0.031*	0.022*	0.016*	0.030*	0.012*	0.010*	0.019*	0.029*
		ET2	5.143*	4.581*	4.360*	4.851*	4.337*	4.280*	4.417*	4.661*
$\kappa_2 = 0.3$	CO1	EPD	-0.053*	-0.001*	-0.004*	-0.043*	-0.027	-0.160	-0.387	N/A
		EPP	-0.176*	-0.072*	-0.063*	-0.035*	-0.046	-0.160	0.613	N/A
	CO2	EPD	0.213*	0.015*	0.035*	0.040*	0.015*	0.015*	0.002*	0.002*
		EPP	-0.331*	-0.095*	-0.041*	-0.021*	-0.002*	-0.029*	-0.049*	0.010*
	CO3	EPD	-0.055*	0.024*	0.025*	0.014*	0.031*	0.020*	0.018*	0.036*
		EPP	-0.138*	-0.036*	-0.022*	-0.064*	-0.008*	-0.015*	-0.032*	-0.026*
$\kappa_2 = 0.7$	CO1	EPD	-0.244*	-0.006*	-0.003*	-0.026*	-0.071	0.026	N/A	N/A
		EPP	-0.358*	-0.020*	-0.015*	-0.024*	-0.087	0.026	N/A	N/A
	CO2	EPD	-0.063	-0.014*	0.001*	-0.003*	-0.001*	0.005*	-0.007*	-0.012*
		EPP	-0.790	-0.050*	-0.025*	-0.015*	-0.002*	-0.005*	-0.019*	-0.011*
	CO3	EPD	-0.278*	-0.008*	-0.008*	0.000*	0.001*	-0.001*	-0.004*	0.003*
		EPP	-0.333*	-0.025*	-0.019*	-0.015*	-0.005*	-0.009*	-0.016*	-0.009*
$\kappa_2 = 1.5$	CO1	EPD	-0.152*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.202*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.048*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.111*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.146*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.057*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.095*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.007*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO3	EPD	-0.054*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
		EPP	-0.073*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, $\lambda = .5$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.034*	0.019*	0.005*	0.005*	-0.003	-0.050	N/A	N/A
		ET2	5.492*	4.327*	4.034*	4.012*	3.699	2.653	N/A	N/A
	CO2	ET1	0.522*	0.041*	0.026*	0.018*	0.003*	0.008*	0.010*	0.007
		ET2	41.823*	4.974*	4.662*	4.489*	4.016*	4.108*	4.018*	4.123
	CO3	ET1	0.072*	0.018*	0.015*	0.011*	0.002*	0.005*	0.009*	0.009*
		ET2	6.389*	4.623*	4.276*	4.212*	3.895*	4.046*	4.113*	4.007*
$\kappa_2 = 0.3$	CO1	EPD	-0.087*	-0.004*	-0.010*	-0.070*	-0.063	0.211	N/A	N/A
		EPP	-0.203*	-0.044*	-0.028*	-0.081*	-0.051	0.393	N/A	N/A
	CO2	EPD	0.218*	-0.003*	0.004*	0.006*	0.001*	-0.018*	0.008*	-0.018*
		EPP	-0.355*	-0.086*	-0.066*	-0.062*	-0.015*	-0.050*	-0.008*	-0.042*
	CO3	EPD	-0.086*	-0.006*	0.013*	0.026*	0.011*	0.028*	0.004*	0.024*
		EPP	-0.226*	-0.064*	-0.021*	-0.011*	0.002*	0.006*	-0.022*	0.007*
$\kappa_2 = 0.7$	CO1	EPD	-0.281*	-0.008*	-0.009*	-0.013	-0.025	N/A	0.015	N/A
		EPP	-0.362*	-0.012*	-0.011*	-0.013	-0.025	N/A	0.015	N/A
	CO2	EPD	-0.056	-0.008*	0.002*	0.001*	-0.002*	-0.005*	-0.007*	-0.011*
		EPP	-0.789	-0.026*	-0.010*	-0.008*	-0.003*	-0.009*	-0.011*	-0.015*
	CO3	EPD	-0.284*	-0.006*	-0.003*	-0.006*	-0.005*	-0.001*	-0.001*	0.000*
		EPP	-0.408*	-0.017*	-0.010*	-0.011*	-0.005*	-0.003*	-0.003*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.143*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.195*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.041*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.119*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.187*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.069*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.106*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO3	EPD	-0.048	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	-0.101	0.000*	0.000	0.000	0.000	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, $\lambda = .7$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.048*	0.021*	0.012*	-0.001*	-0.008*	-0.006	-0.022	-0.050
		ET2	5.232*	4.409*	4.371*	3.837*	3.644*	3.695	2.916	1.201
	CO2	ET1	0.362*	0.039*	0.036*	0.029*	0.010*	0.007*	0.007*	-0.003*
		ET2	21.552*	5.284*	4.768*	4.776*	4.248*	4.141*	4.082*	3.635*
	CO3	ET1	0.044*	0.018*	0.022*	0.019*	0.014*	0.010*	0.004*	0.009*
		ET2	5.487*	4.437*	4.553*	4.479*	4.267*	4.248*	3.965*	4.215*
$\kappa_2 = 0.3$	CO1	EPD	-0.083*	0.046*	0.009*	-0.017*	-0.075	-0.062	-0.029	0.054
		EPP	-0.170*	-0.012*	-0.044*	-0.017*	-0.063	-0.055	0.054	0.388
	CO2	EPD	0.130*	0.011*	0.015*	0.018*	0.004*	0.003*	-0.014*	-0.025*
		EPP	-0.358*	-0.107*	-0.059*	-0.075*	-0.036*	-0.028*	-0.039*	-0.006*
	CO3	EPD	-0.062*	0.023*	0.003*	0.010*	0.017*	0.029*	0.008*	0.007*
		EPP	-0.163*	-0.025*	-0.057*	-0.051*	-0.021*	-0.010*	-0.001*	-0.029*
$\kappa_2 = 0.7$	CO1	EPD	-0.250*	-0.003*	-0.013*	0.001*	-0.024	-0.019	0.011	N/A
		EPP	-0.307*	-0.008*	-0.019*	0.001*	-0.024	-0.019	0.011	N/A
	CO2	EPD	-0.035*	-0.006*	-0.003*	0.001*	0.002*	0.001*	-0.009*	0.000*
		EPP	-0.521*	-0.021*	-0.011*	-0.007*	0.000*	-0.003*	-0.012*	0.000*
	CO3	EPD	-0.252*	-0.009*	-0.003*	-0.006*	-0.001*	0.002*	0.002*	-0.005*
		EPP	-0.326*	-0.014*	-0.010*	-0.011*	-0.003*	0.000*	0.000*	-0.009*
$\kappa_2 = 1.5$	CO1	EPD	-0.134*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.162*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.019*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.124*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.155*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.022*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.028*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A
		EPP	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A
	CO3	EPD	-0.007*	0.000	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.012*	0.000	0.000	0.000	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.020*	0.016*	0.007*	-0.008*	0.008	-0.024	-0.050	-0.050
		ET2	4.727*	4.376*	4.179*	3.586*	4.219	3.653	0.187	0.113
	CO2	ET1	0.449*	0.027*	0.022*	0.015*	0.002*	0.007*	-0.011*	0.009*
		ET2	27.231*	4.698*	4.522*	4.250*	3.898*	4.034*	3.483*	3.998*
	CO3	ET1	0.044*	0.010*	0.015*	0.009*	0.004*	-0.004*	0.009*	0.004*
		ET2	5.116*	4.158*	4.245*	4.060*	3.915*	3.683*	4.110*	3.930*
$\kappa_2 = 0.3$	CO1	EPD	-0.121*	0.009*	0.002*	-0.061*	-0.069	-0.219	-0.153	0.514
		EPP	-0.172*	-0.052*	-0.034*	-0.041*	-0.131	-0.219	0.514	0.514
	CO2	EPD	0.084*	-0.004*	0.018*	-0.016*	-0.014*	0.003*	-0.026*	-0.031*
		EPP	-0.405*	-0.079*	-0.038*	-0.052*	-0.020*	-0.012*	0.008*	-0.049*
	CO3	EPD	-0.080*	-0.001*	0.004*	-0.014*	0.012*	0.022*	0.007*	0.015*
		EPP	-0.168*	-0.026*	-0.031*	-0.032*	0.003*	0.037*	-0.015*	0.003*
$\kappa_2 = 0.7$	CO1	EPD	-0.253*	-0.003*	-0.004*	-0.024	-0.025	0.006	N/A	N/A
		EPP	-0.283*	-0.004*	-0.008*	-0.016	-0.055	0.006	N/A	N/A
	CO2	EPD	-0.015*	-0.003*	0.000*	-0.001*	-0.005*	-0.003*	-0.004*	-0.004*
		EPP	-0.652*	-0.007*	-0.003*	-0.003*	-0.005*	-0.007*	-0.002*	-0.006*
	CO3	EPD	-0.229*	-0.003*	-0.001*	-0.003*	0.002*	-0.002*	-0.002*	-0.002*
		EPP	-0.281*	-0.004*	-0.005*	-0.005*	0.002*	-0.001*	-0.002*	-0.003*
$\kappa_2 = 1.5$	CO1	EPD	-0.124*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	-0.152*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.024*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.148*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.177*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.015	N/A	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.018	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A
		EPP	-0.004*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A
	CO3	EPD	-0.029	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.035	0.000	0.000	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 100, λ = .7, p = 7

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.017*	0.011*	0.008*	-0.010*	-0.014	0.017	-0.050	N/A
		ET2	4.406*	4.284*	4.096*	3.419*	2.902	4.606	1.040	N/A
	CO2	ET1	0.480*	0.016*	0.012*	0.016*	0.003*	-0.006*	-0.002*	-0.012
		ET2	25.390*	4.341*	4.182*	4.492*	3.951*	3.688*	3.772*	3.493
	CO3	ET1	0.015*	0.011*	0.009*	0.003*	0.007*	0.003*	0.006*	0.008*
		ET2	4.402*	4.175*	4.056*	4.014*	4.023*	3.927*	4.062*	4.165*
$\kappa_2 = 0.3$	CO1	EPD	-0.166*	-0.015*	0.008*	-0.052*	-0.098	-0.106	N/A	N/A
		EPP	-0.206*	-0.056*	-0.020*	-0.010*	-0.006	-0.206	N/A	N/A
	CO2	EPD	0.066*	0.007*	-0.003*	-0.006*	-0.035*	-0.037*	-0.041*	-0.055*
		EPP	-0.411*	-0.042*	-0.032*	-0.071*	-0.046*	-0.021*	-0.032*	-0.030*
	CO3	EPD	-0.101*	0.002*	0.015*	-0.011*	0.007*	-0.007*	-0.003*	0.008*
		EPP	-0.132*	-0.029*	-0.002*	-0.031*	-0.009*	-0.014*	-0.019*	-0.024*
$\kappa_2 = 0.7$	CO1	EPD	-0.218*	-0.003*	-0.003*	-0.007	-0.218	0.004	N/A	N/A
		EPP	-0.246*	-0.006*	-0.004*	-0.007	0.004	0.004	N/A	N/A
	CO2	EPD	-0.035*	-0.005*	-0.002*	-0.001*	0.002*	-0.002*	0.000*	-0.001*
		EPP	-0.588*	-0.008*	-0.002*	-0.003*	0.001*	-0.001*	0.000*	0.001*
	CO3	EPD	-0.229*	-0.003*	0.000*	-0.001*	-0.003*	-0.001*	-0.001*	-0.003*
		EPP	-0.254*	-0.003*	-0.002*	-0.002*	-0.005*	-0.001*	-0.001*	-0.005*
$\kappa_2 = 1.5$	CO1	EPD	-0.113*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.135*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.132*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.155*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
$\kappa_2 = 3$	CO1	EPD	-0.004	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.004	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	-0.002*	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
	CO3	EPD	-0.008	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	-0.016	0.000	N/A	N/A	N/A	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .3$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.134	0.083*	0.056*	0.045*	0.051*	0.062*	0.059*	0.074*
		ET2	9.455	6.759*	5.821*	5.068*	5.484*	5.542*	5.317*	5.723*
	CO2	ET1	0.230*	0.093*	0.079*	0.069*	0.087*	0.083*	0.109*	0.140*
		ET2	63.204*	6.917*	6.126*	6.182*	6.696*	6.134*	6.650*	6.537*
	CO3	ET1	0.159	0.082*	0.083*	0.094*	0.060*	0.075*	0.080*	0.083*
		ET2	9.583	6.443*	6.347*	6.188*	5.529*	6.421*	6.210*	6.069*
$\kappa_2 = 0.3$	CO1	EPD	-0.040	0.051*	0.035*	0.050*	0.058*	0.068*	0.071*	0.075*
		EPP	-0.345	-0.155*	-0.115*	-0.044*	-0.076*	-0.074*	-0.083*	-0.073*
	CO2	EPD	0.006*	0.011*	0.070*	0.058*	0.064*	0.096*	0.103*	0.113*
		EPP	-0.570*	-0.191*	-0.110*	-0.140*	-0.146*	-0.074*	-0.119*	-0.117*
	CO3	EPD	-0.030	0.055*	0.080*	0.088*	0.084*	0.095*	0.086*	0.063*
		EPP	-0.285	-0.141*	-0.134*	-0.114*	-0.061*	-0.117*	-0.095*	-0.132*
$\kappa_2 = 0.7$	CO1	EPD	-0.045	-0.001*	-0.002*	-0.001*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.110	-0.005*	-0.003*	-0.001*	-0.002*	-0.001*	0.000*	0.000*
	CO2	EPD	-0.066*	-0.001*	0.000*	0.000*	-0.002*	-0.001*	0.000*	0.000*
		EPP	-0.862*	-0.006*	-0.004*	-0.001*	-0.003*	-0.002*	-0.001*	-0.001*
	CO3	EPD	-0.059	-0.004*	0.000*	0.000*	0.000*	-0.002*	0.000*	0.000*
		EPP	-0.093	-0.009*	-0.003*	-0.001*	0.000*	-0.004*	-0.001*	-0.001*
$\kappa_2 = 1.5$	CO1	EPD	-0.005	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	-0.013	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.009	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.018	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, λ = .3, p = 5

