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The robustness of Rasch true score preequating to violations of model assumptions under equivalent and nonequivalent populations

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The Robustness of Rasch True Score Preequating to Violations of Model Assumptions Under Equivalent and Nonequivalent Populations

by

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DEDICATION

I dedicate this dissertation to my parents and to my wife. I dedicate this work to my parents for their loving support and encouragement. They gave me a wonderful upbringing, a stable home, and an enduring faith. I have been very fortunate indeed to have been raised and cared for by such fine people. My parents instilled in me an appreciation and respect for truth and a love for learning. For this, I am deeply grateful.

I also dedicate this dissertation to my wife. For me, this dissertation represents the culmination of six years of course work and thousands of hours of labor conducting the dissertation study; for my wife, this dissertation represents countless personal sacrifices on my behalf. Completing a doctoral degree certainly requires much from the spouse of a student. Our situation was no exception. The demands of full time employment and course work at times left little of me to give to my wife and daughter; nonetheless, my wife fulfilled her roles of wife, mother, and, most recently, employee without complaint. She has remained steadfastly supportive, both in words and in deeds, through my entire graduate education experience. Clearly this dissertation is an accomplishment I share with my family, without which I would neither have had the inspiration to start, nor the wherewithal to complete.

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ABSTRACT

This study examined the feasibility of using Rasch true score preequating under violated model assumptions and nonequivalent populations. Dichotomous item responses were simulated using a compensatory two dimensional (2D) three parameter logistic (3PL) Item Response Theory (IRT) model. The Rasch model was used to calibrate difficulty parameters using two methods: Fixed Parameter Calibration (FPC) and separate calibration with the Stocking and Lord linking (SCSL) method. A criterion equating function was defined by equating true scores calculated with the generated 2D 3PL IRT item and ability parameters, using random groups equipercentile equating. True score preequating to FPC and SCSL calibrated item banks was compared to identity and Levine's linear true score equating, in terms of equating bias and bootstrap standard errors of equating (SEE) (Kolen & Brennan, 2004). Results showed preequating was robust to simulated 2D 3PL data and to nonequivalent item discriminations, however, true score equating was not robust to guessing and to the interaction of guessing and nonequivalent item discriminations. Equating bias due to guessing was most marked at the low end of the score scale. Equating an easier new form to a more difficult base form produced negative bias. Nonequivalent item discriminations interacted with guessing to magnify the bias and to extend the range of the bias toward the middle of the score distribution. Very easy forms relative to the ability of the examinees also produced substantial error at the low end of the score scale. Accumulating item parameter error in the item bank increased the SEE across five forms. Rasch true score preequating produced less equating error than Levine's true score linear equating in all simulated conditions. FPC with Bigsteps performed as well as separate calibration with the Stocking and Lord linking method. These results support earlier findings, suggesting that Rasch true score preequating can be used in the presence of guessing if accuracy is required near the mean of the score distribution, but not if accuracy is required with very low or high scores.

CHAPTER ONE

INTRODUCTION

Equating is an important component of any testing program that produces more than one form for a test. Equating places scores from different forms onto a single scale. Once scores are on a single scale, scores from different forms are interchangeable (Holland & Dorans, 2006; Kolen & Brennan, 2004). This permits standards defined on one test form to be applied to other forms, permitting classification decisions to be consistent and accurate across forms. Without equating, scores from different forms would not be interchangeable, scores would not be comparable, and classification decisions made across forms would not be consistent or accurate. For this reason, equating is critically important to testing programs that use test scores for the measurement of growth and for classifying examinees into categories. When equating is properly performed, scores and the decisions made from them can be consistent, accurate, and fair.

This study compares one type of equating, preequating, to conventional equating designs in terms of random and systematic equating error. Preequating differs from conventional equating in that preequating uses predicted scores rather than observed scores for equating purposes. Preequating is especially useful for testing programs that need to report scores immediately at the conclusion of a test. Preequating has a research history of mixed results. The purpose of this study is to determine the limitations of preequating under testing conditions that past researchers have found to affect preequating.

Organization of the Paper

Chapter one is an introduction to the topic of equating and the purpose of the study. An explanation of the research problem, a rationale for the research focus, and the research questions are provided. Chapter Two presents a literature review of relevant research, and, as a whole, provides support for the research questions. Chapter Three presents the chosen research design, measures, manipulated factors, simulation design, and data analysis. Chapter four presents the results of the simulation study. Chapter five presents a discussion of the results and provides recommendations to practitioners.

The research questions that are being addressed by this study are relevant to a wide range of professionals that span the spectrum of test developers, psychometricians, and researchers in education, certification, and licensing fields. The audience for this study includes anyone who wants to know the practical limitations of preequating. This study is particularly relevant to those who use dichotomously scored tests and who desire to preequate on the basis of small sample sizes of 100 to 500 examinees per test form. Psychometricians who need additional guidance in evaluating the appropriateness of preequating to a calibrated item pool for their particular testing program should find this study informative. This paper has been written for a professional and academic audience that has minimal exposure to test equating.

Preview of Chapter One

Given the technical nature of the research questions of this study, I devote the introductory chapter to presenting the conceptual background of the study. First, I provide an overview of equating, including the rationale of equating and preequating. I then discuss scores that are used in equating, including true scores, equated scores, and scale scores. After providing an explanation of scores used in equating, I present the rationale, purpose, and questions of the research study. A list of psychometric terms used throughout this paper is provided at the end of Chapter One.

Rationale for Equating

When test forms are used with high stakes tests, cheating is a continual threat to the validity of the test scores. Cheating has many undesirable consequences including a reduction of test reliability, test validity, and an increase in false positive classifications in criterion referenced tests (Cizek, 2001). In an effort to combat cheating and the learning of items, testing programs track, limit, and balance the exposure of items. Testing programs often strive to create large item banks to support the production of multiple *alternate forms*, so that new items are continually being introduced to the would-be cheater. Alternate forms are forms that have equivalent content and are administered in a standardized manner, but are not necessarily equivalent statistically (AERA, APA, & NCME, 1999).

Even though efforts are made to make alternate test forms as similar as possible, small differences in form difficulty appear across forms. When the groups taking two forms are equivalent in ability, form differences manifest as differences in *number correct (NC) raw scores*. Number correct scores are calculated by summing the scored responses. If the differences in form difficulty are ignored, the NC raw score of individual examinees to some degree depends on the particular form they received. Easier forms increase NC raw scores, while more difficult forms lower NC raw scores of an equivalent group. In tests that produce pass/fail decisions, these small changes in form difficulty increase classification error. Therefore, the percentage of examinees passing a test to some degree depends on the particular form taken. Easier forms increase the percent passing, while more difficult forms lower the percent passing of equivalent groups. In real testing situations, groups of examinees are usually not equivalent unless care is taken to control for differences in ability between groups. Without controlling test form equivalence and population equivalence, group ability differences and test form difficulty differences become confounded (Kolen & Brennan, 2004). Resulting NC raw scores depend on the interaction of ability and test form difficulty, rather than solely on the ability of an examinee.

To prevent the confounding of group ability and test form difficulty, psychometricians have developed a large number of *data collection designs*. An equating data collection design is the process by which test data are collected for equating, in such a way that ability differences between groups taking forms can be controlled. Some designs, such as the *random groups design*, control ability differences through random assignment of forms to examinees. The random groups design can be considered an example of an *equivalent groups design* (Von Davier, Holland, & Thayer, 2004), because the method produces groups of equivalent ability, thereby disconfounding ability differences from form differences in NC raw scores. Other data collection designs control for ability differences across forms through statistical procedures. For instance, in linear equating under the *common item nonequivalent groups* design (CINEG), examined in this study, common items are used across forms to estimate the abilities of the two groups, allowing ability and form differences to be disconfounded. Additional equating data collection designs are presented in Chapter Two.

While there are few equating designs, there are many *equating methods*. An equating method is a mathematical procedure that places NC raw scores from one alternate form onto the scale of another form, such that the scores across forms are interchangeable. Equating methods are based on Classical True Score Theory (CTT) or Item Response Theory (IRT). With the exception of *identity equating,* which assumes scores from two forms are already on the same scale, equating methods work by aligning the relative position of scores within the distribution across forms using a select statistic. For instance, in equivalent groups mean equating, it is assumed that the mean NC score on a new form is equivalent to the mean NC score on the base form. The equating relationship between the mean NC scores is applied to all scores (Kolen & Brennan, 2004). In equivalent groups linear equating, *z scores* are used as the basis of aligning scores (Crocker & Algina, 1986). Z scores are obtained by subtracting each NC raw score from the mean raw score and dividing by the standard deviation. In linear equating, a z score of 1 is assumed to be equivalent to a z score of 1 on the base form. Linear equating assumes that a linear formula can explain the equating relationship, hence, the magnitude of the score adjustments vary across the score continuum. In equivalent groups equipercentile equating, percentiles are used to align scores (Crocker & Algina, 1986). Under this equating method, the new form score associated with the 80th percentile, for example, is considered to be equivalent to the score associated with the 80th percentile on the base form. Equipercentile equating produces a curvilinear function. In IRT true score equating, estimates of the latent ability, *theta,* are used to align scores. In IRT true score equating, a NC raw score associated with a theta estimate of 2.2 on the new form is assumed to be equivalent to a NC raw score associated with a theta estimate of 2.2 on the base form. Like equipercentile equating, IRT equating produces a curvilinear function.

Scores Used in Equating

The most commonly used score for equating is the NC raw score (Crocker & Algina, 1986; Kolen & Brennan, 2004). NC raw scores are often preferred over formula scores because of their simplicity. Examinees have little trouble understanding the meaning of raw scores. Even in many IRT applications that produce estimates of the latent ability distribution theta, NC raw scores are often used rather than thetas. An equating process places NC raw scores of a new form onto the scale of the base form. These equated scores are referred to as *equivalent raw scores*. An equivalent raw score for a new form is the expected NC raw score of a given examinee on the base form. Equivalent raw scores are continuous measures, and can be rounded to produce rounded equivalent raw scores. Rounded equivalent raw scores can be used for reporting purposes; however, Kolen and Brennan report that examinees tend to confuse rounded equivalent raw scores with NC raw scores (2004).

To prevent the confusion of rounded equivalent raw scores with NC raw scores, testing organizations prefer to use a *primary scale.* A primary scale is designed expressly for reporting scores to examinees. Equivalent raw scores from any number of forms can be placed on the primary scale. The end result is scale scores that are completely interchangeable, regardless of what form the score originated from. Just like rounded equivalent scores, scale scores permit examinee scores to be compared regardless of what form the scores originated from; however, there is less risk that examinees will confuse the NC raw score with the scale score. Another benefit to using a primary scale score rather than a rounded equivalent raw score, is that fact that normative information and content information can be integrated into a primary scale (Kolen & Brennan, 2004).

NC raw scores are not the only type of scores that can be used for equating. In true score equating, *true scores* of examinees are equated rather than NC scores. The true score equating relationship is then applied to NC raw scores. The definition of a true score depends on the test theory used. According to CTT, a true score is defined as the hypothetical mean score of an infinite number of parallel tests administered to an examinee (Crocker & Algina, 1986). In CTT, true scores are equivalent to NC raw scores when the test is perfectly reliable. One way to estimate CTT true scores is with Kelley’s formula, which uses the reliability of the test to adjust scores toward the mean:

$$\hat{\tau} = \hat{\rho}_{xx'}x' + (1 - \hat{\rho}_{xx'})\hat{\mu} \tag{1.1}$$

Where τ = the true score,

ρ = the reliability of the form,

μ = the mean of the NC raw score, and

x = observed scores.

In IRT true score equating, true scores are estimated using item parameter estimates and latent ability estimates rather than observed scores. In the simplest IRT model, the one parameter logistic (1PL) response model, true scores are given by:

$$\hat{\tau} = \sum_{\gamma=1}^{n} [\ \frac{\exp(\theta - b_\gamma)}{1 + \exp(\theta - b_\gamma)}\ ] \tag{1.2}$$

Where θ = the latent ability estimate,

b = the item difficulty parameter of item γ,

exp = the exponent.

According to the 1PL model, or Rasch model, a true score is the sum of the probabilities of a positive response for each item in a test for a person of ability θ. IRT true scores can be estimated using item parameter estimates and ability estimates. However, before true scores can be equated, the item parameter estimates themselves, must be 'equated', or placed on the same scale. For this reason, IRT preequating is sometimes referred to as *item preequating* (De Champlain, 1996; Kolen & Brennan, 2004). The process of estimating item parameters and placing the item parameter estimates onto the same scale is also known as *calibrating* the items (Kolen & Brennan, 2004). Items that have been preequated to an item bank form a calibrated item pool. IRT true score equating can either be performed between two forms, or between a form and a calibrated item pool. Because the probability of a positive response can be estimated for each item, items can be selected for a new form and the expected test score can be estimated in the form of a true score, even though the entire form has not been administered.

While IRT does provide many benefits, including greater precision in measurement and greater flexibility in test assembly, the validity of the model rests on the satisfaction of model assumptions. Violations of these assumptions may render IRT equating less effective than CTT equating. For this reason, this study simulated item responses using a two dimensional (2D) three parameter (3PL), IRT model (Reckase, Ackerman, & Carlson, 1988). The 2D 3PL IRT model specifies item discrimination parameters, difficulty parameters, and guessing parameters for two abilities. This means that the probability of a positive response to an item is a function of the item's discrimination, it's difficulty, and the likelihood of the examinee to guess, given the examinee's ability in two knowledge domains. The type of multidimensional data modeled in this study was a *compensatory* model. Compensatory models allow high scores on one ability to compensate for low scores on a second ability. The performance of the Rasch model, a unidimensional (1D) 1PL IRT model, after it has been fit to data that was simulated by a 2D 3PL compensatory IRT model, indicates the robustness of the model to model violations.