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.143	0.069*	0.035*	0.023*	0.017*	0.018*	0.034*	0.038*
		ET2	7.377	5.940*	4.915*	4.836*	4.451*	4.232*	4.806*	4.821*
	CO2	ET1	0.470	0.074*	0.037*	0.047*	0.036*	0.082*	0.095*	0.111*
		ET2	230.150	6.161*	5.215*	5.367*	5.043*	6.699*	6.372*	6.173*
	CO3	ET1	0.077	0.065*	0.034*	0.042*	0.041*	0.044*	0.032*	0.055*
		ET2	7.403	5.048*	4.938*	5.053*	5.135*	5.338*	4.868*	5.601*
$\kappa_2 = 0.3$	CO1	EPD	-0.162	-0.026*	0.005*	-0.011*	0.022*	0.039*	0.017*	0.013*
		EPP	-0.285	-0.168*	-0.068*	-0.076*	-0.008*	0.022*	-0.046*	-0.057*
	CO2	EPD	0.030	-0.030*	-0.006*	-0.010*	0.009*	0.035*	0.027*	0.088*
		EPP	-0.730	-0.183*	-0.089*	-0.101*	-0.086*	-0.176*	-0.167*	-0.082*
	CO3	EPD	-0.142	-0.008*	0.008*	-0.010*	0.024*	0.027*	0.037*	0.052*
		EPP	-0.288	-0.083*	-0.070*	-0.106*	-0.070*	-0.071*	-0.019*	-0.073*
$\kappa_2 = 0.7$	CO1	EPD	-0.114	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	-0.002*
		EPP	-0.160	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	-0.002*
	CO2	EPD	-0.065	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.932	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.082	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.136	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.024	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.034	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.589	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.016	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.032	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.004*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
		EPP	-0.004*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, λ = .3, p = 7

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.097	0.030*	0.027*	0.018*	-0.004*	0.011*	0.009*	0.030*
		ET2	7.165	5.028*	4.561*	4.299*	3.754*	4.110*	4.362*	4.946*
	CO2	ET1	0.539	0.060*	0.042*	0.030*	0.030*	0.065*	0.078*	0.104*
		ET2	311.059	5.656*	5.267*	4.772*	4.857*	5.355*	5.692*	6.645*
	CO3	ET1	0.058	0.034*	0.022*	0.017*	0.032*	0.040*	0.030*	0.009*
		ET2	6.427	4.718*	4.610*	4.469*	4.545*	4.871*	4.666*	4.148*
$\kappa_2 = 0.3$	CO1	EPD	-0.174	-0.029*	-0.008*	-0.008*	0.019*	-0.012*	-0.009*	0.002*
		EPP	-0.328	-0.095*	-0.038*	-0.039*	0.022*	-0.022*	-0.034*	-0.067*
	CO2	EPD	0.008	-0.017*	-0.009*	-0.011*	-0.015*	0.017*	0.013*	-0.008*
		EPP	-0.803	-0.113*	-0.094*	-0.057*	-0.063*	-0.071*	-0.090*	-0.157*
	CO3	EPD	-0.204	0.016*	-0.010*	0.010*	0.013*	0.005*	0.024*	0.013*
		EPP	-0.320	-0.031*	-0.052*	-0.030*	-0.028*	-0.047*	-0.012*	0.001*
$\kappa_2 = 0.7$	CO1	EPD	-0.122	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.202	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.066	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.934	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.081	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.124	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.014	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.032	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.752	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.012	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.027	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000*	0.000*	0.000	0.000	0.000	N/A	0.000
		EPP	0.000	0.000*	0.000*	0.000	0.000	0.000	N/A	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS $\geq$ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.071*	0.049*	0.023*	0.017*	0.022*	0.007*	0.000*	0.011*
		ET2	6.247*	5.440*	4.509*	4.218*	4.358*	4.203*	3.845*	4.263*
	CO2	ET1	0.416*	0.064*	0.045*	0.028*	0.025*	0.019*	0.013*	0.005*
		ET2	119.504*	5.811*	5.250*	4.607*	4.567*	4.485*	4.335*	4.049*
	CO3	ET1	0.081*	0.025*	0.010*	0.008*	0.005*	0.010*	0.026*	0.025*
		ET2	6.504*	5.065*	4.353*	4.193*	3.991*	4.139*	4.579*	4.495*
$\kappa_2 = 0.3$	CO1	EPD	-0.131*	-0.012*	-0.004*	0.008*	0.014*	-0.006*	-0.009*	-0.003*
		EPP	-0.254*	-0.082*	-0.037*	-0.005*	-0.012*	-0.017*	-0.009*	-0.017*
	CO2	EPD	-0.046*	-0.024*	-0.019*	-0.011*	-0.011*	0.001*	-0.013*	0.015*
		EPP	-0.874*	-0.109*	-0.089*	-0.044*	-0.053*	-0.019*	-0.027*	0.005*
	CO3	EPD	-0.164*	-0.005*	-0.011*	-0.011*	-0.002*	0.008*	-0.010*	0.010*
		EPP	-0.303*	-0.057*	-0.033*	-0.031*	-0.008*	0.002*	-0.042*	-0.015*
$\kappa_2 = 0.7$	CO1	EPD	-0.089*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.116*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.013*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.909*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.092*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.115*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.023*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.028*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.013*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.028*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .5$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.029	0.017*	0.021*	0.016*	0.007*	0.010*	0.005*	-0.003*
		ET2	4.774	4.422*	4.605*	4.442*	3.950*	4.054*	3.983*	3.741*
	CO2	ET1	0.469	0.046*	0.013*	0.034*	0.008*	0.003*	0.017*	0.005*
		ET2	141.238	4.939*	4.242*	4.638*	4.095*	3.911*	4.376*	3.966*
	CO3	ET1	0.042	0.024*	0.007*	0.005*	0.013*	0.003*	0.012*	0.003*
		ET2	4.709	4.642*	4.024*	4.057*	4.281*	3.893*	4.175*	3.928*
$\kappa_2 = 0.3$	CO1	EPD	-0.161	-0.021*	-0.019*	-0.017*	-0.005*	-0.007*	0.001*	0.000*
		EPP	-0.201	-0.038*	-0.038*	-0.042*	-0.006*	-0.010*	-0.002*	0.001*
	CO2	EPD	-0.108	-0.013*	-0.009*	-0.009*	-0.001*	0.004*	0.007*	0.000*
		EPP	-0.883	-0.047*	-0.020*	-0.029*	-0.004*	0.002*	0.002*	-0.002*
	CO3	EPD	-0.176	-0.009*	-0.014*	-0.006*	-0.004*	-0.005*	-0.012*	-0.007*
		EPP	-0.218	-0.028*	-0.019*	-0.013*	-0.015*	-0.006*	-0.018*	-0.010*
$\kappa_2 = 0.7$	CO1	EPD	-0.071*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	-0.082*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
	CO2	EPD	-0.005	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.869	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.066	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.082	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.036*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.039*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.027*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.029*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	-0.001*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	-0.001*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .5$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.043	0.020*	0.018*	0.013*	0.003*	0.011*	-0.007*	-0.001*
		ET2	4.975	4.765*	4.388*	4.082*	3.978*	4.186*	3.639*	3.793*
	CO2	ET1	0.568	0.026*	0.016*	0.015*	0.015*	0.020*	-0.003*	0.007*
		ET2	174.352	4.564*	4.290*	4.545*	4.252*	4.361*	3.690*	3.956*
	CO3	ET1	0.031	0.026*	0.008*	0.010*	0.003*	0.005*	-0.010*	0.018*
		ET2	5.274	4.695*	4.246*	4.326*	3.914*	4.078*	3.597*	4.356*
$\kappa_2 = 0.3$	CO1	EPD	-0.201	-0.012*	-0.007*	-0.006*	0.005*	-0.008*	0.006*	-0.003*
		EPP	-0.245	-0.030*	-0.017*	-0.010*	0.002*	-0.011*	0.012*	-0.003*
	CO2	EPD	-0.101	-0.016*	-0.003*	0.002*	-0.002*	0.004*	-0.005*	-0.002*
		EPP	-0.921	-0.029*	-0.007*	-0.015*	-0.010*	-0.006*	-0.004*	-0.004*
	CO3	EPD	-0.151	-0.001*	-0.008*	-0.004*	-0.011*	0.001*	-0.008*	0.000*
		EPP	-0.208	-0.012*	-0.014*	-0.015*	-0.012*	-0.003*	-0.004*	-0.007*
$\kappa_2 = 0.7$	CO1	EPD	-0.104	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.122	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.856	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.054	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.065	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.017	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.025	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.018*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.026*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000*	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, λ = .7, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.066*	0.011*	0.015*	0.014*	0.006*	-0.003*	-0.001*	-0.014*
		ET2	6.082*	4.158*	4.475*	4.350*	4.170*	3.803*	3.828*	3.576*
	CO2	ET1	0.380*	0.032*	0.022*	0.006*	-0.004*	0.019*	0.011*	0.002*
		ET2	86.218*	4.777*	4.691*	4.227*	3.764*	4.390*	4.107*	3.909*
	CO3	ET1	0.027*	0.026*	0.015*	0.019*	-0.001*	0.013*	0.015*	0.020*
		ET2	4.734*	4.681*	4.152*	4.487*	3.752*	4.290*	4.376*	4.419*
$\kappa_2 = 0.3$	CO1	EPD	-0.120*	-0.016*	-0.001*	0.000*	0.005*	0.000*	-0.008*	-0.002*
		EPP	-0.197*	-0.022*	-0.012*	-0.004*	0.001*	0.000*	-0.008*	-0.001*
	CO2	EPD	-0.130*	-0.012*	-0.010*	-0.011*	-0.001*	-0.004*	-0.005*	0.002*
		EPP	-0.918*	-0.025*	-0.026*	-0.017*	-0.001*	-0.010*	-0.008*	0.002*
	CO3	EPD	-0.104*	-0.011*	-0.007*	0.001*	-0.004*	0.001*	0.000*	-0.001*
		EPP	-0.120*	-0.027*	-0.010*	-0.006*	-0.004*	-0.003*	-0.007*	-0.010*
$\kappa_2 = 0.7$	CO1	EPD	-0.036*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	-0.055*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.344*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.037*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.049*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.014*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
		EPP	-0.023*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.006*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO3	EPD	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	0.000
		EPP	-0.001*	0.000*	0.000	0.000	0.000	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.024*	0.014*	-0.003*	0.012*	0.005*	0.004*	0.000*	0.020*
		ET2	5.262*	4.260*	3.793*	4.316*	4.178*	3.952*	3.846*	4.333*
	CO2	ET1	0.421*	0.031*	0.013*	0.008*	0.020*	0.010*	-0.003*	0.008*
		ET2	98.220*	4.835*	4.243*	3.968*	4.643*	4.062*	3.795*	4.190*
	CO3	ET1	0.015	0.024*	0.015*	0.014*	0.009*	0.001*	0.012*	0.000*
		ET2	4.570	4.351*	4.284*	4.198*	4.248*	3.876*	4.239*	3.857*
$\kappa_2 = 0.3$	CO1	EPD	-0.117*	-0.011*	-0.003*	-0.009*	0.000*	-0.004*	0.002*	0.003*
		EPP	-0.152*	-0.015*	-0.002*	-0.010*	0.000*	-0.004*	0.002*	-0.006*
	CO2	EPD	-0.157	-0.001*	-0.001*	-0.001*	-0.001*	0.003*	-0.002*	-0.005*
		EPP	-0.900	-0.011*	-0.009*	-0.003*	-0.009*	-0.001*	-0.002*	-0.007*
	CO3	EPD	-0.154*	-0.002*	-0.007*	-0.009*	0.002*	-0.005*	-0.002*	-0.002*
		EPP	-0.168*	-0.008*	-0.010*	-0.009*	-0.001*	-0.005*	-0.006*	-0.002*
$\kappa_2 = 0.7$	CO1	EPD	-0.039*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.045*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.454	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.038*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.042*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.009*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
		EPP	-0.011*	0.000*	0.000*	0.000	0.000	0.000	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.005*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.007*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO3	EPD	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A
		EPP	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 500, $\lambda = .7$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.040	0.020*	0.009*	0.009*	-0.006*	-0.009*	-0.001*	-0.016*
		ET2	4.836	4.395*	4.141*	4.244*	3.669*	3.614*	3.787*	3.243*
	CO2	ET1	0.483	0.025*	0.006*	-0.004*	0.015*	-0.003*	0.004*	0.006*
		ET2	87.182	4.483*	3.935*	3.708*	4.323*	3.712*	4.122*	4.058*
	CO3	ET1	0.013	0.015*	0.011*	0.005*	-0.003*	0.019*	0.015*	0.001*
		ET2	4.184	4.303*	4.121*	3.973*	3.785*	4.379*	4.367*	3.884*
$\kappa_2 = 0.3$	CO1	EPD	-0.115	-0.007*	-0.001*	0.001*	-0.001*	0.000*	0.004*	-0.005*
		EPP	-0.145	-0.009*	-0.003*	-0.004*	0.000*	0.002*	0.004*	0.000*
	CO2	EPD	-0.165	-0.004*	-0.003*	-0.004*	-0.003*	-0.004*	0.000*	-0.001*
		EPP	-0.889	-0.006*	-0.003*	-0.003*	-0.005*	-0.003*	-0.003*	-0.001*
	CO3	EPD	-0.127	-0.001*	-0.007*	0.002*	-0.005*	0.001*	-0.001*	-0.002*
		EPP	-0.144	-0.006*	-0.007*	0.002*	-0.005*	-0.001*	-0.004*	-0.002*
$\kappa_2 = 0.7$	CO1	EPD	-0.017	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.027	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.292	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.025	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.027	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A
		EPP	0.000	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	0.000	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO3	EPD	0.000	0.000*	0.000	0.000	0.000	N/A	N/A	N/A
		EPP	0.000	0.000*	0.000	0.000	0.000	N/A	N/A	N/A