Rationale for True Score Preequating to a Calibrated Item Pool

True score preequating to a calibrated item pool differs from traditional equating in two respects: first, forms are equated prior to the administration of the test using true scores derived from previously estimated item parameters; second, once items have been placed onto the scale of the items in the item bank, any combination of items that satisfy the test specifications can be preequated. These features of preequating with a calibrated item pool minimize time and labor costs because they provide greater flexibility in test assembly, do not require complex form to form linking plans, and provide for more control of item exposure (Table 1). The flexibility in test assembly is made possible because common items for a new form can be sampled from any prior forms in the pool and joined together in a new form (Kolen & Brennan, 2004). This flexibility maximizes control over item exposure. In the event that items are exposed, preequating to a calibrated item pool provides flexibility in assembling new forms. As previously mentioned, preequating allows for the reporting of test scores immediately following a test administration, which is ideal for fixed length computer based tests (CBT). In contrast to computer adaptive testing, preequating permits forms to be assembled and screened by subject matter experts to ensure that items do not interact in unexpected ways. Preequating with a calibrated item pool is an ideal equating solution for fixed length CBTs.

Table 1. Form to Form Equating Versus Preequating to a Calibrated Item Pool

Form to Form Equating	Preequating to a Calibrated Item Pool
Requires more time after a test administration to equate and produce scores	Provides scores at the conclusion of a test
Requires complex linking plans to ensure that common items are imbedded in each form	Permits the use of items from any prior forms to be used for linking purposes
Common items tend to become overexposed	The freedom to select any items from prior forms helps to minimize item exposure
If common items are compromised new linking plans must be constructed	If items are compromised new forms can be easily assembled

Using the Rasch model rather than the 2 parameter logistic model (2PL) or the 3 parameter logistic model (3PL) provides three unique benefits. First, the Rasch model produces 'sufficient' statistics, thereby not requiring the entire response string to calculate an ability estimate as in the 2PL or 3PL models (Bond & Fox, 2001; Kolen & Brennan, 2004). This makes the model easier to understand for staff, stakeholders, and examinees. Second, equating under the Rasch model can work effectively with as few as 400 examinees, whereas the 3PL model needs approximately 1500 examinees (Kolen & Brennan, 2004). Third, the Rasch model produces parallel item characteristic curves. This means that the relative item difficulty order remains constant across different levels of ability. One consequence of this is that a single construct map can be produced for all ability levels. A construct map visually describes items and ability estimates on the same scale. Producing one construct map for all ability levels is possible only if the order of item responses is consistent across ability levels, and the order of respondents remains the same for all item responses (Wilson, 2006). For these reasons, the Rasch model is an attractive model to use for criterion referenced tests that have small sample sizes of 500 examinees.

While the Rasch model does provide many benefits, it does come with a high price tag. The Rasch model assumes equivalent item discriminations and items with little or no guessing (Hambleton & Swaminathan, 1985). Considerable resources can be expended during the test development and item writing process to create items that conform to these assumptions. The cost of implementing Rasch preequating could be reduced considerably if preequating was shown to be robust to moderate violations of these assumptions. Cost concerns aside, if the violations of the assumptions are too severe, Rasch preequating will likely not produce better results than equating using conventional methods.

Generally, IRT equating methods produce less equating error (Kolen & Brennan, 2004) than conventional CTT equating methods; however, IRT methods require strong assumptions that cannot always be satisfied (Livingston, 2004). As a result, equating studies are necessary to test the robustness of IRT equating methods to violations of IRT assumptions in a given testing context (Kolen & Brennan, 2004).

Statement of the Problem

There are three major threats to the viability of preequating to a calibrated item pool using the Rasch model: violations of Rasch model assumptions, nonequivalence of groups, and item parameter bias in piloted items. The Rasch model assumes unidimensionality, item response independence, no guessing, and equivalent item discriminations (Hambleton & Swaminathan, 1985). Prior research has shown that preequating is vulnerable to multidimensionality (Eignor & Stocking, 1986). The probable cause for preequating error is the presence of bias in the item parameter estimates caused by the violation of the assumption of item independence (Kolen & Brennan, 2004). It is well known that multidimensionality can bias item parameter estimates (Li & Lissitz, 2004). Eignor and Stocking (1986) discovered positive bias in difficulty parameter estimates under multidimensional data. This effect was magnified when population nonequivalence interacted with multidimensionality (Eignor & Stocking, 1986). It is rare for any test to be completely free of multidimensionality (Lee & Terry, 2004). Multidimensionality is especially common among professional certification and licensing exams where all the vital job duties of a profession are often included in one test blueprint.

The second major threat to the viability of Rasch preequating is population nonequivalence. The Rasch model has been criticized in years past for not working effectively when group ability differences are large (Skaggs & Lissitz, 1986; Williams, Pommerich, & Thissen, 1998). However, Linacre and Wright (1998), DeMars (2002) and more recently Pomplun, Omar, and Custer (2004) obtained accurate item parameter estimates when scaling vertically, i.e. placing scores from different educational grade levels onto the same scale. These researchers used the Joint Maximum Likelihood Estimation (JMLE) method. The results that favored the Rasch model were based on data that mostly satisfied the model assumptions. It is unclear how these results would have differed if the assumptions were mildly or moderately violated. If Rasch preequating is to be used with groups that differ moderately or substantially in ability, it will need to be robust to mild violations of assumptions, and to be cost-effective, robust to moderate violations.

The third major threat to the viability of Rasch preequating is the threat of obtaining biased pilot item parameter estimates. Preequating to a calibrated item bank requires that items are piloted to obtain item parameter estimates. This can be achieved by administering intact pilot tests to representative groups of examinees, or placing subsets of pilot items in operational exams. This study is focusing on the latter case, because placing pilot items in operational forms is very conducive to computer based testing. Kolen and Brennan (2004) warn of the risk that piloted items may become biased during estimation because they are not calibrated within the context of an intact test form. Prior studies have demonstrated preequating's sensitivity to item parameter instability (Du, Lipkins, & Jones, 2002) and item context effects (Kolen & Harris, 1990). Item context effects can be controlled to some degree by keeping common items in fixed locations across forms (Kolen & Brennan, 2004) and selecting stable items (Smith & Smith, 2004) that are resistant to context effects. They can also be minimized by piloting content representative sets of items rather than isolated items, which keeps the factor structure constant across all the calibrations of piloted items (Kolen & Brennan, 2004).

Another factor that may contribute to item parameter bias is the method used for calibrating items. This study contrasted fixed parameter calibration (FPC) to the commonly used method of separate calibration and linking with the Stocking and Lord method (SCSL). FPC holds previously estimated item parameters constant and uses a parameter estimation method, in this case Joint Maximum Likelihood, to estimate item parameter estimates for the new items. In contrast, SCSL finds linking constants by minimizing the difference between estimated *Test Characteristic Curves (TCCs)*. In IRT, TCCs are curves that describe the relationship between thetas and true scores. FPC is one method that can work under a preequating approach that can potentially simplify the calibration procedures because it does not require a separate linking step. It can simplify the calibration process, only if convergence problems reported by some (Kim, 2006) are not too common. Much of the prior research on FPC has focused on the software programs PARSCALE (Jodoin, Keller, & Swaminathan, 2003; Prowker, 2006), Bilog MG, Multilog, and IRT Code Language (ICL) software (Kim, 2005). All of these software programs implement Marginal Maximum Likelihood Estimation (MMLE) through the Expectation Maximization algorithm. FPC has been shown to work less effectively under nonnormal latent distributions (Paek & Young, 2005; Kim, 2005; Li, Tam, & Tompkins, 2004) when conducted with MMLE. Very little, if any, published research can be found on FPC in conjunction with Bigsteps/Winsteps which uses a Joint Maximum Likelihood Estimation method. It is unclear how well FPC will perform under a JMLE method when groups differ in ability and are not normally distributed. Data from criterion referenced tests often exhibit ceiling or floor effects, which produce skewed distributions. FPC would be the most attractive estimation method to work in a preequating design because of its ease of use; however, it is not known how biased its estimates will be under mild to moderate levels of population nonequivalence and model data misfit.

This study was conducted to evaluate the performance of Rasch preequating to a calibrated item pool under conditions that pose the greatest threat to its performance: multidimensionality, population nonequivalence, and item parameter misfit. Using FPC in conjunction with preequating would lower the costs and complexity of preequating; however, prior research has not established whether or not FPC will produce unbiased estimates under violated assumptions when estimated with JMLE.

Purpose of the Study

The purpose of this study was to compare the performance of Rasch true score preequating methods to conventional linear equating under violated Rasch assumptions (multidimensionality, guessing, and nonequivalent discrimination parameters) and realistic levels of population nonequivalence. The outcome measures of interest in this study included random and systematic error. In order to measure systematic error, a simulation study was performed. A simulation study was chosen because simulations provide a means of defining a criterion equating function from which bias can be estimated. The main goal of this study was to delineate the limits of Rasch true score preequating under the realistic test conditions of multidimensionality, population nonequivalence, item discrimination nonequivalence, guessing, and their interactions for criterion referenced tests. A secondary purpose was to compare FPC to the established method of separate calibration and linking with SCSL.

Research Questions

1. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when the IRT assumption of unidimensionality is violated, but all other IRT assumptions are satisfied? As for the preequating methods, does the FPC method perform at least as well as the SCSL method under the same conditions?

2. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when populations are nonequivalent, and IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

3. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and Linear equating) when the Rasch model assumption of equivalent item discriminations is violated, but populations are equivalent and other IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

4. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when the Rasch model assumption of no guessing is violated, but populations are equivalent and other IRT model assumptions

are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

5. How does Rasch preequating perform when response data are simulated with a three parameter, compensatory two dimensional model, the assumption of equivalent item discriminations is violated at three levels (mild, moderate, severe violations), the assumption of no guessing is violated at three levels (mild, moderate, severe), population non-equivalence is manipulated at three levels (mild, moderate, severe) and the unidimensional assumption is violated at three levels (mild, moderate, severe)?

   a. What are the interaction effects of multidimensionality, population non-equivalence, nonequivalent item discriminations, and guessing on random and systematic equating error?

   b. At what levels of interaction does Rasch preequating work less effectively than identity equating or linear equating?

   c. How does FPC compare to SCSL in terms of equating error under the interactions?

   d. Does equating error accumulate across four equatings under the interactions?

Importance of the Study

Methods do exist for estimating random error in equating; however, overreliance on estimates of random error to the neglect of systematic error can give a false sense of security since bias may pose a substantial threat to equated scores (Angoff, 1987; Kolen & Brennan, 2004). When IRT assumptions are violated, it is probable that systematic error will appear in the item parameter estimates (Li & Lissitz, 2000) which will likely increase equating error (Kolen & Brennan, 2004). Without knowing how sensitive Rasch preequating methods are to sources of systematic error such as violated assumptions, practitioners may underestimate the true amount of total error in the method.

Understanding the interaction of multidimensionality and ability differences is important to many testing applications including the study of growth, translated and adapted tests, and certification tests that administer tests to professional or ethnic groups that differ in ability. For instance, many educational testing programs designed to measure Annual Yearly Progress (AYP) utilize IRT equating. Estimates of AYP are only as accurate as the equating on which they are based. Much of the prior research on FPC has focused on Bilog MG, Multilog, Parscale, and ICL. There is little, if any, published research testing the accuracy of IRT preequating when performed with Bigsteps/Winsteps. Since Bigsteps and Winsteps are popular software programs worldwide for implementing the Rasch model, many groups could benefit from the preequating design if it is found to be robust to violations.

FPC potentially is less expensive to use than other item calibration strategies (Li, Tam, & Tomkins, 2004). This is due to the fact that FPC does not require a separate item linking process. FPC is an increasingly popular method because of its convenience and ease of implementation (Li, Tam, & Tomkins, 2004). A number of states such as Illinois, New Jersey, and Massachusetts, use FPC to satisfy No Child Left Behind (NCLB) requirements to measure AYP (Prowker, 2005). Professional certification companies use

FPC in conjunction with preequating. Few studies have examined FPC with multidimensional tests, which are common in this context. Computer adaptive testing programs use FPC (Ban, Hanson, Wang, Yi, & Harris, 2001). Previous studies have demonstrated FPC's vulnerability to nonnormal, nonequivalent latent distributions when parameters are estimated using MMLE. FPC produces biased item parameter estimates when the priors are misspecified (Paek & Young, 2006). However, I am not aware of any research to date that has examined how well FPC performs under a JMLE method with nonnormal, nonequivalent latent distributions.

Definition of Terms

Alternate forms- Alternate forms measure the same constructs in similar ways, share the same purpose, share the same test specifications, and are administered in a standardized manner. The goal of creating alternate forms is to produce scores that are interchangeable. In order to achieve this goal, alternate forms often have to be equated. There are three types of alternate forms: parallel forms, equivalent forms, and comparable forms, the latter two require equating (AERA, APA, NCME, 1999).

Calibration- In linking test score scales, the process of setting the test score scale, including mean, standard deviation, and possibly shape of the score distribution, so that scores on a scale have the same relative meaning as scores on a related scale (AERA, APA, NCME, 1999). In IRT item parameter estimation, calibration refers to the process of estimating items from different test forms and placing the estimated parameters on the same theta scale. Once item parameters have been estimated and placed on the same scale as a base form or item bank, the item parameters are said to be calibrated (Kolen & Brennan, 2004).

Common Item Nonequivalent Groups Design- Two forms have one set of items in common. Different groups (nonequivalent groups) are given both tests. The common items are used to link the scores from the two forms. The common items can be internal, which are used in the arriving at the raw score or external to the test, which are not used in determining the raw score.

Comparable forms- Forms are highly similar in content, but the degree of statistical similarity has not been demonstrated (AERA, APA, NCME, 1999).

Equating- The process of placing scores from alternate (equivalent) forms on a common scale. Equating adjusts for small differences in difficulty between alternate forms (AERA, APA, NCME, 1999). "Equating adjusts for differences in difficulty, but not differences in content" (Kolen & Brennan, 2004).

Equating data collection design- An equating data collection design is the process by which test data are collected for equating, such that ability differences between groups can be controlled (Kolen & Brennan, 2004).

Equipercentile equating- Equipercentile equating produces equivalent scores with equivalent groups by assuming the scores associated with percentiles are equivalent across forms (Kolen & Brennan, 2004).

Equivalent forms (i.e., equated forms)- Small dissimilarities in raw score statistics are compensated for in the conversions to derived scores or in form-specific norm tables. The scores from the equated forms share a common scale (AERA, APA, NCME, 1999).

External- In the context of common item nonequivalent groups design, common (anchor) items that are used to equate test scores, but that are not used to calculate raw scores for the operational test (Holland & Dorans, 2006).

Identity equating- This equating method assumes that scores from two forms are already on the same scale. Identity equating is appropriate when alternate test forms are essentially parallel.

Internal- In the context of common item nonequivalent groups design, common (anchor) items that are used to equate and to score the tests (Holland & Dorans, 2006).

IRT preequating- See preequating

Item Characteristic Curve (ICC)- In IRT, an ICC relates the theta parameter to the probability of a positive response to a given item.

Item preequating- See preequating

Item Response Theory (IRT)- A family of mathematical models that describe the relationship between performance on items of a test and level of ability, trait, or proficiency being measured usually denoted θ. Most IRT models express the relationship between an item mean score and θ in terms of a logistic function which can be represented visually as an Item Characteristic Curve (AERA, APA, NCME, 1999).

Linear equating- Linear equating uses a linear formula to relate scores of two forms. It accomplishes equating by assuming z scores across forms are equivalent among equivalent groups.

Linking (i.e., linkage)- Test scores and item parameters can be linked. When test scores are linked, multiple scores are placed on the same scale. All equating is linking, but not all linking is equating. When linking is performed on scores derived from test forms that are very similar in difficulty, then this type of linking is considered an equating. When linking is done to tests that differ in content or difficulty or if the populations of the groups differ greatly in ability, then this type of linkage is not considered an equating (Kolen & Brennan, 2004). When item parameter estimates are linked, parameters are placed on the same calibrated theta scale. Kolen and Brennan also refer to this process as item preequating (2004).

Mean equating- Mean equating assumes that the relationship between the mean raw scores of two forms given to equivalent groups defines the equating relationship for all scores along the score scale.

Parallel forms (i.e., essentially parallel)- Test versions that have equal raw score means, equal standard deviations, equal error structures, and equal correlations with other measures for any given population (AERA, APA, NCME, 1999).

Preequating- The process of using previously calibrated items to define the equating function between test forms prior to the actual test administration.

Random equating error- see standard error of equating.

Scaling- Placing scores from two or more tests on the same scale (Linn, 1993). See linking.

Standard error of equating- The standard error of equating is defined as the standard deviation of equated scores over hypothetical replications of an equating procedure in samples from a populations of examinees. It is also an index of the amount of equating error in an equating procedure. The standard error of equating takes the form of random error, which reduces as sample size increases. In contrast, systematic error will not change as sample size increases.

Systematic equating error- Equating error that is not affected by sample size, usually caused by a violation of a statistical assumption of the chosen equating method or psychometric model.

Test Characteristic Curve (TCC)- In IRT, a TCC relates theta parameters to true scores.

Test specifications- Formally defined statistical characteristics that govern the assembly of alternate test forms.

Transformation- See linking

True Score- An examinee's hypothetical mean score of an infinite number of test administrations from parallel forms. If the reliability of a form was perfect, then the true score and raw scores are equivalent. As reliability reduces, true scores and raw scores diverge. Given the relationship between raw scores, true scores, and test reliability, regression can be used to estimate the true score within a Classical True Score theory point of view. Item Response Theory also provides models that can estimate true scores.

CHAPTER TWO

LITERATURE REVIEW

Chapter Two is divided into five sections. The first section provides a brief overview of the relationship between linking and equating. Section one clarifies many concepts that are closely related to equating but differ in important ways, giving a needed context to the remainder of the chapter. The second section provides a review of three data collection designs for equating methods. Reviewing all three designs provide the historical and theoretical basis for the design used in this study. The third section presents the equating methods utilized in this study, including formulas and procedures. The fourth section reviews the factors that affect equating effectiveness, including findings and gaps in the literature concerning preequating. The final section summarizes the literature review.

Equating in the Context of Linking

Equating is a complex and multifaceted topic. Equating methods and designs have been developed and researched intensely for many decades. Efforts have been made in years past to better delineate equating from other closely related concepts. Currently, there are at least two classification schemes that attempt to organize equating and related topics. The first is the Mislevy/Linn Taxonomy (Mislevy, 1992). The second is a classification scheme adopted by the National Research Council for their report *Uncommon Measures: Equivalence and linkage among educational tests* (Feuer, Holland, Green, Bertenthal, & Hemphill, 1999). Holland and Dorans present an introduction to linking and equating in the latest edition of *Educational Measurement* which provides a useful summary of the many concepts shared in the two classification schemes (Holland & Dorans, 2006).

Holland and Dorans divide linking into three types: prediction, scale alignment, and test equating. They define a link as a transformation of a score from one test to another (Holland & Dorans, 2006). What follows is a brief overview of their classification scheme. The reader is encouraged to read the full article for a more complete description of the scheme.

Prediction

The purpose of prediction is to predict Y scores from X scores. The relationship between form Y and form X scores is asymmetric. For instance, a regression equation does not equal its inverse. Typically, observed scores are used to predict expected scores from one test to a future test. An example of an appropriate use of predicting observed scores is predicting future SAT scores from PSAT scores (Holland & Dorans, 2006). In addition to predicting Y observed scores from form X scores, one can also predict Y true scores from form X scores. Kelley provided a formula to predict form Y true scores from form Y observed scores. Later this formula was modified to predict form Y true scores from form X observed scores (Holland & Dorans, 2006).

Scale Alignment

When form X and Y measure different constructs or are governed by different test specifications scale aligning can be employed to place the scores onto the same scale. When the scores from form Y and X come from the same population, aligned scores are referred to as comparable scores, comparable measures (Kolen & Brennan, 2004), or comparable scales (Holland & Dorans, 2006). When scores from form Y and X come from different populations the terms anchor scaling (Holland & Dorans, 2006), statistical moderation, or 'distribution matching' (Kolen & Brennan, 2004) are used. An example of statistical moderation is an attempt to link translated or adapted tests. Even if the translated test consists of the same items as those in the original language, the constructs may not be equivalent across cultures. In addition, the abilities of language groups probably differ (Kolen & Brennan, 2004).

Vertical scaling is a type of scale alignment that is performed when constructs and reliabilities of form X and Y scores are similar, but the groups being linked come from different populations or are very different in ability (Kolen & Brennan, 2004). The most common use of vertical scaling is placing the scores of students across many grades onto the same scale. It should be noted that it is common for researchers to use the phrase 'vertical equating' to describe vertical scaling. Tests designed for different grades that share common items, would not qualify as equating, because a requirement of equating is that the forms should be made as similar as possible (Kolen & Brennan, 2004). Equating adjusts for small differences in form difficulty (AERA, APA & NCME, 1999). Tests designed for vertical scaling are often assembled to be very different in difficulty to match the ability levels of various groups.

When form X and Y scores measure similar constructs, have similar reliabilities, similar difficulties, and the same population of examinees, but different test specifications, then the only appropriate type of scale aligning that can be performed is a concordance (Holland & Dorans, 2006). Concordances can be made of two similar tests that were not originally designed to be equated. A common example of this type of scale alignment is relating SAT scores to ACT scores. It is important to note that none of the examples of scale aligning presented here produce equivalent scores, a designation reserved for test equating.

Test Equating

The Standards for Educational and Psychological Testing define equating as, "The process of placing scores from alternate forms on a common scale. Equating adjusts for small differences in difficulty between alternate forms (AERA, APA, NCME, 1999)". In order for the results of an equating procedure to be meaningful a number of requirements must be satisfied. The requirements of equated scores include symmetry, equal reliabilities, interchangeability or equity, similar constructs, and population invariance (Angoff, 1971; Kolen & Brennan, 2004; Holland & Dorans, 2006).

Symmetry refers to the idea that the equating relationship is the same regardless if one equates from form X to form Y or vice versa. This property supports interchangeability, the idea that an examinee's score should not depend on which form he/she takes. It should be noted that these forms should be interchangeable across time or location. If the items in an item bank become more and more discriminating over time, there is a possibility that test forms constructed from such items may become more and more reliable. Ironically, improving a test too much may work against equating to some extent. The implication to testing programs that plan to equate forms across many years is to ensure that the initial item pool is robust enough to support a high level of reliability, because the reliability of the test should not improve or degrade.

Interchangeability is also supported by the concept of equal reliabilities, for if one equated form had more or less reliability, the performance of the examinee may depend on which form is taken. For instance, lower performing examinees may benefit from less reliable tests (Holland & Dorans, 2006).

Population invariance requires that the equating relationship hold across subgroups in the population, otherwise, subgroups could be positively or negatively affected. The concern in population invariance of equating functions usually focuses on ethnic groups who perform below the majority group (De Champlain, 1996).

Finally, similar constructs are required of two equated forms to ensure that the meaning of scores is preserved. This requirement implies that equating is intolerant of changing content. If the content of a test changes too much, a new scale and cut score may have to be defined. Some other type of linking, other than equating, could then be used to relate the new scale to the prior scale.

There are a number of requirements of equating that are not altogether required of other forms of linking. Equating requires that forms are similar in difficulty, with similar levels of reliability, high reliability, similar constructs, proper quality control, and identical test specifications (Dorans, 2004; Kolen & Brennan, 2004).

A distinction should be made between vertical and horizontal equating. Horizontal equating refers to equating that occurs between groups of very similar ability, while vertical equating refers to equating that occurs between groups that have different abilities. An example of horizontal equating is the equating of scores from a well defined population, such as graduates from a specific graduate school program. Such examinees are expected to be similar in ability. An example of vertical equating is the equating of forms from a majority group and a minority group, in which the minority group has a different ability distribution than the majority group.

Summary of Linking and Equating

Equating is distinguished from other forms of linking in that equating is the most rigorous type of linking, requiring forms similar in difficulty, with similar levels of reliability, high reliability, similar constructs, and identical test specifications (Dorans, 2004). Equated forms strive to exemplify the ideal psychometric qualities of symmetry, equal reliabilities, interchangeability, similar constructs, and population invariance. When these ideals are met, the goal of equating is achieved: test scores from two forms are interchangeable (Von Davier, Holland, & Thayer, 2004). Kolen and Brennan (2004) stress that equating cannot adjust for differences in content, only differences in difficulty. Vertical scaling and vertical equating are similar in that they both relate scores from groups that differ in ability. However, vertical scaling is distinguished from vertical equating in that equating relates forms that are very similar in difficulty and vertical scaling relates forms that are very different in difficulty. What follows next is an explanation of the data collection designs that can be used for equating.

Data Collection Designs for Equating

As mentioned previously, there are a number of ways to prevent the confounding of group ability and test form difficulty. An equating data collection design is the process by which data are collected to ensure that group ability and test form difficulty are disconfounded, allowing forms to be equated (Holland & Dorans, 2006). In the literature one can find at least three designs commonly employed to collect data for equating (Skaggs & Lissitz, 1986). The common designs include the random groups, the single group with counter balancing, and the common item nonequivalent group design. A less commonly cited design is the common item equating to an IRT calibrated item pool (Kolen & Brennan, 2004). Each design separates ability from form difficulty in different ways.

Random Groups Design

The random groups design achieves equivalent group abilities through the use of random assignment of forms to examinees. If the sample of examinees is large enough, it can be assumed that the difference between scores on the forms is caused by form differences. This design accommodates more than two forms, but requires large sample sizes of at least 1500 examinees (Kolen & Brennan, 2004). The design requires that all forms to be equated are administered simultaneously. If cheating is a concern, equating more than two forms simultaneously is undesirable because of item exposure (Kolen & Brennan, 2004). It is not an appropriate method if forms are to be equated across time.

Single Groups with Counterbalancing Design

Single groups with counterbalancing is a data collection design that requires each examinee to take the base form and the new form. Examinees are randomly assigned to one of two groups. Group One receives form X and then form Y. Group two receives form Y and then form X. This is referred to as counterbalancing and is used to control for order effects. Mean, linear, or equipercentile equating methods can then be used to isolate the differences caused by form difficulty (Kolen & Brennan, 2004; Holland & Dorans, 2006). The major drawback to this design is the fact that each examinee is required to take two test forms. Not only is this inconvenient and time consuming for examinees, but item exposure increases.

Common Item Designs

The final two methods employ common items rather than common persons between forms. The CINEG, also known as, the nonequivalent group with anchor test (NEAT), is the most commonly used design. A lesser used design is known as the common item equating to a calibrated item pool. The two designs differ in that the former links two or more forms, while the latter equates new forms to a calibrated item bank. Both methods use the same logic that the single group design employs, except that rather than requiring all examinees to complete all forms, examinees are required to complete one form and a mini version of the other form. In such equating designs, the mini test is used to predict scores on the entire form, and then mean, linear, or equipercentile methods are used to estimate differences caused by form difficulty (Holland & Dorans, 2006). IRT methods require the linking of items on a single theta calibrated scale through the use of common items. Because all the items are calibrated to the same scale, common items from any prior form can be used to link new forms to the entire pool of items rather than to just a prior form (Kolen & Brennan, 2004). This last design, common item to a calibrated item pool, permits preequating.