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, λ = .3, p = 3

			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.133	0.104*	0.032*	0.049*	0.025*	0.048*	0.038*	0.036*
		ET2	8.875	6.986*	4.886*	5.832*	4.812*	5.700*	4.783*	5.091*
	CO2	ET1	0.200*	0.125*	0.082*	0.041*	0.064*	0.076*	0.068*	0.112*
		ET2	19.193*	7.208*	6.670*	4.868*	5.861*	6.100*	5.688*	6.532*
	CO3	ET1	0.121	0.031*	0.051*	0.063*	0.043*	0.041*	0.055*	0.063*
		ET2	9.353	4.921*	5.559*	5.952*	4.936*	5.377*	5.892*	5.440*
$\kappa_2 = 0.3$	CO1	EPD	-0.073*	-0.017*	-0.010*	0.017*	0.017*	0.027*	0.006*	0.016*
		EPP	-0.284*	-0.178*	-0.053*	-0.104*	-0.018*	-0.066*	-0.040*	-0.041*
	CO2	EPD	-0.077*	-0.025*	-0.003*	-0.007*	0.001*	0.000*	0.027*	0.021*
		EPP	-0.605*	-0.198*	-0.151*	-0.047*	-0.086*	-0.105*	-0.060*	-0.116*
	CO3	EPD	-0.072	0.000*	-0.001*	-0.006*	0.024*	0.013*	0.018*	0.036*
		EPP	-0.316	-0.042*	-0.097*	-0.102*	-0.025*	-0.059*	-0.091*	-0.029*
$\kappa_2 = 0.7$	CO1	EPD	-0.015*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.031*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.012*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.059*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.026*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.048*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, $\lambda = .3$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.077	0.034*	0.020*	0.018*	0.012*	0.018*	0.013*	0.023*
		ET2	7.453	5.007*	4.713*	4.359*	4.380*	4.514*	4.298*	4.633*
	CO2	ET1	0.360*	0.061*	0.036*	0.015*	0.032*	0.055*	0.072*	0.106*
		ET2	437.903*	5.255*	5.252*	4.357*	5.127*	5.813*	5.333*	5.648*
	CO3	ET1	0.079	0.026*	0.003*	0.028*	0.019*	0.018*	0.038*	0.026*
		ET2	6.798	4.612*	4.006*	4.798*	4.526*	4.680*	5.199*	4.705*
$\kappa_2 = 0.3$	CO1	EPD	-0.117*	-0.014*	0.000*	-0.011*	0.004*	-0.007*	0.001*	0.002*
		EPP	-0.227*	-0.042*	-0.010*	-0.019*	-0.002*	-0.017*	-0.010*	-0.014*
	CO2	EPD	-0.009*	-0.020*	-0.013*	-0.007*	-0.009*	-0.013*	0.004*	0.003*
		EPP	-0.926*	-0.058*	-0.043*	-0.012*	-0.041*	-0.058*	-0.038*	-0.044*
	CO3	EPD	-0.146*	-0.002*	-0.003*	0.001*	-0.003*	-0.006*	0.011*	0.002*
		EPP	-0.231*	-0.024*	-0.005*	-0.018*	-0.012*	-0.020*	-0.018*	-0.014*
$\kappa_2 = 0.7$	CO1	EPD	-0.035*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.069*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.041*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.951*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.043*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.064*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.010*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.010*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.668*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.
URV Option Results

URV Option Results when n = 1000, $\lambda = .3$, $p = 7$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.065	0.043*	0.010*	0.010*	0.018*	0.005*	0.023*	0.006*
		ET2	6.308	5.053*	4.145*	4.181*	4.506*	3.991*	4.767*	3.941*
	CO2	ET1	0.345*	0.048*	0.044*	0.021*	0.027*	0.054*	0.087*	0.121*
		ET2	482.151*	5.106*	5.059*	4.447*	4.482*	5.476*	5.642*	6.456*
	CO3	ET1	0.056	0.032*	0.021*	0.023*	0.018*	0.018*	0.020*	0.034*
		ET2	5.457	4.844*	4.448*	4.673*	4.519*	4.539*	4.729*	5.154*
$\kappa_2 = 0.3$	CO1	EPD	-0.122*	-0.020*	0.003*	-0.005*	0.003*	0.000*	-0.006*	-0.001*
		EPP	-0.177*	-0.033*	-0.001*	-0.006*	-0.005*	-0.001*	-0.014*	-0.001*
	CO2	EPD	-0.010	-0.014*	-0.011*	-0.002*	-0.003*	0.004*	-0.005*	-0.007*
		EPP	-0.888	-0.035*	-0.024*	-0.010*	-0.009*	-0.012*	-0.017*	-0.044*
	CO3	EPD	-0.135*	-0.005*	-0.007*	0.001*	-0.003*	-0.002*	0.000*	0.003*
		EPP	-0.171*	-0.021*	-0.015*	-0.002*	-0.012*	-0.005*	-0.010*	-0.007*
$\kappa_2 = 0.7$	CO1	EPD	-0.043*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.068*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.056	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.928	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.043*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.055*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.432	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, $\lambda = .5$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.053*	0.031*	0.024*	0.010*	0.021*	0.001*	0.001*	0.003*
		ET2	5.887*	4.683*	4.264*	4.200*	4.456*	3.863*	3.943*	3.950*
	CO2	ET1	0.342*	0.045*	0.021*	0.020*	0.020*	0.019*	0.012*	0.014*
		ET2	202.724*	5.432*	4.424*	4.308*	4.606*	4.330*	4.288*	4.501*
	CO3	ET1	0.065*	0.014*	0.027*	0.007*	0.018*	0.003*	0.009*	0.002*
		ET2	5.692*	4.524*	4.693*	4.036*	4.187*	3.913*	4.145*	3.932*
$\kappa_2 = 0.3$	CO1	EPD	-0.084*	-0.004*	-0.001*	0.001*	0.001*	-0.002*	0.000*	0.000*
		EPP	-0.117*	-0.010*	-0.004*	0.000*	-0.001*	-0.002*	0.000*	0.000*
	CO2	EPD	-0.029*	-0.009*	-0.007*	-0.002*	-0.003*	0.003*	-0.001*	0.001*
		EPP	-0.964*	-0.019*	-0.007*	-0.004*	-0.008*	0.003*	-0.002*	-0.003*
	CO3	EPD	-0.088*	-0.002*	0.001*	0.000*	0.001*	-0.003*	0.000*	0.001*
		EPP	-0.129*	-0.005*	-0.002*	0.000*	0.001*	-0.003*	-0.001*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	-0.024*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.032*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.940*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.027*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.036*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	-0.009*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	N/A
		EPP	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, $\lambda = .5$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.023*	0.001*	-0.001*	0.003*	-0.004*	0.011*	-0.009*	0.004*
		ET2	5.335*	3.915*	3.774*	4.055*	3.715*	4.350*	3.487*	4.045*
	CO2	ET1	0.365*	0.031*	0.004*	0.015*	0.013*	0.006*	0.017*	-0.006*
		ET2	280.415*	4.767*	4.006*	4.515*	4.182*	3.906*	4.447*	3.614*
	CO3	ET1	0.043*	0.021*	0.013*	-0.003*	0.011*	-0.001*	-0.004*	0.008*
		ET2	5.451*	4.249*	4.450*	3.790*	4.195*	3.777*	3.688*	4.239*
$\kappa_2 = 0.3$	CO1	EPD	-0.082*	-0.001*	-0.001*	-0.002*	0.000*	-0.001*	0.000*	0.000*
		EPP	-0.107*	-0.001*	-0.001*	-0.002*	0.000*	-0.001*	0.000*	0.000*
	CO2	EPD	-0.035*	0.000*	-0.001*	-0.001*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.953*	-0.002*	-0.001*	-0.001*	0.000*	0.000*	-0.001*	0.000*
	CO3	EPD	-0.077*	-0.005*	0.000*	-0.002*	0.000*	0.000*	-0.001*	0.000*
		EPP	-0.095*	-0.005*	0.000*	-0.002*	0.000*	0.000*	-0.001*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	-0.024*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.037*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.933*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.024*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.034*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.004*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, λ = .5, p = 7