Equating Methods

This section will focus on CINEG equating methods that are relevant to samples sizes of less than 500. This includes identity equating, linear equating, and preequating with the Rasch model. There are many other methods of CINEG equating that are not reviewed in this study. Mean equating, conventional equipercentile methods, IRT observed score equating, as well as Kernel equating are also possible methods that could be employed with a CINEG data collection design. However, all of these methods, except for mean equating, require sample sizes that exceed the sample sizes being investigated by this study (Kolen & Brennan, 2004). Identity equating and linear equating will be used in this study primarily as criteria to help evaluate the performance of preequating with the Rasch model. Since these methods are not the primary focus of this study the description of these methods will be kept brief. Emphasis will be placed on IRT preequating methods. The reader can find an excellent presentation of identity and linear equating methods in Kolen and Brennan's *Test Equating, Scaling, and Linking* (2004).

Identity Equating

Identity equating defines a score on a new form X to be equivalent to the same score on the base form Y. For instance, a score of 70 on form X would equal a score of 70 on form Y. In some instances identity equating will produce less equating error than other types of equating. For this reason, identity equating is often used as a baseline method to compare the effectiveness of other methods (Bolt, 2001; Kolen & Brennan, 2004). Other equating methods should not be used unless they produce less equating error than the identity function (Kolen & Brennan, 2004). If the scale is equal in difficulty all along the scale, then identity equating equals mean and linear equating. However, as test forms become less parallel other methods will produce less error than the identity method. In some contexts, the term preequating is used to refer to tests that have been assembled to be parallel. Then identity equating is used to relate scores. For practical purposes, identity equating is the same as not equating.

Linear Equating

This section describes general linear equating under the single groups with counter balancing design and then provides a brief description of linear equating used in CINEG designs. There are a variety of ways to use common items in linear equating methods, including “chained equating” and “conditioning on the anchor” (Livingston, 2004). Livingston (2004) explains that chained equating operates by linking scores on the new form to scores from the common item set, and then linking scores from the common item set to the base form. Conditioning on the anchor uses the scores from the common item set to predict unknown parameters in a ‘synthetic’ group which are then used as if they were observed for equating (Livingston, 2004). What follows is a description of the general linear formula used in this procedure.

The general linear transformation is defined by setting z scores equal for forms X and Y such that

$$(x-\mu(X))/\sigma(X) = (y-\mu(Y))/\sigma(Y) \tag{2.1}$$

Where x = a raw score on a new form X,

$\mu(X)$ = is the mean score of form X,

$\sigma(X)$ = the standard deviation of form X,

y = a raw score on the base form Y,

$\mu(Y)$ = is the mean score of form Y, and

$\sigma(Y)$ = the standard deviation of form Y.

Formula 2.2 gives the linear transformation of a form X score to a form Y score:

$$\lambda_{Y_S}(x) = \left(\frac{\sigma_s(Y)}{\sigma_s(X)}\right)\left(x - \mu_s(X)\right) + \mu_s(Y) \tag{2.2}$$

where *s* indicates the synthetic population (Kolen & Brennan, 2004). Formulas 2.3 through 2.6 can be used to calculate the four synthetic parameter estimates needed for formula 2.2.

$$\mu_s (X) = w_1\mu_1 (X) + w_2\mu_2(X) \tag{2.3}$$

$$\mu_s (Y) = w_1\mu_1 (Y) + w_2\mu_2 (Y) \tag{2.4}$$

$$\sigma_s^2 (X) = w_1\sigma_1^2 (X) + w_2\sigma_2^2 (X) + w_1 w_2 [\mu_1(X) - \mu_2(X)]^2 \tag{2.5}$$

$$\sigma_s^2 (Y) = w_1\sigma_1^2 (Y) + w_2\sigma_2^2 (Y) + w_1 w_2 [\mu_1(Y) - \mu_2(Y)]^2 \tag{2.6}$$

Where subscripts 1 and 2 represent the two populations and w are weights. If all examinees were administered all forms, as in the single groups with counter balancing design, formulas 2.1 through 2.6 could be used to calculate the linear equating relationship.

In the CINEG data collection design, all examinees do not take all items from both exams. Rather, each group of examinees is given a representative sample of items (common items) from the form they did not receive. The common items provide the basis for predicting examinees' raw scores for the entire exam they did not complete. The common items can be internal, meaning they are used in obtaining the raw score, or external to the test meaning they are not used to calculate the raw score (Holland & Dorans, 2006; Kolen & Brennan, 2004).

There are a variety of ways to estimate the unknown parameters μ_2(X), σ_2^2 (X), μ_1 (Y), and σ_1^2 (Y) in formulas 2.2 through 2.6. In Tucker linear equating parameters are estimated by regressing the raw scores of the common items on the raw scores of the entire form (Livingston, 2004). Since linear regression is used for this prediction, the assumptions of linearity and homoscedasticity apply to linear equating. The unobserved parameters are obtained from the predicted raw scores and are then substituted into formulas 2.2 through 2.6 to define the linear equating function.

True score linear equating can be performed by substituting true scores for observed scores in formula 2.2, as in the Levine true score method (Kolen & Brennan, 2004; Livingston, 2004). In Levine true score equating, true scores on a new form X are equated to true scores on a base form Y with the following equation:

$$\lambda_{Y\,s}(t_x) = \left(\frac{\sigma_s(T_Y)}{\sigma_s(T_X)}\right)\left[t_X - \mu_s\left(T_X\right)\right] + \mu_s(T_Y) \qquad (2.7)$$

Where $\left(\frac{\sigma_s(T_Y)}{\sigma_s(T_X)}\right) = \gamma_2 / \gamma_1$ (2.8)

and $\gamma_1 = \frac{\sigma_1(X)\sqrt{\rho_1\,(X, X')}}{\sigma_1(V)\sqrt{\rho_1\,(V, V')}}$ (2.9)

and $\gamma_2 = \frac{\sigma_2(X)\sqrt{\rho_2(X, X')}}{\sigma_2(V)\sqrt{\rho_2(V, V')}}$ (2.10) where ρ represents estimates for reliability, and V are the scores on common items. As with any true score equating method, the equating relationship between true scores is applied to observed raw scores.

Linear equating can falter when its assumptions are violated. For instance, linear equating can falter if the regression line is curvilinear rather than linear. As with any CINEG design if common items work inconsistently between groups, the equating error of this method will increase quickly. Tucker linear equating is known to produce bias whenever score reliabilities are less than 1. Levine true score equating corrects for this bias (Livingston, 2004). Both the Tucker and Levine methods require scores from common items that correlate highly with the test entire (Livingston, 2004). If group ability differences are greater than .50 of a standard deviation problems can ensue (Kolen & Brennan, 2004).

The ideal sample size for linear equating is at least 300 examinees (Kolen & Brennan, 2004). The random error of linear equating is very susceptible to sample size, so random error increases rapidly moving from the mean. There is evidence that linear equating can work reasonably well with samples as low as 50, especially if the cut score is close to the mean, if common item scores correlate highly with the overall test, and if equating error does not propagate across links (Parshall, Houghton, & Kromrey, 1995). Linear equating methods require relatively small samples in comparison to IRT and equipercentile equating.

Introduction to IRT Equating

Benefits of IRT

IRT consists of a family of probabilistic models that can be used to develop, analyze, and equate tests. The benefits of using IRT models for equating come from the property of invariance of item and ability estimates. Invariance means that item parameter estimates are not dependent on the ability of the group of examinees used for parameter estimation. Given a calibrated item bank, different subsets of items can be used to obtain the same ability estimates for examinees. In addition, for any subset of examinees item parameter estimates will be the same (Skaggs & Lissitz, 1986). The degree to which the property of invariance is achieved depends on the extent to which the model assumptions are satisfied. Invariance is a property of IRT, but it is also an assumption that should be tested (Hambleton & Swaminathan, 1985).

IRT Models for Dichotomous Data

The most general form of the unidimensional, dichotomous IRT model, attributed to Birnbaum (1968), is the three parameter logistic model:

$$P_{\gamma}(\theta) = c_{\gamma} + (1 - c_{\gamma})\frac{\exp[Da_{\gamma}(\theta - \mathrm{b}_{\gamma})]}{1 + \exp[Da_{\gamma}(\theta - \mathrm{b}_{\gamma})]} \qquad (2.11)$$

Where P(θ) represents the probability of a correct response to item γ by an examinee with ability θ, a_γ is the discrimination parameter for item γ, b_γ is the difficulty of item γ, c_γ describes a pseudo-guessing parameter, and D is a scaling constant equal to 1.7. The 3PL model requires around 1500 examinees for precise equating. If testing circumstances will only provide as many as 400 examinees, the 3PL model is not appropriate. In such a case, the Rasch model can be used (Kolen & Brennan, 2004).

The 1PL model is expressed as follows:

$$P_\gamma(\theta) = \frac{\exp(\theta - \mathrm{b}_\gamma)}{1 + \exp(\theta - \mathrm{b}_\gamma)} \tag{2.12}$$

Where $P_\gamma(\theta)$ represents the probability of a correct response to item γ by an examinee with ability θ, and b_γ is the difficulty of item γ. The 3PL model (2.11) simplifies to the 1PL model when D = 1, c = 0, and a = 1. Georg Rasch (1960) developed a model that is equivalent to the 1PL model although proponents of the Rasch model use different notation.

Philosophical differences abound between proponents of the Rasch model and proponents of other IRT models. Proponents of IRT as conceived by Allan Birnbaum, Frederic Lord, Ronald Hambleton, and Hariharan Swaminathan, view the Rasch model as a special case of the three parameter model. However, advocates of the Rasch model- Mike Linacre, Ben Wright, Everett Smith, and Richard Smith- view the Rasch model as the embodiment of objective measurement (Bond & Fox, 2001). They argue that good measurement requires parallel item characteristic curves, sufficient statistics, and true interval scales. Regardless of philosophical differences, both groups agree that the Rasch model is the most appropriate model to use for sample sizes that range from 100 to 500.

IRT Equating Methods

Figure 1 presents the general steps required by IRT calibration and equating. Step 1 involves assembling a new test form in such a way that equating will be successful. Step 2 involves estimating item parameters. This step assumes model data fit. The third step referred to here as item linking, places estimated item parameters from both test forms on the same scale. If theta estimates were being used for scoring purposes, generally the next step would be to simply estimate thetas (Kolen & Brennan, 2004). No other steps would be necessary to achieve score comparability; however, most testing programs score tests using NC raw scores. Whenever NC scores are used rather than thetas, step 4 is necessary (De Champlain, 1996). This step defines the equating function between true or observed raw scores of the new form and the target form. Step 5 is the process of relating equated raw scores obtained from Step 5 to primary scale scores. Primary scale scores are the scores used for score reporting. During this step, conversion tables are created that can be used by measurement staff and scoring programs for reporting purposes.

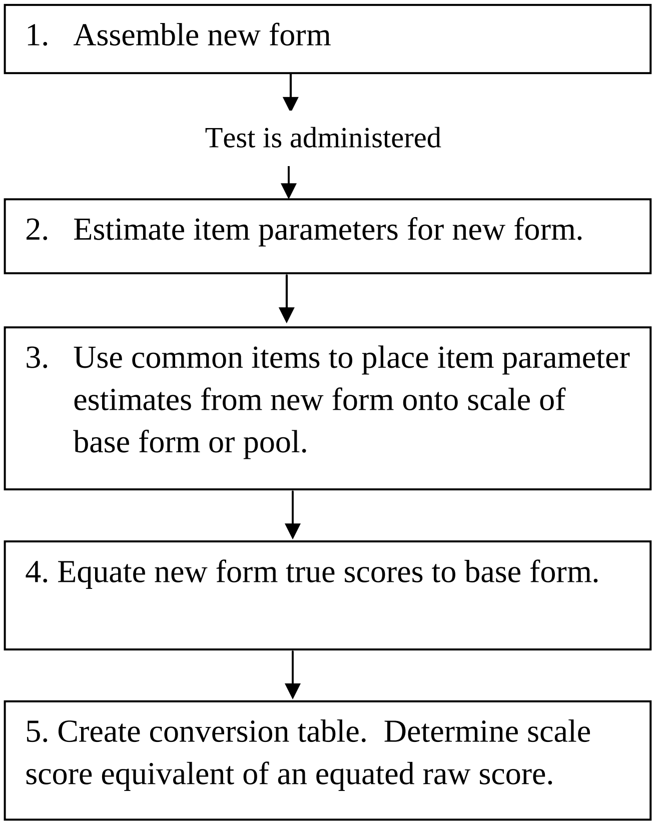

1. Assemble new form
Test is administered
2. Estimate item parameters for new form.
3. Use common items to place item parameter estimates from new form onto scale of base form or pool.
4. Equate new form true scores to base form.
5. Create conversion table. Determine scale score equivalent of an equated raw score.

Figure 1. Steps to IRT Equating

Test Design

It is generally believed that equating requires 'monotonously uniform' test forms (Kolen & Brennan, 2004). Dorans and Holland claim that test forms intended for CINEG equating must adhere strictly to a blueprint, have equal reliabilities, have high reliabilities, and be highly correlated to one another (2006). The most conservative approach to test assembly for equating purposes is to make test forms essentially parallel. While essentially parallel tests by definition do not need to be equated (AERA, APA, NCME, 1999), it may be discovered that test forms assembled to be parallel still need to be equated due to item context effects. For instance, identical tests with shuffled items are sometimes equated if items do not perform consistently (Hendrickson & Kolen, 1999; Moses, Yang, & Wilson, 2007). Equating can also be performed on test forms that are not essentially parallel (Kolen & Brennan, 2004). The standard practice of aligning Test Information Functions (TIF) to the cut score to minimize error and matching Test Characteristic Curves (TCC) of new forms to a target form largely address the test assembly needs of preequating (Hambleton & Swaminathan, 1985). However, special care must be given to the selection of common items.

There are many guidelines for selecting common items. Angoff (1971) claimed that for linear equating not less than 20% of the items of a test should be anchor items. IRT methods can achieve good results with fewer than 20% anchor items (Kim & Cohen, 1998). Hills, Subhihay, and Hirsch (1988) obtained good linking results with 10 items. Raju, Edwards, and Osberg (1983) used 6 to 8 items successfully. Wingersky and Lord (1984) used as few as 2 items with success. Forms to be equated should have content representative common items (Kolen & Brennan, 2004), and have common items that produce scores that correlate highly ($r >.80$) with the total test (Motika, 2003). It is also necessary that the common items perform equally well between the groups and forms intended to be equated. For this reason experts recommend that common items remain in the same or similar position across forms to prevent item order and context effects (Cook & Petersen, 1987).

Calibration and Linking Procedures

A variety of procedures can be performed to accomplish item calibration and item linking including separate calibration with linking, concurrent calibration, or fixed parameter calibration (FPC). Among users of IRT who use Marginal Maximum Likelihood Estimation (MMLE) methods, the most common method used to complete calibration and item linking (Figure 1, Steps 1, 2, and 3) is to estimate the item parameters separately and then use an item linking method to place the item parameters on the same scale. A variety of methods are available to perform this item linking including Mean/Mean, Mean/Standard deviation, Stocking and Lord TCC method, and the Haebara Method (Hambleton & Swaminathan, 1985; Kolen & Brennan, 2004). Any of these methods will produce transformation constants λ and κ, which when entered into equations

$$\theta* = \lambda\theta + \kappa \tag{2.13}$$

$$b_\gamma* = \lambda b_\gamma + \kappa \tag{2.14}$$

$$a_\gamma* = a_\gamma/\lambda \tag{2.15}$$

will place the parameters onto the base scale. Many researchers report that the characteristic curve based methods (Haebra and Stocking & Lord methods) usually outperform the other methods (Tsai, Hanson, Kolen, & Forsyth, 2001; Hanson & Beguin, 2002; Kolen & Brennan, 2004). The Stocking and Lord method achieves the linking constants by minimizing the differences between TCCs. SCSL has received consistently better performance reviews than other linking methods (Kolen & Brennan, 2004; Hanson & Beguin, 2002).

Another commonly used method, concurrent calibration, performs Steps 1, 2, and 3 during one run of IRT software. Concurrent calibration can be performed using a common person or common items design (Smith & Smith, 2005). Because all the items are estimated simultaneously, the items are already on the same scale and do not require linking. If multiple forms are administered across time, more and more forms can be added to the score matrix and concurrent calibration can be performed again. Linking may still be used with concurrent calibration, if equating is necessary to relate groups of concurrently calibrated forms across time. Prior research has shown that the parameter estimates acquired over time increase in precision because the sample size for the common items increase (Hanson & Beguin, 2002; Kim & Kolen, 2006). Potential drawbacks to concurrent calibration include long convergence cycles and the risk of nonconvergence.

FPC is a variation of concurrent calibration. FPC, also referred to as anchoring, is a commonly used method among those who use Joint Maximum Likelihood Estimation (JMLE). FPC is an attractive alternative to separate calibration with linking because it can simplify the process of calibrating new items (Li, Tam, & Tomkins, 2004). In the literature, FPC has many names including Pretest-item Calibration/scaling methods (Ban, Hanson, Wang, Yi, & Harris, 2001), Fixed Common Item Parameter Equating (Jodoin, Keller, & Swaminathan, 2003; Prowker, 2004), Fixed Common-Precalibrated Parameter Method (Li, Tam, & Tompkins, 2004), Fixed Item Linking (Paek & Young, 2005), and fixed parameter calibration (FPC) (Kim, 2006).

In FPC, the parameters of the common items in the new form are fixed to those of the old form (Domaleski, 2006; Paek & Young, 2005; Li, Tam, & Tompkins, 2004; Kim, 2006). The remaining items are then allowed to be estimated using conventional estimation algorithms. No linking is necessary at any stage of a testing program if FPC is used.

A variety of software options and methods exist for estimating parameters. With Bilog MG, multigroup concurrent calibration and FPC can be implemented using MMLE. The advantage to multigroup estimation is that the distributions of the groups are free to vary during the parameter estimation process. Multilog can also be used to perform concurrent calibration with or without prior distributions specified using MMLE. Bigsteps and Winsteps can perform FPC for the Rasch model using JMLE which does not assume any prior distribution. Also, IRT Code Language (Hanson, 2002) can be used to perform concurrent calibration or FPC procedures using MMLE.

IRT True Score Equating Procedures

Regardless of how calibration (Steps 2 and 3) is performed, if raw scores are reported rather than thetas, equating is necessary to define the functional relationship between NC scores across test forms (Step 4)(De Champlain, 1996). Either true or observed scores can be the focal point of this equating process. In true score equating, the TCC visually expresses the relationship between number correct true scores and thetas. The expected true score (τ) for an examinee with ability of θ_j is given by,

$$\tau = \sum_{\gamma=1}^{n} P_{\gamma}(\theta_j) \qquad (2.16)$$

where P_γ is the probability of correctly answering item γ. In IRT true score equating, for a given theta, a true score for form X is considered equivalent to a true score for form Y. The form Y true score equivalent of a given true score on form X is

$$\text{irt}_y = (\tau_x) = \tau_y(\tau_x^{-1}), \qquad (2.17)$$

where τ_x^{-1} is the θ_j associated with true score τ_x,

τ_x equals a true score on form x,

τ_y equals a true score on form y.

Kolen and Brennan (2004) describe a three step process to equation 2.17. First, specify a true score τ_x on form X. Second, find the θ_j that corresponds to that true score (τ_x^{-1}). Third, find the true score on Form Y, τ_y, that corresponds to that θ_j. In this way, true scores from the two forms are associated through their common theta. The process of finding the theta that corresponds to a true score, step 2, is achieved with an iterative process such as the Raphson Newton method. Once this is completed, the functional relationship between true scores of two forms is used to equate observed scores (De Champlain, 1996; Hambleton & Swaminathan, 1985; Kolen & Brennan, 2004). A SAS macro was developed to implement the Raphson Newton method (Appendix A).

Many large-scale testing programs employ some combination of the above mentioned calibration, item linking, and true score equating procedures. This process usually entails equating individual forms, one to another, after a test has been administered. Much of the equating research over the past 20 years has focused on equating relationships between forms after data have been collected during a test administration. A handful of studies have been conducted on preequating. Some of the studies reached opposing conclusions concerning the effectiveness of preequating. Fewer still have examined equating with a calibrated item pool for fixed length tests. The next section will review the procedures of IRT preequating, followed by a review of studies that have investigated the performance of IRT preequating.

Preequating Procedures

Preequating can use any of the IRT CINEG estimation, item linking, and equating procedures used in conventional IRT CINEG equating. IRT preequating differs from postequating (Figure 1) in the sequence of steps. Figure 2 presents the steps of preequating as it has been described by Kolen and Brennan (2004). The first step (1) is assembling the form. The second step (2) is performing true score equating. The third step (3) is the creation of conversion tables. After these steps are done, the test can be administered, and scores, pass/fail decisions, and score reports can be provided immediately upon completion of the test. Steps 1 through 3 are all that are necessary to equate a test under the preequating model. For this reason preequating is especially attractive to testing programs that use CBT or that have a small window of time to score, equate, and report scores.

Steps 4 and 5 of preequating are performed simply to add new calibrated items to the item pool. Step 4 involves estimating item parameters, and step 5 uses the common items to place the pilot items onto the same scale as the calibrated item pool. Any of the previously presented item calibration methods can be used to perform these steps.

It should be noted that some researchers have adopted the term ‘item preequating’ to describe steps 4 and 5 (De Champlain, 1996). In contrast, Kolen and Brennan’s (2004) use of the term item preequating implies steps 1 through 5. For the purposes of this study, I am using the term preequating to refer to steps 1 through 3, and item calibration to refer to 4 and 5.

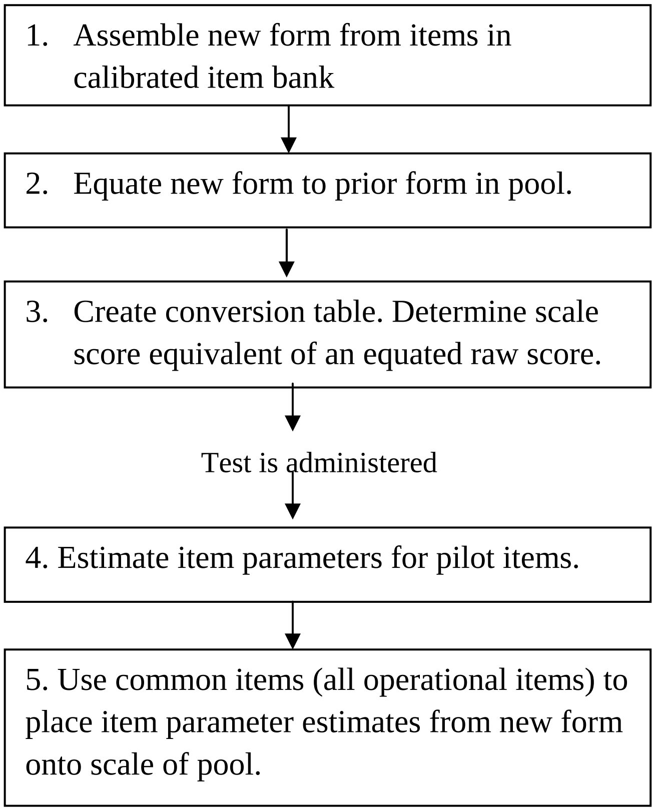

1. Assemble new form from items in calibrated item bank
2. Equate new form to prior form in pool.
3. Create conversion table. Determine scale score equivalent of an equated raw score.
Test is administered
4. Estimate item parameters for pilot items.
5. Use common items (all operational items) to place item parameter estimates from new form onto scale of pool.

Figure 2. Steps to IRT Preequating

Building a Calibrated Item Pool with Preequating

Kolen and Brennan (2004) describe how preequating can be used to create a calibrated item pool by piloting items in each new form. Piloted items are calibrated and linked to the scale of items from preceding forms. Table 2 presents a plan for creating a calibrated item pool. In this simplified example, each new form contains three operational and two pilot items. Operational items are used for two purposes: (1) to score the tests, and (2) to link the pilot items to the pool. To start, a five item form is assembled. Items 1 through 3 are operational and items 4 and 5 are pilot items. The form is assembled (step 1) and data are collected. Item parameters are estimated (step 2) using an IRT software program for the operational form (e.g., items 1 through 3). Then after scoring (step 3) is complete, the pilot items are calibrated (step 4) and linked (Step 5) to the operational items.   The linked pilot items are then added to the calibrated item pool (Step 6). Form 2 is then assembled consisting of items 3 through 7 (Step 1). True score equating (Step 2) is then performed using the common items 3 - 5. Conversion tables are made (Step 3) and form 2 is administered. Scores can be determined with the use of the conversion tables. Some time after the tests have been scored, the piloted items can be calibrated, linked, and added to the item bank (steps 4 through 6). Steps 1 through 6 can be repeated as many times as necessary to build a calibrated item pool.

Table 2. A Plan to Create a Calibrated Item Pool

Administration	Step
1	Step 1. Form 1 is assembled (item 1 - item 5)
	Step 2. Operational test is calibrated
	Step 3. Operational test is scored.
	Step 4. Pilot items are calibrated and linked to the test.
	Step 5. Link pilot items to pool
	Step 6. Place linked pilot items in item bank
2	Step 1. Form 2 is assembled (item 3 – item 7)
	Step 2. True score equating is performed using common items (item 3-item 5).
	Step 3. Conversion tables are made.
	Form 2 is administered
	Step 4. Estimate Item Parameters for pilot items (item 6 - item 7).
	Step 5. Link new items to pool
	Step 6. Place new parameters in item bank

Factors Affecting IRT Equating Outcomes

The factors reported in the equating literature that contribute to IRT common item equating error include violation of IRT assumptions, population nonequivalence, parameter estimation method, linking method, and quality of common items (Kolen & Brennan, 2004). Of all these threats to equating, the greatest cause for concern for the Rasch model is violations of model assumptions and their interaction with population nonequivalence. Hambleton and Swaminathan (1985) describe four assumptions of the Rasch model: unidimensionality, equal discrimination indices, minimal guessing, and nonspeeded test administrations. This next section will present the assumptions of unidimensionality, equal discrimination indices, minimal guessing, and then discuss the issues of population nonequivalence, quality of common items, and calibration linking method.

Assumption of Unidimensionality

Many studies have examined the robustness of IRT equating to violations of the assumption of unidimensionality. The majority of these studies concluded that IRT equating was robust to violations of IRT assumptions (Bogan & Yen, 1983; Camili, Wang, & Fesq, 1995; Cook, Dorans, Eignor, & Petersen, 1985; Dorans & Kingston, 1985; Wang, 1985; Yen, 1984; Smith, 1996). However, most of these referenced studies were performed with actual data using the 3PL model, a few on the 2PL model, and one on the Rasch model. None of these studies examined IRT preequating.

A few studies have explicitly examined IRT Preequating with the 3PL model. Stocking and Eignor (1986) found that when the assumption of unidimensionality was violated the *b* parameters were overestimated, which led to substantial equating error. Prior research on the American College Test (ACT) and the Scholastic Aptitude Test (SAT) showed that preequating is sensitive to multidimensionality and item context effects (Eignor, 1985; Kolen & Harris, 1990; Hendrickson & Kolen, 1999). Kolen and Harris (1990) found that with the ACT Mathematics Test, preequating produced more equating error than identity equating, which is equivalent to not equating at all. These problems were so severe that the idea of preequating was abandoned for these programs. The probable cause for equating error under multidimensionality is the presence of bias in the item parameter estimates (Kolen & Brennan, 2004). Li and Lissitz reported the presence of bias in item parameter estimates when data are not strictly unidimensional (2004).

While there are many studies that cast doubt on the viability of IRT preequating under multidimensionality, some studies have obtained favorable results with IRT preequating under known multidimensional tests. The Law School Admissions Test (LSAT) used a section preequating design with the 3PL model in the 1990s. A section preequating design pilots items within test sections that are spiraled to achieve equivalent groups during test administration. Concurrent calibration is then used to calibrate the pilot items with the operational items (De Champlain, 1995). This design is essentially the same as the preequating design used in this study, except that in a section preequating design pilot items are piloted in sections. Perhaps one benefit of piloting items in this manner is that it can control for item context effects.