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.017*	0.016*	0.015*	-0.008*	-0.004*	-0.013*	-0.011*	0.008*
		ET2	4.347*	4.167*	4.323*	3.530*	3.703*	3.608*	3.553*	3.972*
	CO2	ET1	0.385*	0.028*	0.009*	0.012*	0.004*	-0.007*	0.007*	0.006*
		ET2	303.381*	4.779*	4.238*	4.064*	4.107*	3.516*	4.072*	4.117*
	CO3	ET1	0.042*	0.011*	-0.003*	0.007*	0.003*	0.005*	-0.009*	0.001*
		ET2	5.079*	4.288*	3.773*	4.114*	3.884*	4.042*	3.555*	3.875*
$\kappa_2 = 0.3$	CO1	EPD	-0.069*	0.000*	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*
		EPP	-0.069*	0.000*	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*
	CO2	EPD	-0.050*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.925*	-0.001*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.083*	-0.001*	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*
		EPP	-0.102*	-0.001*	-0.001*	0.000*	-0.001*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	-0.005*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.903	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.020*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.028*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
		EPP	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.002*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000*	0.000	0.000	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, $\lambda = .7$, $p = 3$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.057*	0.007*	0.005*	-0.001*	-0.009*	-0.004*	-0.004*	0.002*
		ET2	5.272*	4.159*	3.988*	3.780*	3.635*	3.667*	3.710*	3.879*
	CO2	ET1	0.279*	0.048*	0.018*	0.028*	0.021*	0.001*	0.007*	-0.001*
		ET2	120.971*	5.496*	4.468*	4.809*	4.346*	3.882*	4.025*	3.741*
	CO3	ET1	0.032*	0.028*	0.004*	0.007*	0.020*	0.021*	0.007*	0.010*
		ET2	4.964*	4.753*	4.041*	4.039*	4.594*	4.596*	4.033*	4.136*
$\kappa_2 = 0.3$	CO1	EPD	-0.043*	-0.001*	-0.001*	0.000*	0.000*	0.000*	-0.001*	0.000*
		EPP	-0.054*	-0.001*	-0.001*	0.000*	0.000*	0.000*	-0.001*	0.000*
	CO2	EPD	-0.049*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.936*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.044*	-0.001*	-0.001*	0.000*	0.000*	0.000*	0.000*	-0.001*
		EPP	-0.052*	-0.002*	-0.001*	0.000*	0.000*	0.000*	0.000*	-0.001*
$\kappa_2 = 0.7$	CO1	EPD	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.015*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.049*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.009*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.011*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.002*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.004*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000	0.000	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

URV Option Results when n = 1000, $\lambda = .7$, $p = 5$

			$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$
$\kappa_2 = 0$	CO1	ET1	0.020*	0.018*	0.004*	0.003*	-0.007*	-0.007*	0.004*	0.001*
		ET2	4.388*	4.311*	3.932*	3.949*	3.540*	3.621*	3.985*	3.872*
	CO2	ET1	0.324*	0.028*	0.007*	0.014*	0.012*	0.002*	0.018*	0.007*
		ET2	161.993*	5.272*	4.097*	4.244*	4.124*	3.872*	4.386*	4.112*
	CO3	ET1	0.007*	0.010*	0.034*	-0.004*	0.000*	0.018*	0.007*	0.006*
		ET2	4.317*	4.276*	4.673*	3.701*	3.848*	4.326*	3.970*	4.062*
$\kappa_2 = 0.3$	CO1	EPD	-0.040*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.045*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.077*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.923*	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.050*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.050*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	-0.010*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.010*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.156*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.005*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.006*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	-0.001*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.001*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000
	CO3	EPD	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000

Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

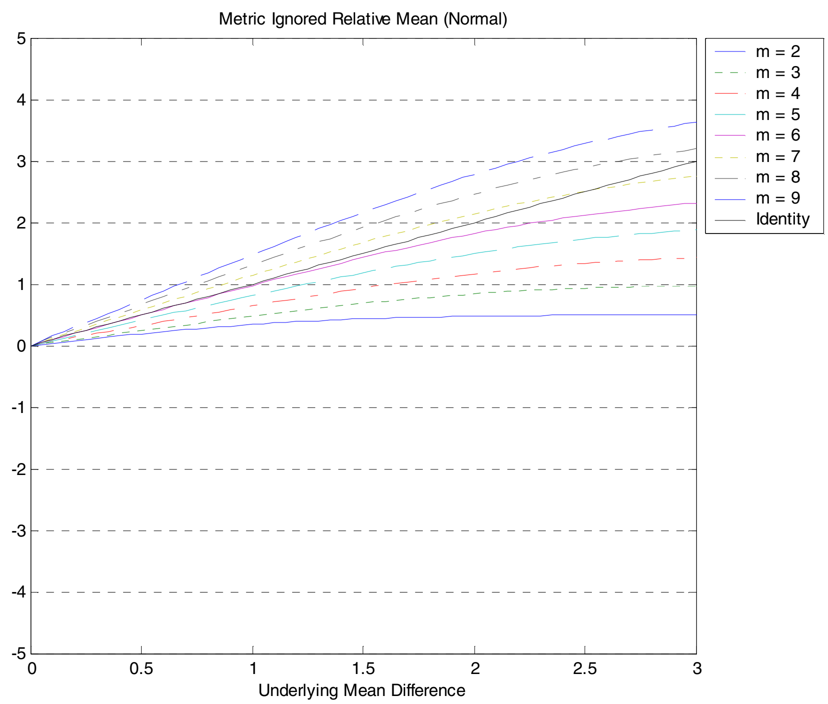
URV Option Results when n = 1000, λ = .7, p = 7

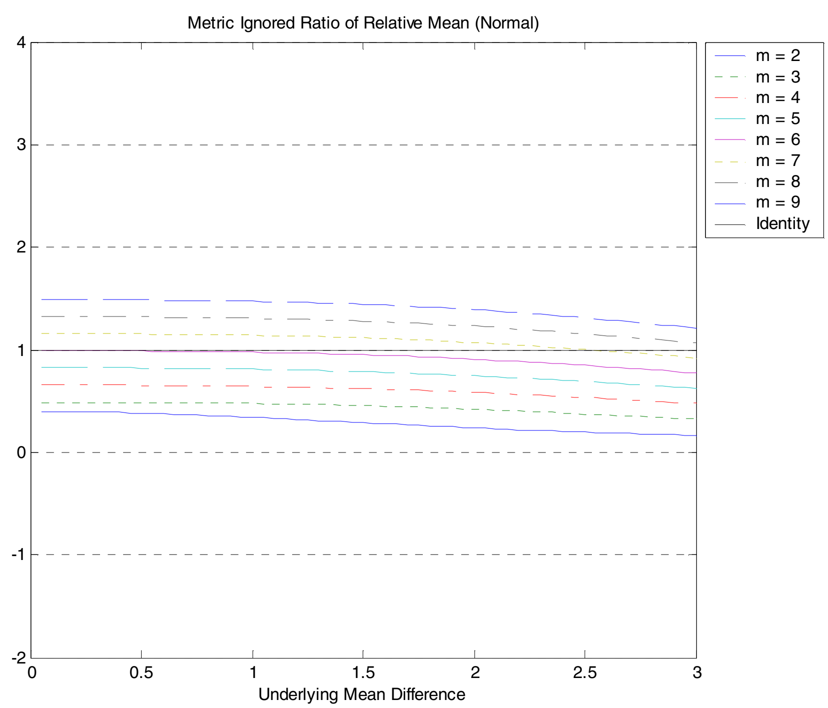
			m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9
$\kappa_2 = 0$	CO1	ET1	0.000*	0.021*	0.005*	-0.010*	0.006*	0.001*	0.003*	-0.001*
		ET2	3.825*	4.501*	4.172*	3.659*	4.006*	3.968*	3.997*	3.803*
	CO2	ET1	0.309*	0.014*	0.005*	0.008*	0.014*	0.008*	-0.002*	0.010*
		ET2	139.977*	4.402*	4.102*	4.204*	4.485*	4.043*	3.786*	4.083*
	CO3	ET1	0.030*	-0.010*	0.010*	-0.001*	0.002*	0.008*	0.001*	-0.006*
		ET2	4.380*	3.564*	4.154*	3.790*	3.919*	4.041*	3.866*	3.668*
$\kappa_2 = 0.3$	CO1	EPD	-0.042*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.041*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	-0.091*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.904*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.042*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.042*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 0.7$	CO1	EPD	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.003*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.105*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	-0.008*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	-0.010*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 1.5$	CO1	EPD	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A
		EPP	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	CO3	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\kappa_2 = 3$	CO1	EPD	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
		EPP	0.000*	0.000	N/A	N/A	N/A	N/A	N/A	N/A
	CO2	EPD	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	CO3	EPD	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000
		EPP	0.000*	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000

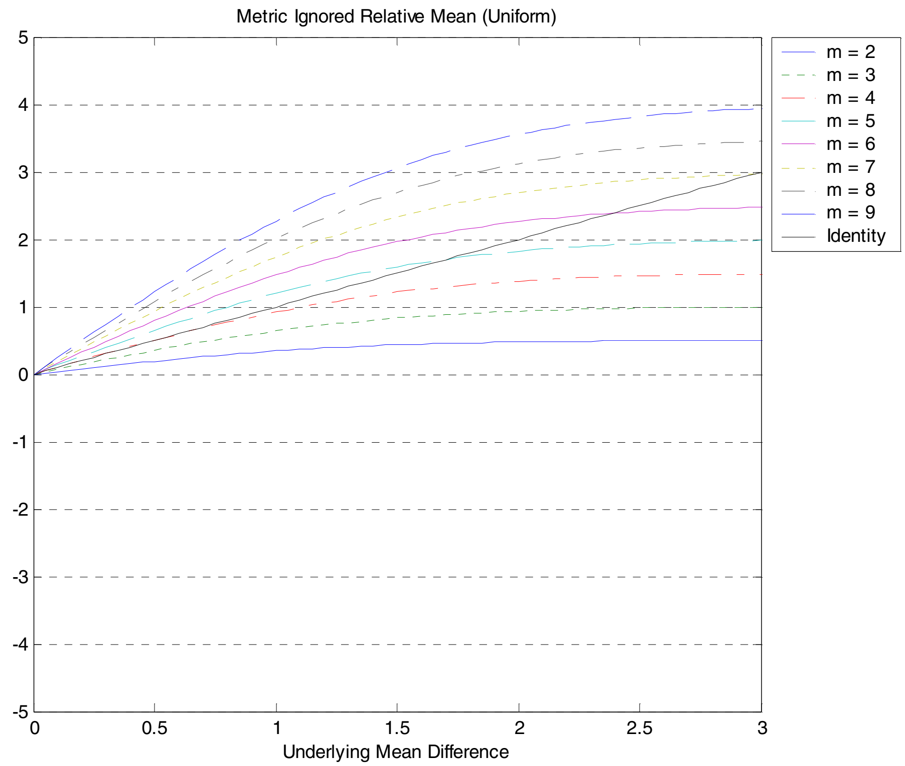
Note: CO1, CO2, and CO3 refers to the normal, the asymmetric (positively skewed), the uniform categorization option, respectively. ET1 refers to the empirical Type I error deviation (ETIED). ET2 refers to the empirical critical value (ECV). EPD refers to the empirical power deviation using ECV. EPP refers to the empirical power deviation using PCV. * indicates TPCS ≥ 500. N/A indicates TPCS = 0.