Camilli, Wang, and Fesq (1995) used actual LSAT data from six different test administrations to estimate parameters for the 3PL model. They compared TCCs and true score conversion tables based on item parameters from two item pools: 1) a heterogeneous item set based on calibrations from an intact test, containing two distinct content areas, and 2) a homogenous item set that was based on separate calibrations of content area 1 and content area 2. They found that the converted true scores differed by less than two points for all six forms and all conditions examined. These differences were quite small considering the standard deviation for the LSAT was around 15 raw score points.

De Champlain (1995) used LSAT data to examine the interaction effects of multidimensionality and ethnic subgroup on true score preequating. In contrast to prior studies that assumed constant multidimensional factors across groups, De Champlain examined how different factor structures between ethnic groups may affect true score preequating. Even though a two dimensional model did account for the item responses in the majority group, it did not account for the item responses of a minority subgroup. The subgroup differed from the majority group in ability by .56 of a standard deviation. Despite the different factor structures between the subgroup and the majority group, the mean absolute difference of true score preequated scores was negligible.

Bolt modeled simulated data after LSAT data (1999) with the 3PL model. He examined the effects of two dimensional test data when the dimensions were correlated at different levels. Using an equity criterion in which the first two moments of the conditional equated score distributions were compared, Bolt found that true score preequating was fairly robust to violations of unidimensionality when compared to equipercentile equating. When dimensions were correlated $\geq .70$ true score equating was usually superior to equipercentile and linear equating methods. Even when the correlations of the dimensions was as low as .30 true score equating was similar though not as effective as equipercentile equating.

Assumption of Equal Discriminations

The assumption of equal item discriminations is an assumption of the Rasch model. Curry, Bashaw, and Rentz (1978) examined the robustness of the Rasch model to violations of the assumption of equal item discriminations. Estimated abilities were quite similar to generated abilities, suggesting that the Rasch model was robust to nonequivalent discriminations. Gustafsson (1980) examined the effects of a negative correlation between difficulty and discrimination parameter estimates. Results showed that when difficulty and discrimination were statistically independent, mean ability estimates from high and low groups were nearly identical. However, as the correlation between difficulty and discrimination moved away from zero, bias in the ability estimates increased. For instance, if the correlation of the difficulty and discrimination were negative, ability estimates were positively biased if they were calculated with parameters estimated by the low ability group. This finding corroborated Slinde and Linn's (1978) finding. Forsyth, Saisangijan, and Gilmer (1981) observed that item parameter invariance depended on the difference between mean discrimination values for two sets of items. A more recent study compared the performance of the 1PL, 2PL, and 3PL models and concluded that even though the 2PL and 3PL models better accounted for the response data, the Rasch model produced better ability estimates (Du, Lipkins, & Jones, 2002). This was true despite the fact that as much as 20 percent of the items had discriminations that did not fit the Rasch model. The poor performance of the 2PL and 3PL models was attributed to the sample size (500) of this study, which produced item parameter estimates with relatively large standard errors.

Assumption of Minimal Guessing

The studies that examined Rasch vertical scaling demonstrated the tendency for low ability groups to guess. This phenomenon has occurred repeatedly across tests, contexts, and studies (Slinde & Linn, 1978; Loyd & Hoover, 1981; Skaggs & Lissetz, 1986). Some studies that minimized guessing did show parameter invariance (Forsyth, Saisangijan, & Gilmer, 1981). These studies underscore the importance of minimizing guessing. Minimizing guessing can be done by producing forms that are well matched to the ability of the target group and/or by careful development of option choices. Matching the ability level of different groups is appropriate for vertical scaling contexts, such as grade levels. However, producing forms of different difficulty is not always appropriate for testing programs that administer fixed lengths tests to populations and subgroups that differ in ability. For instance, certification and licensing exams that are designed to produce pass/fail decisions, are usually created to produce maximum information surrounding the cut score, which would require forms of equal difficulty, regardless of what group of examinees are taking the exam. In such settings, the Rasch model requires item writers to create items with attractive distracters to prevent guessing among low ability examinees. Developing tests that have high conditional reliabilities around the expected means of the majority and subgroups is another strategy that can be employed.

Holland and Dorans consider forms of high reliability to be a requirement of equating (2006). Holland and Dorans contend that highly reliable forms are necessary in order to obtain equating functions that are population invariant (2006). Population invariance is an indication of the effectiveness of an equating method. As guessing increases, the maximum information decreases which will result in less reliability (Yen & Fitzpatrick, 2006). So, it is easy to infer that test forms with substantial guessing may not be population invariant. While forms with high reliability are important, perhaps an even more important consideration is the similarity of the reliability of the forms being equated (Kolen & Brennan, 2004). It is unclear to what extent test reliability will be reduced as a result of guessing, and what affects reduced reliability may have on equating nonequivalent populations.

Quality of Common Items

It is well established that CINEG equating depends largely on the representativeness of the common items to the larger test (AERA, NCME, APA, 1999; Cook & Petersen, 1987; Michaelides, 2004; Holland & Dorans, 2002; Kolen & Brennan, 2004; Motika, 2001). Holland and Dorans identified three factors that are most important in common items: 1) integrity over time, 2) stability over time, and 3) the common items' correlations with the scores being equated (Holland & Dorans, 2006).

Some researchers recommend that raw scores from common items and raw scores from the total test should be similar in difficulty and should correlate highly. Recommendations include correlations of .80 or higher (Motika, 2001). One way to increase the correlation is to ensure that the common items are content representative (Motika, 2001). Larger sets of common items usually increase the correlation. It is necessary that the common items perform equally well between the groups. Zwick attributed considerable equating error found in links from 1984 to 1986 in the National Assessment of Educational Progress (NAEP) to change in item order and the time permitted to answer the items. For this reason, experts recommend that common items remain in the same or similar position across forms so as to prevent item order and context effects (Cook & Petersen, 1987). Kolen and Brennan (2004) recommend that common items be screened to ensure that they work equally well between groups. Their recommendation is that the proportion of examinees correctly answering a common item across forms should not differ by more than 0.10.

Instability in the common items can be detected when using concurrent calibration or separate calibration with a linking method by comparing the parameter estimates of the common items from two administrations. In Rasch equating, a number of indices have been proposed as measures of stability for common items. These indices include the p-value cut off criterion of .30, Wright and Stone's T statistic, robust Z statistics, Linacre's displace measure (Arce-Ferrer, 2008), item-within-link fit analysis, and item-between-link fit analysis (Wright & Bell, 1984). Some researchers recommend the use of Differential Item Functioning (DIF) analysis, where the base form examinees are treated as the reference group and the new form examinees are treated as the focal group (Cook & Petersen, 1987; Holland & Dorans, 2006). Enough common items have to be included in the test to allow for the removal of some in case of inconsistent performance, without under-representing subdomains. All of these guidelines assume unidimensionality and may have to be made stricter if this assumption is violated (Kolen & Brennan, 2004).

Another issue that arises when using calibrated item pools is related to *item parameter drift* of the common items. Item parameter drift is defined as any significant changes in item parameters across time, not attributed to context or order effects. Most prior studies that have examined the effects of item parameter drift on equating have shown negligible effects when analyzing real data (Wollack, Sung, & Kang, 2006). Wollack et al.'s explanation for this was that in real data the drift was bidirectional and canceled itself out (2006). Du et al.’s study showed that instability in the 2PL and 3PL item parameter estimates caused by sample sizes of 500 can also contribute to differences in item parameter estimates across time and undermine preequating (2002).

Context effects can also affect the stability of common items which can threaten equating. Ideally, the performance of an item will not depend on its location in an exam or its relation to other items in the exam. However, prior studies have demonstrated that the item order and context does change the performance of items (Kolen & Brennan, 2004). The best remedy to this threat is to keep items in fixed locations and similar contexts in a test. Another strategy is to identify items that are inconsistent in performance and remove them from the linking process, provided that the content representativeness of the common items is not destroyed. Context effects may be more prevalent in exams that are more multidimensional (Eignor, 1985; Hendrickson & Kolen, 1999; Kolen & Harris, 1990;).

Equivalence of Populations

Another factor that can contribute to equating error is population nonequivalence. Population nonequivalence--differences in latent ability distributions between groups taking alternate forms--can be caused by many factors, including time of year effects (Kolen & Brennan, 2004), differential preparation of examinees by trainers (Prowker, 2006), ethnicity (De Champlain, 1996), and native language (Kolen & Brennan, 2004). Equating methods usually assume that the two groups taking the two forms are from the same population. Linear equating addresses this assumption by creating a weighted synthetic group, representing a single population from which the two groups came (Kolen

& Brennan, 2004). Even though the CINEG design was especially designed to accommodate nonequivalent groups, experts warn that CINEG methods cannot equate data from groups if differences in mean ability are too large (Kolen & Brennan, 2004). Kolen and Brennan urged practitioners to conduct their own simulation studies for their specific contexts. Kolen and Brennan (2004) report that equating methods diverge when mean differences between scores on common items reach 0.30 of a standard deviation unit. Equating methods begin to fail when differences reach 0.50. Also, Kolen and Brennan report that ratios of group standard deviations on common items of less than 0.80 or greater than 1.2 lead to differences in methods (2004). One study demonstrated that mean differences of one standard units increased equating error in the Angoff IV linear equating method by 50 percent (Motika, 2001).

Studies conducted in the 1970s and 1980s that investigated parameter invariance in a vertical scaling context tend to cast doubt on the viability of the Rasch model for vertical scaling. Rasch invariance did not hold in a study by Slinde and Linn (1978). The ability level of the group used for calibration affected the accuracy of the linking results (according to Wright's standardized difference statistic). The differences in ability between groups used in this study were as large as 1.8 logits or nearly two standard deviations. Similar results were obtained when Slinde and Linn conducted a similar study with different test data. In this study they found that comparable ability estimates were obtained from two subtests when using groups of moderate to high ability. However, when low ability groups were used to estimate the ability of moderate to high ability examinees, ability estimates were variable. Gustafsson (1979), Slinde, and Linn (1978) concluded that the root cause for the inconsistent ability estimates was guessing.

Loyd and Hoover (1980) found similar results as Slinde and Linn (1978) with groups that differed less in ability. Scaling between any two levels of test difficulty was influenced by the group upon which the parameters were based. Loyd and Hoover (1980) believed multidimensionality contributed to the problems of vertical scaling. Skaggs and Lissitz (1986) suggested that for at least some tests, the factor structure changed across ability levels, so items were unidimensional at one level of ability, but multidimensional at another level. Divgi (1981) found in an investigation of Rasch vertical scaling, that low and high ability examinees obtained higher equivalent scores if their ability estimates were based on a difficult test rather than an easier test. One of Divgi's conclusions was that Wright's standardized difference statistic should not be used as a sole criterion for assessing equating bias.

Using Wright's standardized difference statistic, Forsyth, Saisangijan, and Gilmer (1981) investigated item and person invariance using data that slightly violated Rasch assumptions. They obtained reasonably good evidence of item and ability invariance. However, they observed that the degree of invariance was related to the difference between mean discrimination values for the two sets of items. This finding suggests that Rasch equating requires equivalent *a* parameters within each form and across forms. Holmes (1982) performed vertical scaling with data that satisfied Rasch assumptions. His results agreed with the studies conducted by Slinde and Linn (1978, 1979).

All of these studies from the 1970s and 1980s were based on actual data rather than simulated data. Hence, parameter bias was not assessed. More recent studies of Rasch vertical scaling used true experimental designs with simulated data. DeMars conducted a simulation study, comparing MMLE and JMLE under concurrent calibration on nonequivalent groups in which the uncommon items were matched to the ability of the target group. DeMars found the parameter estimates for MMLE and JMLE were very similar, provided that group differences were modeled in the IRT software (2002). Pomplun, Omar, and Custer (2004) compared Bilog MG and Winsteps. The study provided evidence that vertical scaling can produce accurate item and ability parameter estimates. Both of these studies used data modeled with the Rasch model, so violations of assumptions to the model were not assessed. Neither of these studies performed true score equating.

Method of Calibration

The accuracy and precision of item parameter estimates necessarily contribute to equating error. Since calibration methods vary in accuracy and precision, it is likely that equating effectiveness will depend, in part, on calibration method. While concurrent calibration does appear to provide greater precision (Hanson & Beguin, 2002; Kim & Kolen, 2006), it may be more sensitive to violations of unidimensionality than separate calibration. Beguin, Hanson, and Glas compared SCSL with concurent calibration using data generated by a multidimensional model and found SCSL produced more accurate estimates (2000). Kim and Cohen (1998) recommend the use of separate calibrations with a linking method for smaller sample sizes. Kolen and Brennan (2004) as well as Beguin and Hanson (2002) recommend separate calibration rather than concurrent calibration. Hanson views the fact that each common item is estimated twice during separate calibration as a benefit, because any discrepancies between the two parameter estimates may indicate problems with specific items. Proponents of the Rasch model have advocated a number of indices for screening common items (Wolfe, 2006). Except for Linacre's displacement statistic, most of these indices require separate calibrations. So, it appears that concurrent calibration is likely to produce more precise estimates than separate calibration; however, separate calibration is more conducive to detecting problematic common items and is therefore less risky (Kolen & Brennan, 2004). While separate calibration appears to be favored by some experts, FPC should also be considered for its ease of use.