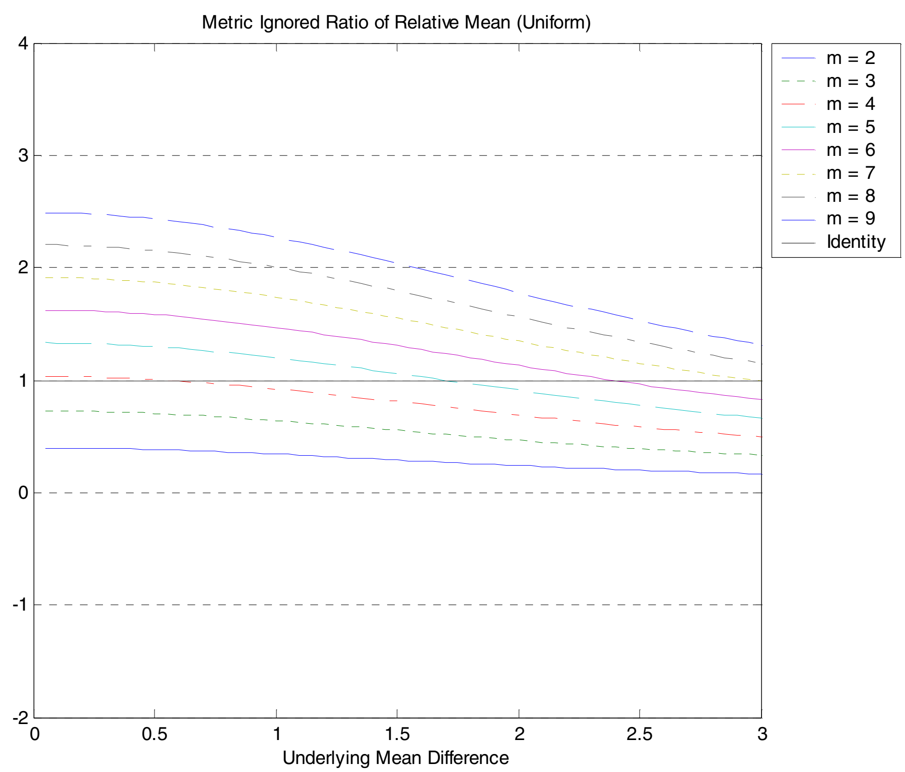
Appendix B: Numerical Results

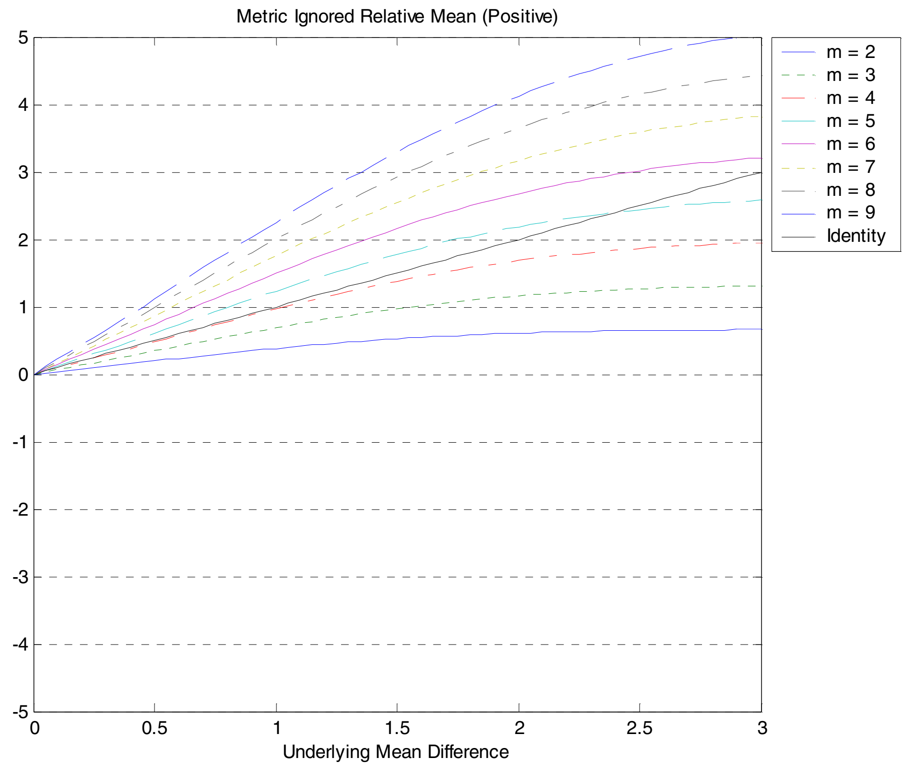
IM option Relative Mean Bias Graph

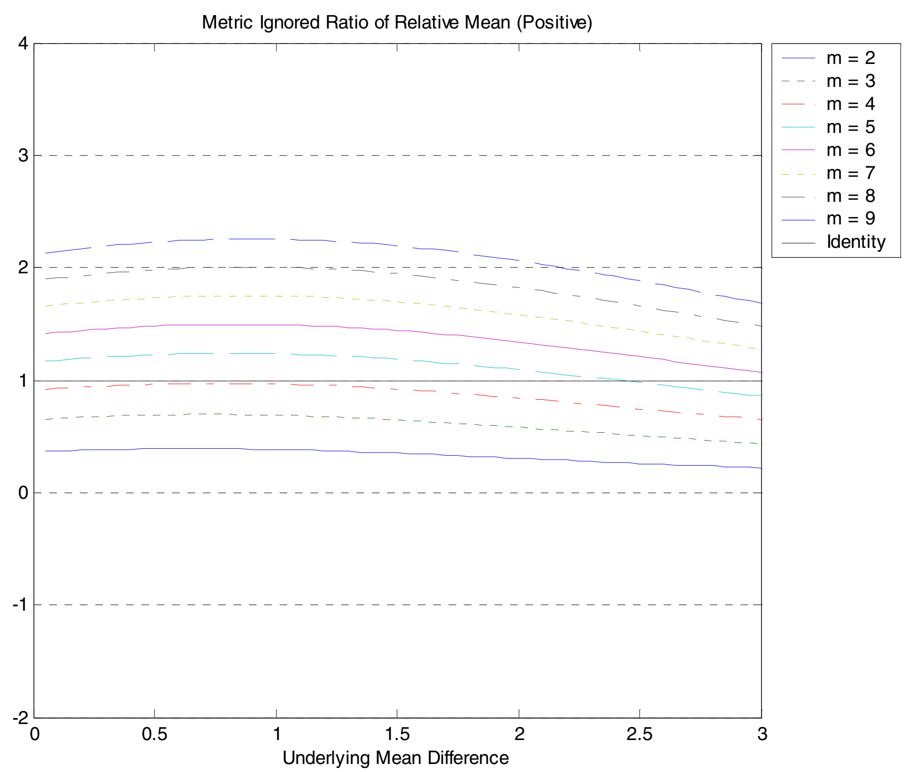


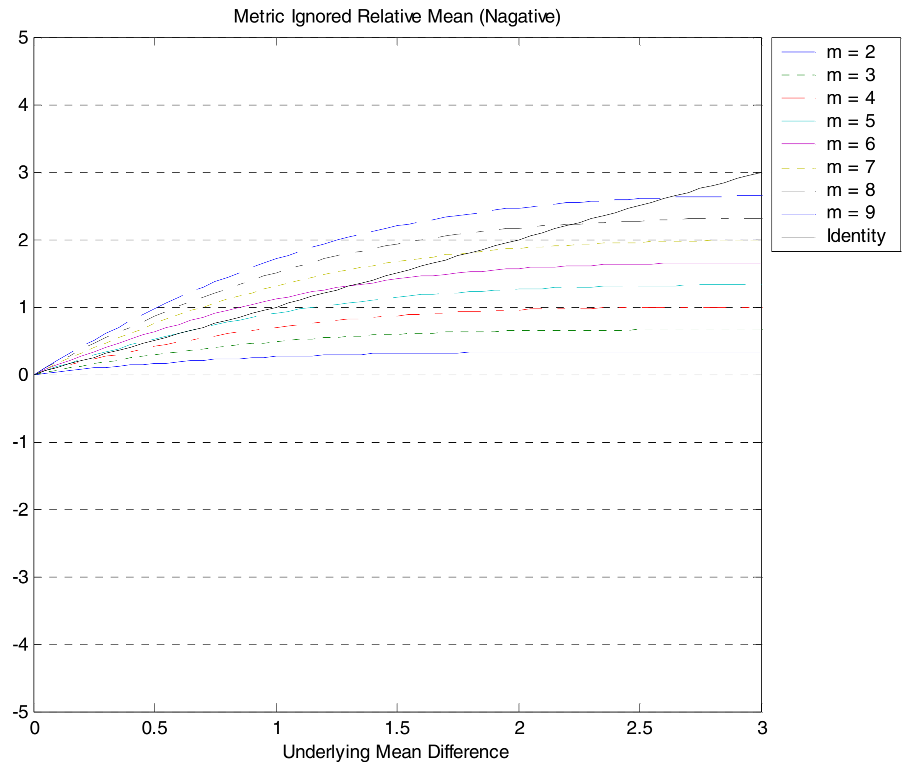



Metric Ignored Relative Mean (Uniform)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
Underlying Mean Difference

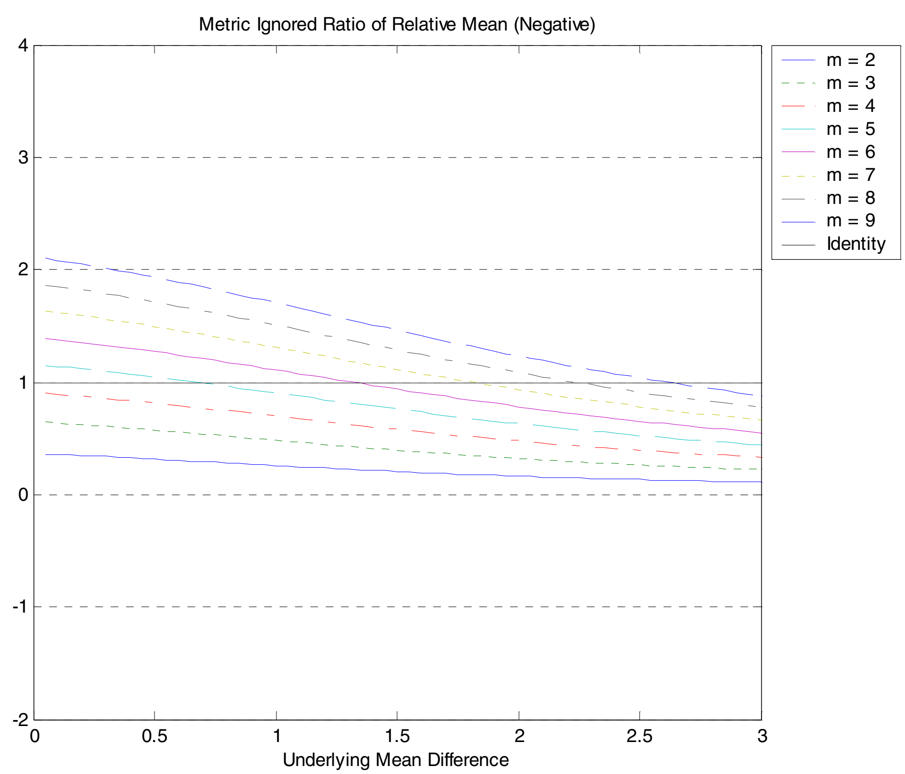

Metric Ignored Ratio of Relative Mean (Uniform)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
Underlying Mean Difference


Metric Ignored Relative Mean (Positive)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
Underlying Mean Difference


Metric Ignored Ratio of Relative Mean (Positive)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
Underlying Mean Difference

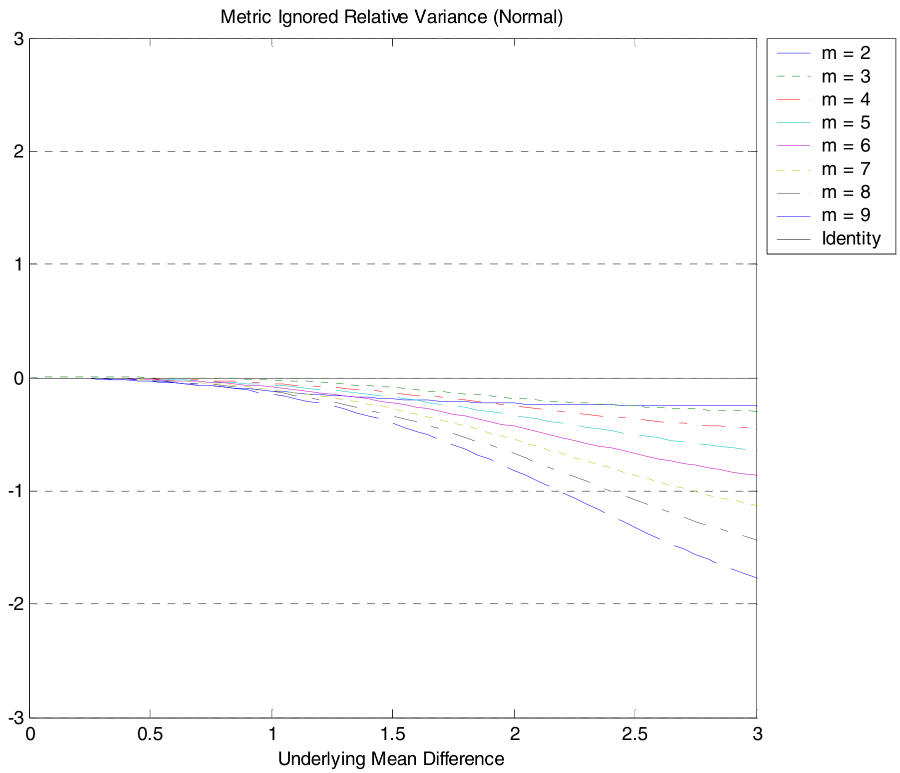


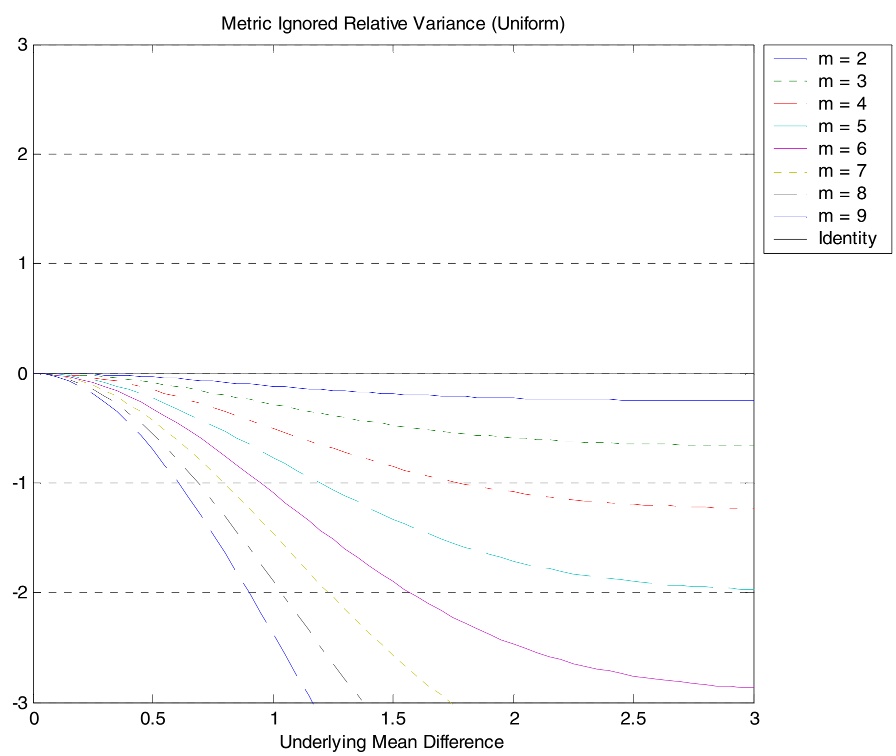
Metric Ignored Relative Mean (Nagative)
5
4
3
2
1
0
-1
-2
-3
-4
-5
0
0.5
1
1.5
2
2.5
3
Underlying Mean Difference
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity

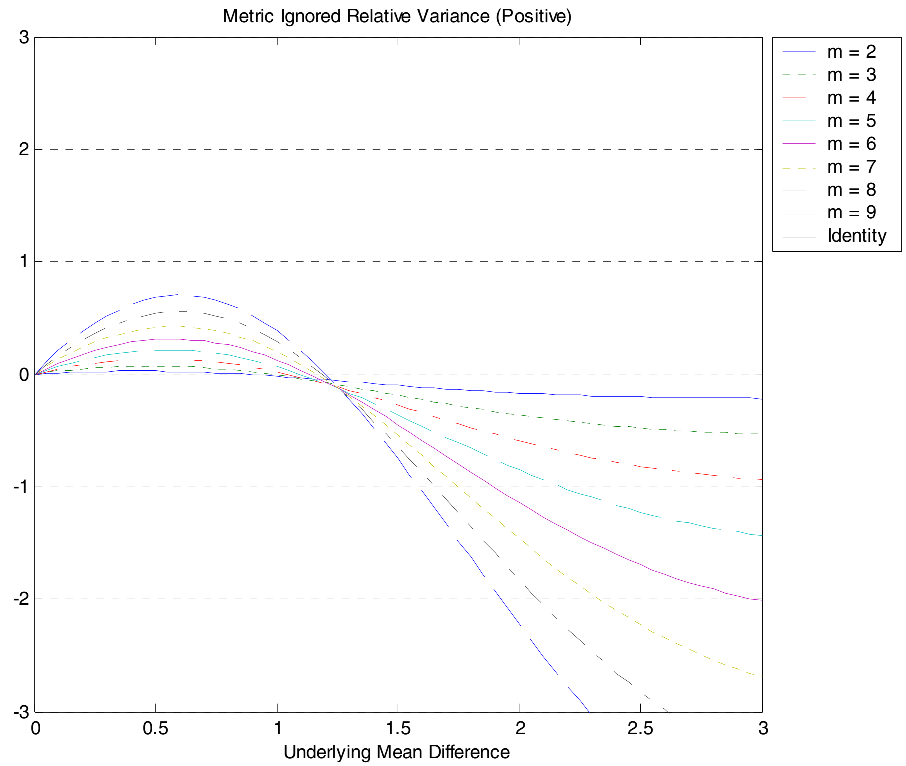


Metric Ignored Ratio of Relative Mean (Negative)
4
3
2
1
0
-1
-2
0
0.5
1
1.5
2
2.5
3
Underlying Mean Difference
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity

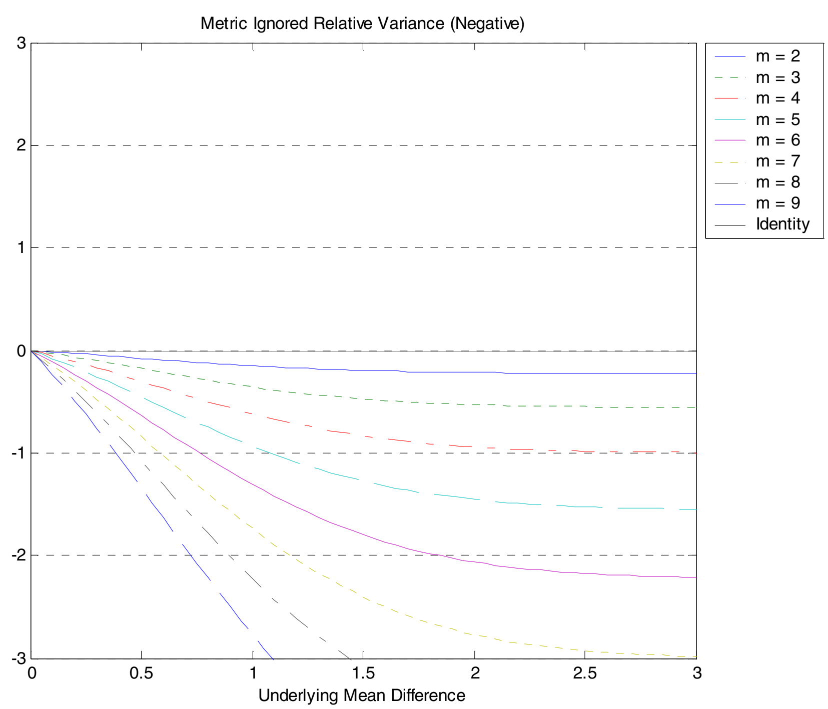
IM option Relative Variance Bias Graph





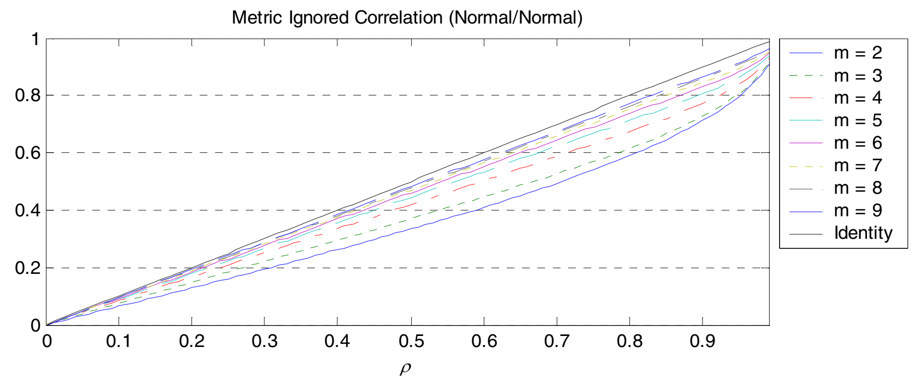


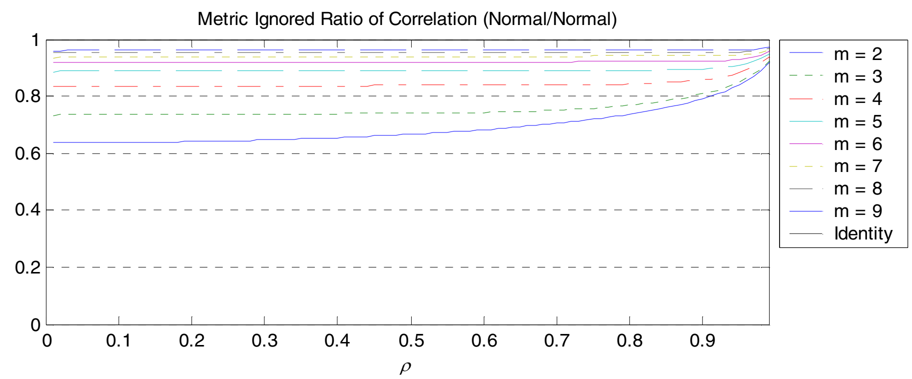
Metric Ignored Relative Variance (Positive)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
3
2
1
0
-1
-2
-3
0
0.5
1
1.5
2
2.5
3
Underlying Mean Difference