FPC with MMLE requires accurate prior distributions for item parameter estimation (Paek & Young, 2005; Kim, 2006). Prowker compared equating effectiveness using FPC, using 1PL, 2PL and 3PL IRT models in the context of student growth. He found that mean differences in ability of greater than .50 had deleterious effects on IRT equating accuracy (Prowker, 2005). Paek and Young (2005) studied the effectiveness of FPC methods when performed with MMLE to capture simulated change in means and standard deviations in scores. They found they could correct equating error introduced by misspecified prior means and standard deviations with an iterative prior update calibration procedure (Paek & Young, 2005). It is unfortunate that this study did not include larger mean differences between groups, since differences greater than .50 seem to introduce more equating error (Kolen & Brennan, 2004; Prowker, 2005). The extent to which these findings generalize to other testing settings is unclear.

FPC may not work well when ability distributions are largely different (Li, Tam, & Tompkins, 2004). No prior research has investigated its robustness to violations of IRT assumptions such as multidimensionality (Kim, 2005). Few studies have compared FPC to concurrent calibration and separate estimation with a linking method (Kim, 2005). Hanson (2002) and Kim (2006) called for more research on FPC methods under violated assumptions. Potential drawbacks to FPC include longer computing times to reach convergence, non-convergence, inaccuracies in estimating non-normal latent distributions, and potentially less precision (Kim, 2005).

Domaleski (2006) conducted Rasch preequating with actual data using Winsteps and FPC. He implemented preequating and postequating in an actual testing program simultaneously and compared conversion tables from both approaches. He found that Rasch preequating results were very similar to postequating. Domaleski's (2006) study differed from the preequating design used in this study in that he obtained item precalibrations from pilot test administrations in which entire intact forms were administered to volunteer examinees, rather than piloting small sets of items with operational forms as done in the present study.

Summary of Literature Review

Prior research clearly shows many threats to Rasch preequating. Prior research has shown that preequating is vulnerable to multidimensionality (Eignor & Stocking, 1986). The probable cause for equating error with multidimensional data is the presence of bias in the item parameter estimates (Kolen & Brennan, 2004). Li and Lissitz (2004) report the presence of bias in item parameter estimates when data are not strictly unidimensional. Eignor and Stocking (1986) discovered positive bias in item parameter estimates under multidimensional data. This effect was magnified when population nonequivalence interacted with multidimensionality (Eignor & Stocking, 1986).

The Rasch model requires equivalent item discriminations and items with little or no guessing (Hambleton & Swaminathan, 1985). Parameter recovery studies provide evidence that the Rasch model does not perform well under the presence of guessing (Skaggs & Lissitz, 1985). Parameter recovery studies provide conflicting results concerning the robustness of the Rasch model to nonequivalent item discriminations (Curry, Bashaw, & Rentz, 1978; Gustafsson, 1980; Slinde & Linn, 1978; Forsyth, Saisangijan, & Gilmer, 1981). A recent study produced evidence that preequating under the Rasch model can produce acceptable levels of precision surrounding the mean of the score distribution, even if item discriminations are not equivalent (Du et al., 2002).

The Rasch model has been criticized in years past for not working effectively when group ability differences are large (Skaggs & Lissitz, 1986; Camilli, Yamamoto, & Wang, 1993; Williams, Pommerich, & Thissen, 1998). However, Linacre and Wright (1998), DeMars (2002) and more recently Pomplun, Omar, and Custer (2004), obtained accurate item parameter estimates when scaling vertically with the JMLE method.

Preequating to a calibrated item bank requires that items are piloted to obtain item parameter estimates. Kolen and Brennan warn of the risk that piloted items may become biased during estimation because they are not calibrated within the context of an intact test form (2004). Prior studies have demonstrated preequating's sensitivity to item parameter instability (Du, Lipkins, & Jones, 2002) and item context effects (Kolen & Harris, 1990). Item context effects can be controlled to some degree by keeping common items in fixed locations across forms (Kolen & Brennan, 2004) and selecting stable items (Smith & Smith, 2006) that are resistant to context effects, and piloting content representative sets of items rather than isolated items. The purpose behind piloting content representative item sets rather than isolated items is to keep the factor structure constant across all the calibrations of piloted items (Kolen & Brennan, 2004).

FPC is one item calibration method that can work under a preequating approach that can potentially simplify the calibration procedures because it does not require a separate linking step. It can simplify the calibration process, only if convergence problems reported by some (Kim, 2006) are not too common. Much of the prior research on FPC has focused on such software as Parscale (Jodoin, Keller, & Swaminathan, 2003; Prowker, 2006), Bilog MG, Multilog, and IRT Code Language (ICL) software (Kim, 2006). All of these software programs implement MMLE through the Expectation Maximization (EM) algorithm. FPC has been shown to work less effectively under non-normal latent distributions (Paek & Young, 2005; Kim, 2005; Li, Tam, & Tompkins, 2004) when conducted with MMLE. Very little if any published research can be found on FPC in conjunction with Bigsteps/Winsteps, which use a JMLE method that does not assume any priors.

The Need for More Research on Preequating with the Rasch Model

The equating literature provides many guidelines to the test developer who plans to implement IRT preequating. These guidelines include directions on how to develop test forms, how to select and screen common items, how many samples are needed for good results, strengths and weaknesses of various equating methods, and how much random error can be expected for specific IRT methods under ideal conditions. To all of these issues, clear recommendations have been made and supported by studies based on simulated and actual data.

However, many questions concerning IRT preequating for smaller sample sizes remain unanswered. How well will Rasch preequating perform when populations differ greatly in ability? How well will Rasch true score preequating perform under moderate to high levels of multidimensionality? How well will Rasch true score preequating perform when the discrimination parameters are not equal? How much guessing can the Rasch true score preequating method tolerate? How will Rasch true score preequating perform when violations of assumptions interact? At the present time, few equating studies have attempted to address the question of interaction of these threats to IRT true score preequating. As a result, test developers who consult the literature are left in a quandary concerning the performance of Rasch true score preequating. This is especially true for test developers who are in circumstances that are not ideal for equating, such as the equating of translated tests in which language groups differ substantially in ability, or the equating of tests designed to measure growth over long spans of time. Clearly, much research is needed in the area of Rasch preequating with a calibrated item pool before the method can be used with the same confidence as conventional IRT equating methods.

The conclusion that Kolen and Brennan (2004, p. 207) reach concerning preequating to a calibrated pool is summed up in the following statement:

"On the surface, preequating seems straightforward. However, its implementation can be quite complicated. Context effects and dimensionality issues need to be carefully considered, or misleading results will be likely."

CHAPTER THREE
METHODS

Purpose of the Study

The purpose of this study was to compare the performance of Rasch true score preequating methods to Levine true score linear equating and identity equating under levels of violated Rasch assumptions (unidimensionality, no guessing, and equivalent discrimination parameters) and realistic levels of population nonequivalence. The main goal of this study was to delineate the limits of Rasch true score preequating under the interactions of multidimensionality, population nonequivalence, item discrimination nonequivalence, and guessing. In contrast to many prior studies, this study investigated the effectiveness of equating to a calibrated item bank, rather than to a single prior form. This study further examined equating error across multiple administrations to determine if error accumulated across links. A secondary purpose was to compare FPC to the SCSL method.

Research Questions

1. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when the IRT assumption of unidimensionality is violated, but all other IRT assumptions are satisfied? As for the

preequating methods, does the FPC method perform at least as well as the SCSL method under the same conditions?

2. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when populations are nonequivalent, and IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

3. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and Linear equating) when the Rasch model assumption of equivalent item discriminations is violated, but populations are equivalent and other IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

4. Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when the Rasch model assumption of no guessing is violated, but populations are equivalent and other IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

5. How does Rasch preequating perform when response data are simulated with a three parameter, compensatory two dimensional model, the assumption of equivalent item discriminations is violated at three levels (mild, moderate, severe violations), the

assumption of no guessing is violated at three levels (mild, moderate, severe), population non-equivalence is manipulated at three levels (mild, moderate, severe) and the unidimensional assumption is violated at three levels (mild, moderate, severe)?

a. What are the interaction effects of multidimensionality, population non-equivalence, nonequivalent item discriminations, and guessing on random and systematic equating error?

b. At what levels of interaction does Rasch preequating work less effectively than identity equating or linear equating?

c. How does FPC compare to SCSL in terms of equating error under the interactions?

d. Does equating error accumulate across four equatings under the interactions?

Hypotheses

Hypothesis 1: Preequating error will begin to exceed criteria when population nonequivalence exceeds 0.50 of a standard deviation of the raw score.

Hypothesis 2: Preequating will be more robust to violations of the *a* parameter than the no guessing assumption.

Hypothesis 3: Preequating error will increase rapidly as assumptions are simultaneously violated.

Hypothesis 4: The violations of model assumptions will result in error in the item parameter estimates. Error in the item parameter estimates will produce error in the Test Characteristic Curves. Error in the TCCs will increase the SEE and bias of preequating.

Hypothesis 5: Item parameter error will accumulate in the item bank as the item bank grows in size across linkings. Equating error will accumulate across equatings, because of the increasing error in item parameter estimates.

Study Design

The study was conducted in two phases. Phase One examined main effects, research questions 1 through 4. Phase Two focused on interaction effects represented by questions 5a through 5d. The purpose of Phase One was to determine the limits of Rasch true score equating under severe violations. The defined limits in Phase One were then used to set the ranges for the levels in Phase Two. The hypotheses were tested using results from Phase One and Phase Two.

Factors Held Constant in Phase One

In order to make this study feasible, a number of factors were held constant. The number of operational items was fixed to 60 items. Many prior simulation studies use test lengths of around 50 items (Hanson & Beguin, 2002; Kim, 2006). Additional factors held constant included the number of pilot items (20 items), the number of operational items associated with each dimension (30 items with theta 1, 30 items with theta 2), the number of pilot items associated with each dimension (10 items with theta 1, 10 items with theta 2), and the difficulty of each new form. The number of pilot items was set to 20, to simulate what is typical among testing programs that use pilot items in operational tests. The number of items associated with each dimension was chosen to be equal (30 and 30) in an effort to produce two equally dominant dimensions, representing a worst case scenario for the violation of unidimensionality. Tables B1, and B2 display the descriptive statistics of the ten forms that were used in Phase One (Appendix B). The *b* parameters were modeled to fit a N(0,1) distribution across all conditions. The same set of *b* parameters was used across all form A test forms. The *b* parameters were then lowered by .50 of a standard deviation and used across all form B test forms. This produced a new form that was substantially easier than the base form, again representing a worse case scenario. Conformity to a test blueprint was modeled by ensuring that 30 operational and 10 pilot items for dimension one, and 30 operational and 10 pilot items from dimension two were included in each form. An important variable that contributes to random error is sample size. Phase One was conducted with a sample size of 500 examinees. Phase Two was conducted with a sample size of 100 in an effort to find the limits of preequating. It was assumed for purposes of this study that item parameter drift and item context effects were adequately controlled, therefore item parameters were not manipulated to simulate any type of random or systematic error.

Manipulated Factors in Phase One

While there are many more than four factors that could affect preequating, four factors stood out as the most important to manipulate. The first manipulated factor was population nonequivalence. Population nonequivalence was selected as a manipulated variable because unlike characteristics of items, the test developer and psychometrician have no control over the ability of populations or subgroups. Population nonequivalence in the present study was defined as differences in the shape of the ability distribution between groups of examinees that completed alternate forms of an exam. I used Fleishmann coefficients to model multidimensional, non-normal ability distributions (Fan & Fan, 2005). Fleishmann coefficients were chosen because they can easily mimic the skewness typically seen in raw scores of criterion referenced tests due to ceiling or floor effects, as well as skewness seen in low ability groups, as in De Champlain's (1995) study.

Tables C1 through C3 in Appendix C show the descriptive statistics of the simulated ability distributions shown in Figure 3. The means ranged from 0 to -1.20. The Fleishman coefficients used to produce these distributions are presented in Table D1 (Appendix D). These levels of nonequivalence were chosen to cover the range of distributions typically seen in criterion referenced tests. Given the magnitude of mean differences between groups reported in prior equating studies, it is improbable to see mean differences much larger than 1.15 standard deviation units (De Champlain, 1996; Prowker, 2006).