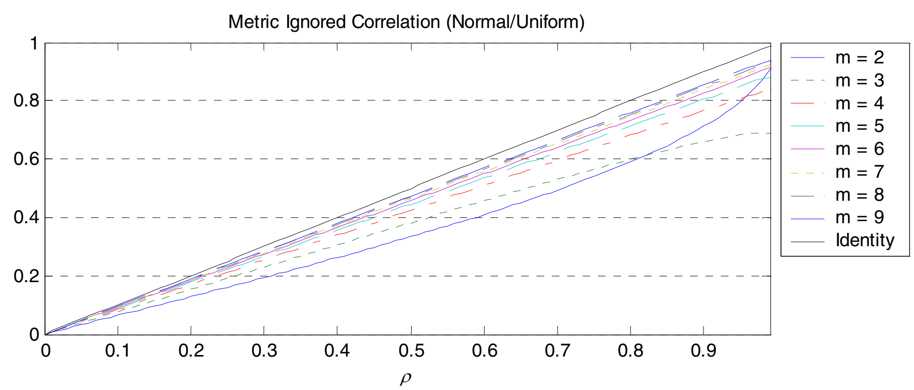


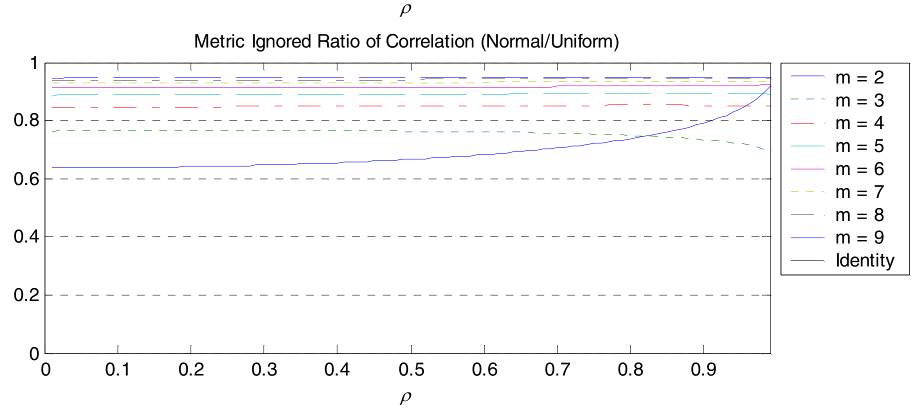
Metric Ignored Relative Variance (Negative)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
3
2
1
0
-1
-2
-3
0
0.5
1
1.5
2
2.5
3
Underlying Mean Difference

IM option Correlation Bias Graph

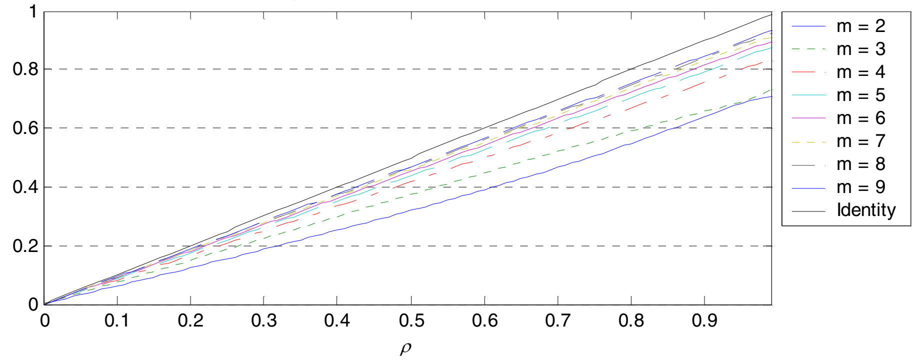




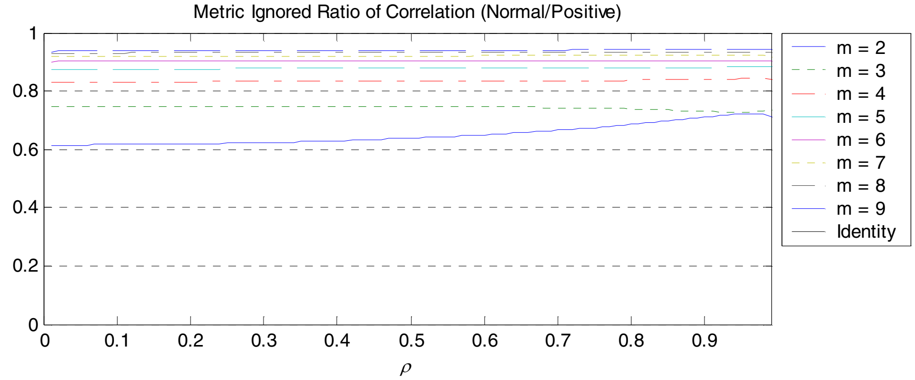




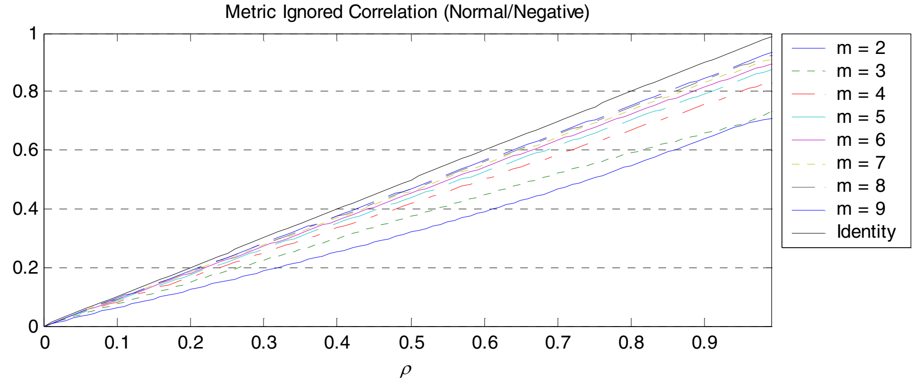
Metric Ignored Correlation (Normal/Positive)



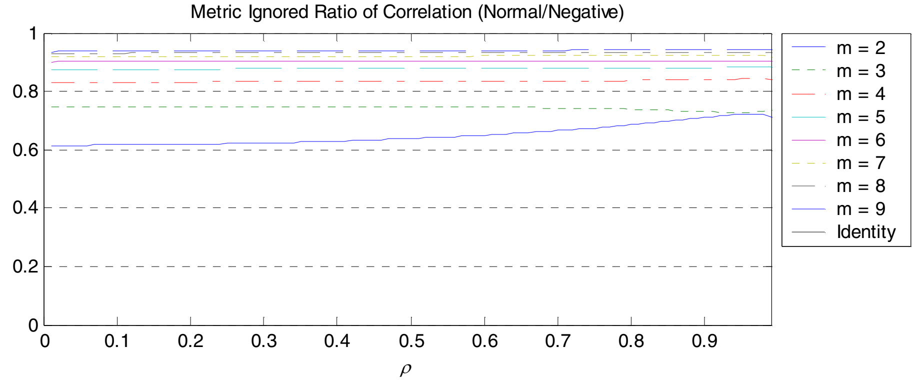
Metric Ignored Ratio of Correlation (Normal/Positive)

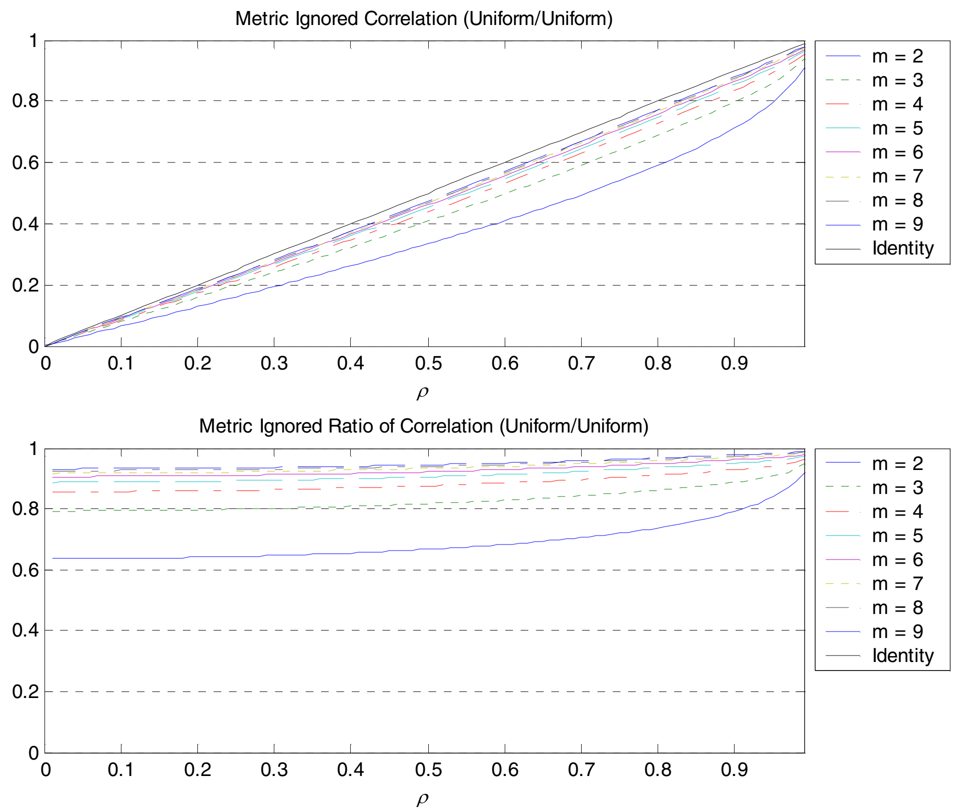


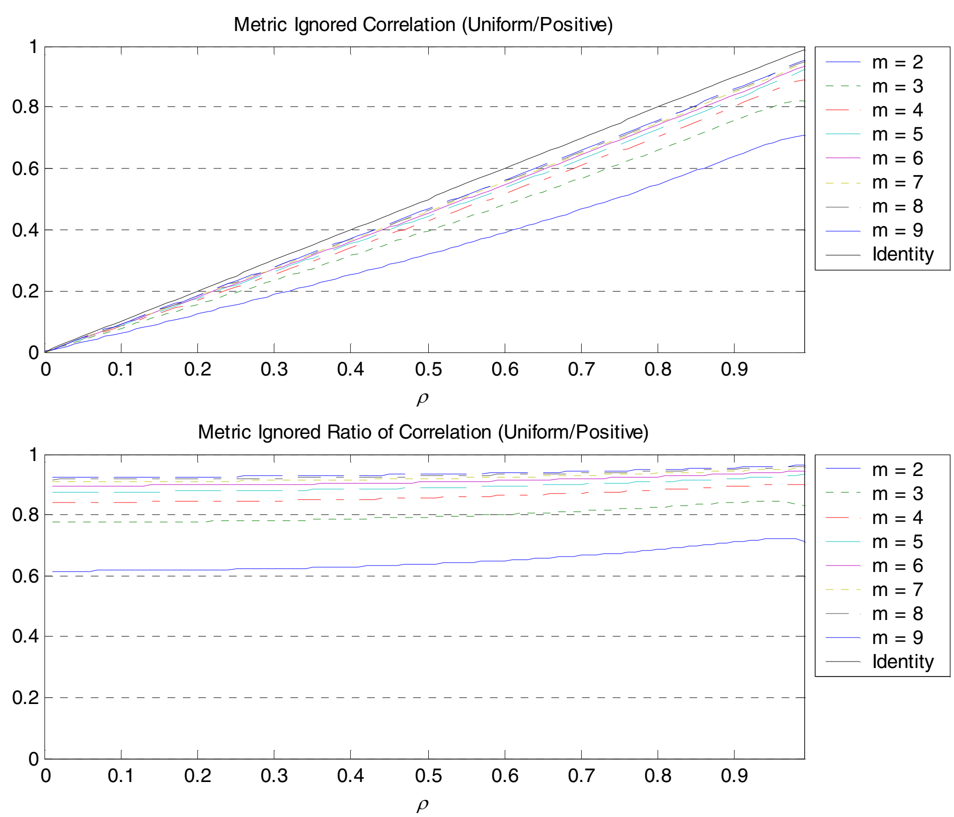
Metric Ignored Correlation (Normal/Negative)

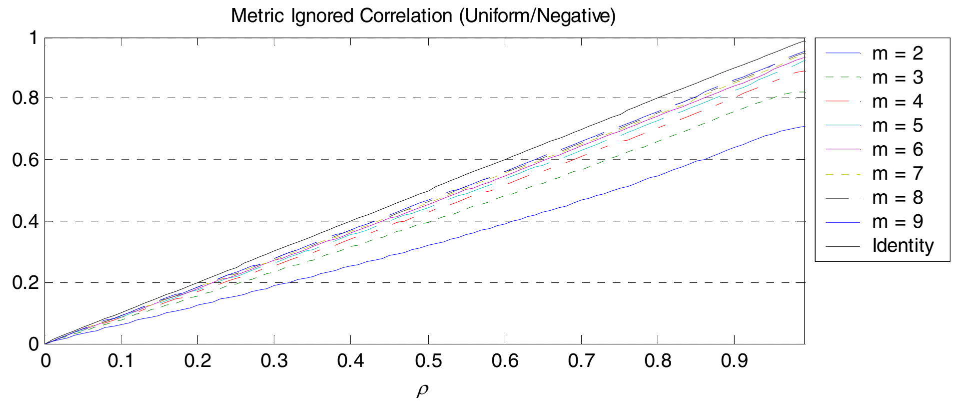


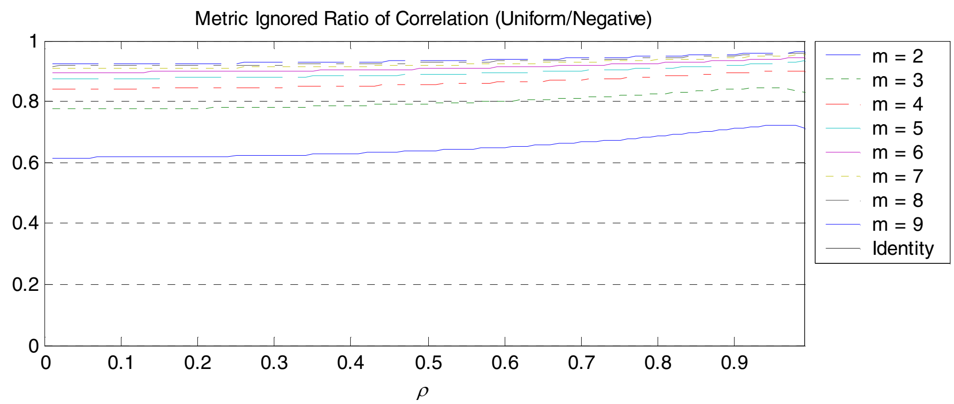
Metric Ignored Ratio of Correlation (Normal/Negative)

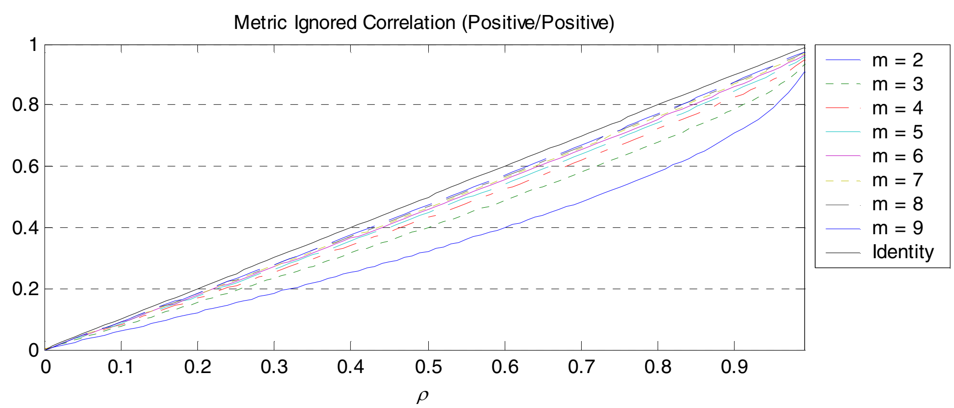


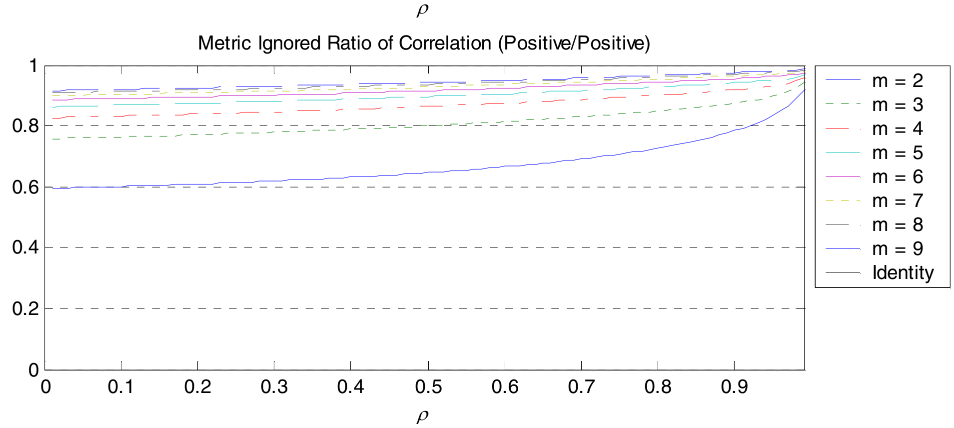

Metric Ignored Correlation (Uniform/Uniform)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ
Metric Ignored Ratio of Correlation (Uniform/Uniform)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ

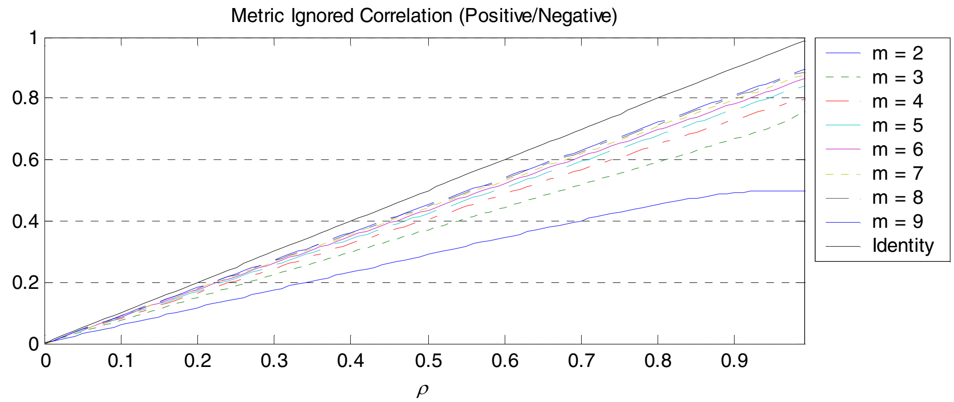

Metric Ignored Correlation (Uniform/Positive)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ
Metric Ignored Ratio of Correlation (Uniform/Positive)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ

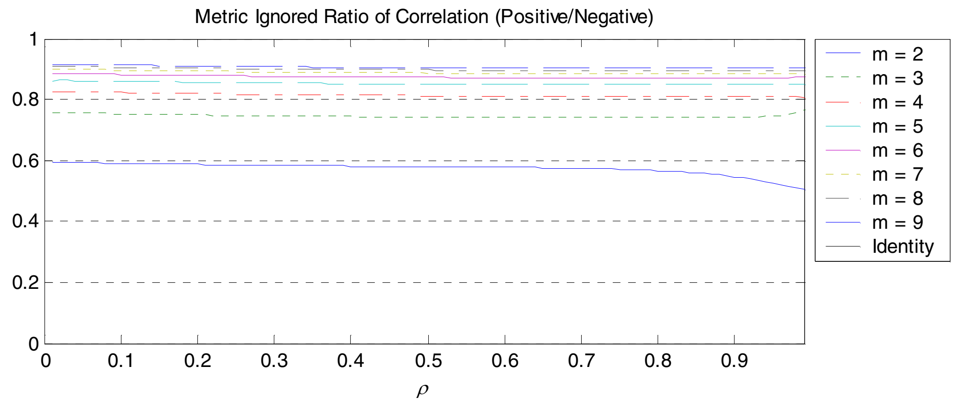

Metric Ignored Correlation (Uniform/Negative)
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
ρ
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity

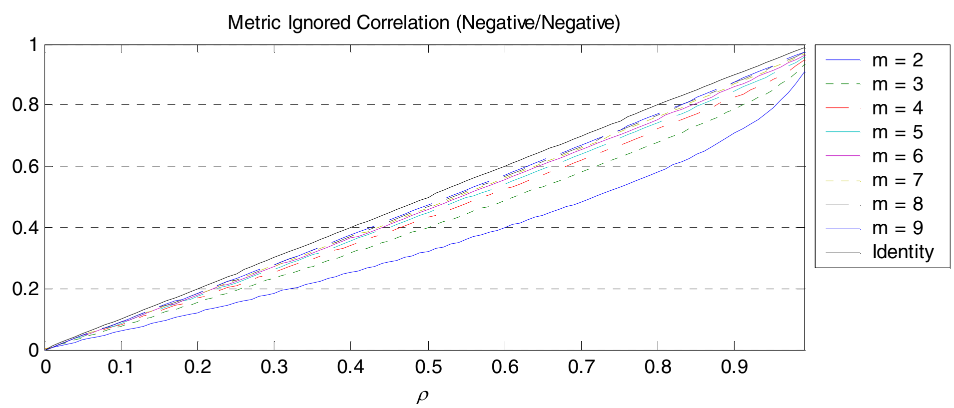

Metric Ignored Ratio of Correlation (Uniform/Negative)
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
ρ
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity

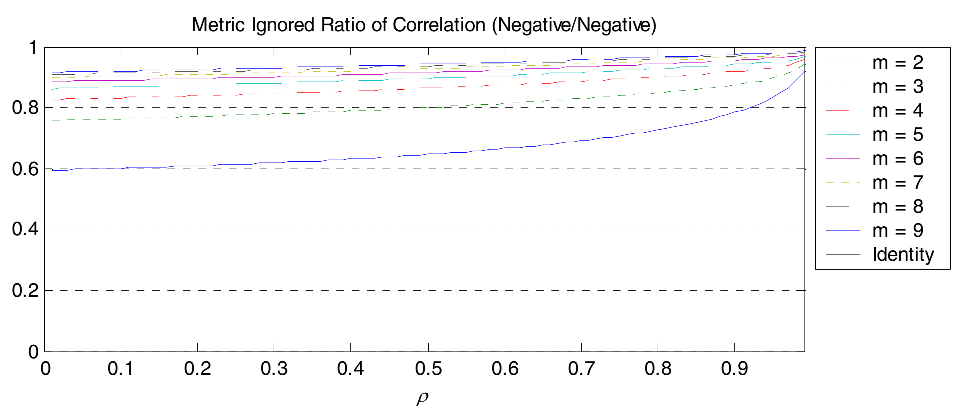

Metric Ignored Correlation (Positive/Positive)
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
ρ
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity


Metric Ignored Ratio of Correlation (Positive/Positive)
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
ρ
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity


Metric Ignored Correlation (Positive/Negative)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ


Metric Ignored Ratio of Correlation (Positive/Negative)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ


Metric Ignored Correlation (Negative/Negative)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ


Metric Ignored Ratio of Correlation (Negative/Negative)
m = 2
m = 3
m = 4
m = 5
m = 6
m = 7
m = 8
m = 9
Identity
ρ

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