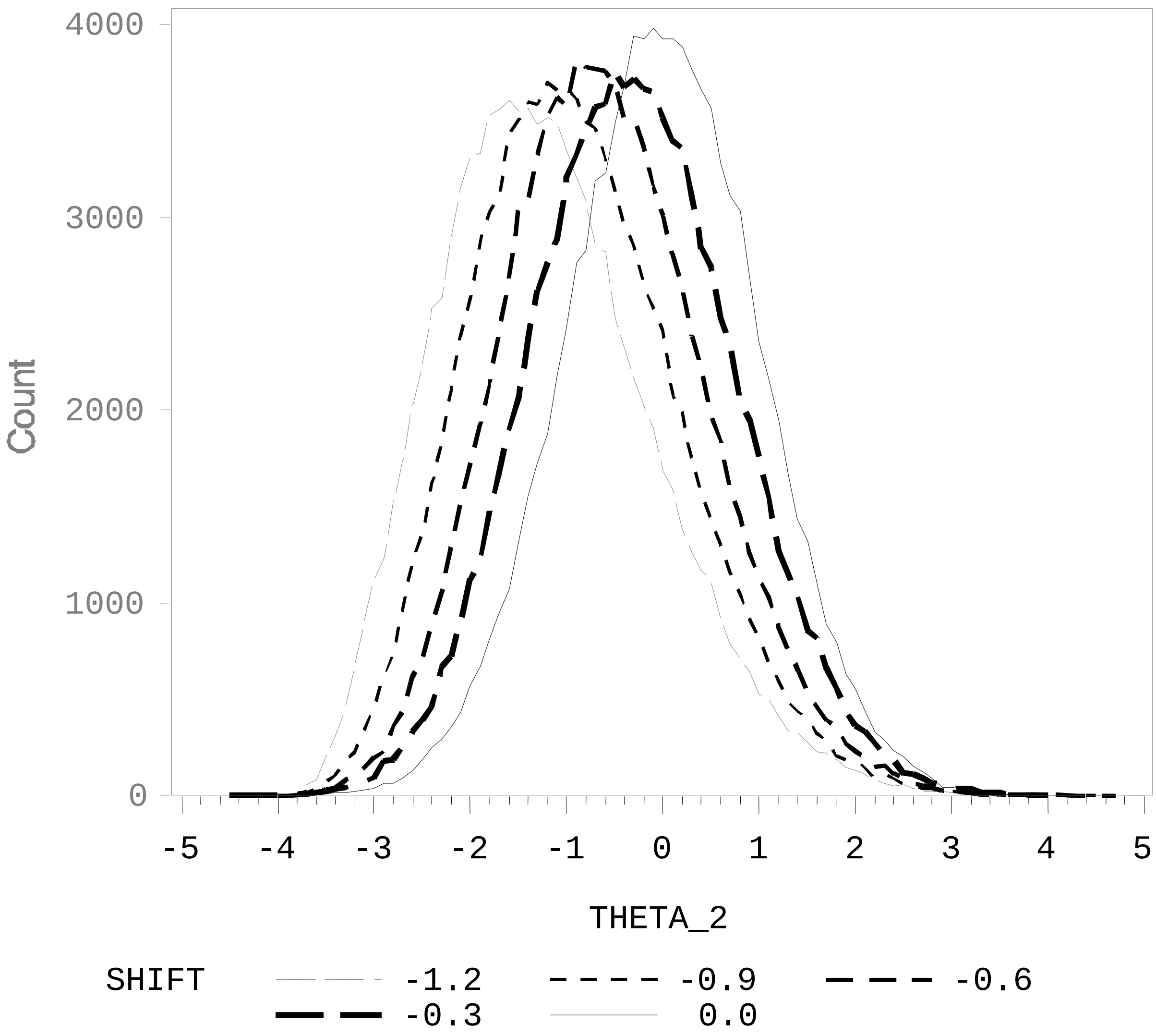


Figure 3. Generated Theta Distributions at Five Levels of Population Nonequivalence

Multidimensionality was also manipulated in this study. Multidimensionality in this study is considered to be present in an exam if responses to items depend on more than one latent trait or ability. Unidimensional IRT assumes that responses to items depend on one ability or dimension. While any number of dimensions is possible, the number of dimensions in this study was restricted to two. The strength of the correlation between the two dimensions was manipulated to model levels of dimensionality. The levels of dimensionality for Phase One, $r_{\theta_1\theta_2}$ = .90, .70, .50, .40, and .30, were selected based on information gleaned from Bolt's (1999) study.

The third and fourth variables I manipulated in Phase One were equivalent item discriminations and the presence of guessing, respectively. Nonequivalent discriminations were chosen to be manipulated, to replicate the findings of previous research conducted with actual test data that showed preequating produced acceptable precision around the mean of the scale score with forms containing nonequivalent point biserial correlations with means of .35 and standard deviations of .17 (Du et al., 2002). Guessing was included in this study because it has repeatedly caused problems for parameter invariance in prior studies. Most importantly, these variables were manipulated to determine how tolerant preequating was to the interaction of multidimensionality, population nonequivalence, equivalent item discriminations, and the presence of guessing. Despite an extensive literature review, I am not aware of any previous studies that have investigated these exact interactions under the 1PL model.

A uniform distribution (U) was used to model the *a* and *c* parameters (Baker & AL-Karni, 1991; Kaskowitz & De Ayala, 2001; Kim, 2006; Swaminathan & Gifford, 1986). To manipulate the equivalence of item discriminations, the *a* parameters were manipulated at five levels (U(1,1), U(.70, 1.0), U(.50, 1.10), U(.40, 1.20), U(.30, 1.30). Since item discriminations contribute to test reliability, the simulated *a* parameters were manipulated so that the height of the TIFs remained approximately constant. This kept the test reliability approximately consistent across levels. The target reliability of the forms was 0.90, which is appropriate for a high stakes test. The levels of the *c* parameter misspecification scale (U(0,.05, U(0,.10), U(0,.15), U(0,.20), U(0, .25)) were chosen to cover the range of what is typically seen in three parameter models under four option multiple choice exams.

Equating Criteria

While there is no consensus on the best measures of equating effectiveness (Kolen & Brennan, 2004), three commonly employed measures used in equating studies include: (1) the Root Mean Square Error (RMSE), (2) the Standard Error of Equating (SEE), and (3) bias of the equated raw scores (Hanson & Beguin, 2002; Pomplun, Omar, & Custer, 2004). These measures represent total equating error, random equating error, and systematic equating error, respectively. Total error and systematic error were calculated with the formulas below:

$$RMSE(H_y) = \sum (\hat{h}_y - h_y)^2 / r \qquad (3.1)$$

$$BIAS(H_y) = \sum (\hat{h}_y - h_y) \ \ / r \qquad (3.2)$$

In calculating equating error, h_y is the criterion equated score and $\hat{h}_y$ is the estimated equated raw score, and r is the number of replications. Negative bias values indicate that the estimated equated score is less than the criterion. In this study r = 20. The RMSE and bias were calculated at each raw score point.

The criterion equated scores were obtained by implementing random groups equipercentile equating on true scores derived from a compensatory two dimensional IRT model. Random groups equipercentile equating was chosen as the criterion equating method because it requires few assumptions to implement. Large samples were used to avoid the need for smoothing. To simulate random groups equating, random samples of 25,000 examinees were drawn from two populations. Test forms were *spiraled* among the examinees by randomly assigning examinees to one of two forms. Spiraling the test forms produced two equivalent groups assigned to each form. The compensatory two dimensional model was used to produce the probabilities of a positive response to each item for all examinees. The probabilities of a positive response for each item were then summed to produce true scores for each examinee. Equipercentile equating was then used to equate the true scores using RAGE-RGEQUATEv3 software (Kolen, Hanson, Zeng, Chien, & Cui, 2005).

The standard error of equating is a measure of random equating error and can be estimated with the RMSE and bias. The standard error of equating at each possible raw score was estimated with:

$$SEE(H_i) = \sqrt{(RMSE(H_i)^2 - BIAS(H_i)^2} \qquad (3.3)$$

Formulas 3.1 through 3.3 were used to calculate total error, random error, and systematic error for equivalent scores at all 61 points on the raw score scale. Standard errors of equating and bias estimates were then plotted and visually inspected.

Parameter Recovery

Formula 3.1 was used to calculate the total error of the assumed a, estimated b, and assumed c item parameters. In calculating item parameter error, h_y was the generated item parameter for item $_\gamma$ and $\hat{h}_y$ was the estimated item parameter, and r was the number of replications.

Phase One Conditions

In Phase One, each variable was manipulated at five levels while all other variables were kept ideal and constant. Table 3 shows the 17 conditions. Each condition consisted of a sample size of 500 examinees. A total number of 20 bootstrap samples were drawn with replacement for each experimental condition. While precedence would suggest 50 replications are necessary to obtain good SEE estimates with the 3PL model (Kim & Cohen, 1998; Hanson & Beguin, 2002; Kim, 2006; Li and Lissitz, 2004), I discovered by experimentation, that only 20 replications were necessary to obtain adequate precision in the SEE with the Rasch model (Figure 4). Figure 4 shows a comparison between standard errors of equating estimated with 20 and 50 replications. These estimates were based on samples of only 100 examinees. These results likely overstate the difference that would be seen with sample sizes of 500. The added investment of computer resources needed to produce 50 replications rather than 20 is hard to justify for such a small improvement in precision.

Table 3. Design Matrix for Main Effects

Condition	Unidimensionality	Population Nonequivalence	*a* parameter	*c* parameter
1	Ideal	Ideal	Ideal	Ideal
2	Mild	Ideal	Ideal	Ideal
3	Moderate	Ideal	Ideal	Ideal
4	Severe	Ideal	Ideal	Ideal
5	Very Severe	Ideal	Ideal	Ideal
6	Ideal	Mild	Ideal	Ideal
7	Ideal	Moderate	Ideal	Ideal
8	Ideal	Severe	Ideal	Ideal
9	Ideal	Very Severe	Ideal	Ideal
10	Ideal	Ideal	Mild	Ideal
11	Ideal	Ideal	Moderate	Ideal
12	Ideal	Ideal	Severe	Ideal
13	Ideal	Ideal	Very Severe	Ideal
14	Ideal	Ideal	Ideal	Mild
15	Ideal	Ideal	Ideal	Moderate
16	Ideal	Ideal	Ideal	Severe
17	Ideal	Ideal	Ideal	Very Severe

Note: See table D1 for operational definitions of each level by factor.

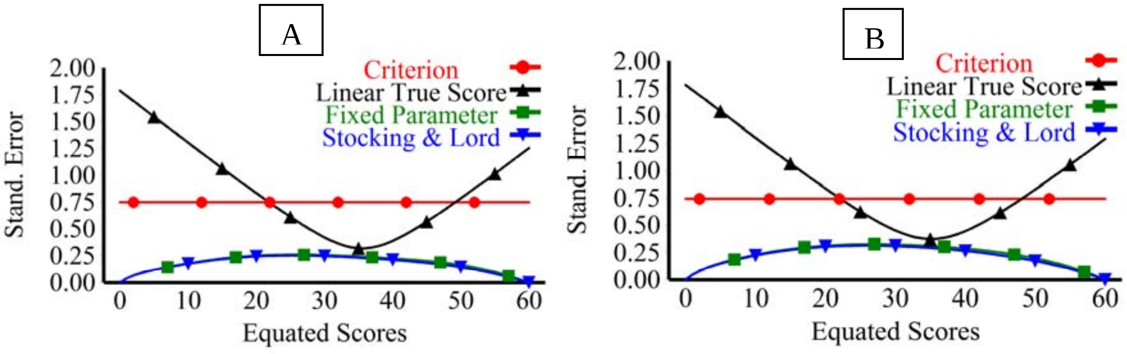


Figure 4. Bootstrap Standard Errors of Equating for 20 (plot A) and 50 replications (plot B). Sample sizes of 100 examinees were used in each replication.

Simulation Methods

Data

Reckase (1985) developed a multidimensional compensatory 3 parameter logistic IRT model which can be considered an extension of the unidimensional 3PL model:

$$P(\theta) = c_\gamma + (1 - c_\gamma)\frac{\exp\left(\boldsymbol{\alpha}'_\gamma \boldsymbol{\theta} + d_\gamma\right)}{1 + \exp\left(\boldsymbol{\alpha}'_\gamma \boldsymbol{\theta} + d_\gamma\right)} \tag{3.4}$$

where

$P_\gamma(\theta)$ is the probability of a correct response on item γ for an examinee at ability θ,

$\boldsymbol{a}'_\gamma$ is a vector of parameters related to the discriminating power of the test item,

d_γ is a parameter related to the difficulty of the test item,

c_γ is a pseudo-chance level parameter, and

$\boldsymbol{\theta}$ is a vector of trait scores for the examinee on the dimensions.

A test containing two subsets of items can be modeled with a compensatory two dimensional IRT model in which $a_2 = 0$ for θ_2 in Subset One, and $a_1 = 0$ for θ_1 in Subset

Two (Reckase, Ackerman, & Carlson, 1988). This is equivalent to using a unidimensional model to simulate Subset One using $\theta_{1,}$ simulating Subset Two using θ_2, and then combining Subset One and Subset Two to form one test. I used the latter of these two methods to generate response data from a two dimensional compensatory model.

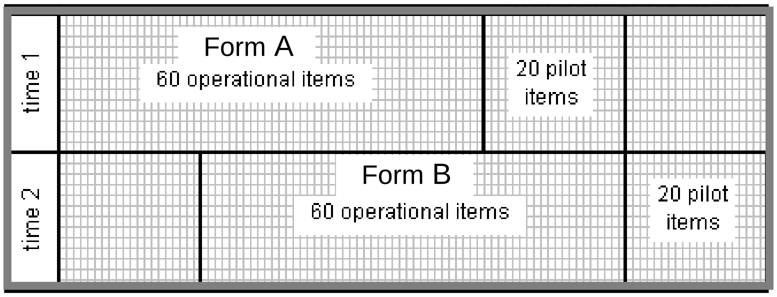
Items 1 - 30 made up Subset One, and items 31 – 60 made up Subset Two. θj_1 was used to simulate Subset One for person *j*, and θj_2 was used for Subset Two and person *j*. The correlation of each theta varied according to the condition. For Subset One, item responses for 100,000 examinees per time period were simulated according to the 3PL IRT model by sampling abilities from the θ_1 distribution and using the IRT item parameters (Tables B1, B2, and B3 in Appendix B). Item response probabilities were then computed according to the IRT 3PL model, and in each case, the probability was compared to a random uniform number. If the response probability was greater than the random number, the response was coded 1; otherwise the response was coded 0. Item responses for subset 2 for person *j* were produced in the same manner by sampling abilities from the θ_2 distribution. Then Subset One and Subset Two were combined to form a single test. Once item responses were generated for each condition, Bigsteps was used to estimate item parameters using the FPC method and separate calibration.

Item Linking Simulation Procedures

In order to perform an item parameter recovery study, it was necessary to place all item parameter estimates on the same scale as the generated item parameters (Yen &

Fitzpatrick, 2006). Yen and Fitzpatrick (2006) recommend linking estimated items to the generated items to ensure that the estimated and generated item parameters are comparable. Because the modeled data were multidimensional, an extra procedure was necessary to link the estimated item parameters to the generating item parameters. Doran and Kingston (1985) devised a five step procedure to place item parameters estimated under multidimensional conditions onto the scale of the item parameters estimated under unidimensional conditions. I used a variation of this Doran and Kingston procedure to place the estimated item parameters from multidimensional tests onto the scale of the generated item parameters. First, I calibrated Subset One and linked these item parameter estimates to the scale of the generated items. Second, I calibrated Subset Two and linked these item parameter estimates to the scale of the generated items. Finally, I combined the linked item parameter estimates from Subset One and Subset Two to form a complete set. Once the estimated item parameters were placed on the generated scale, I linked all subsequent pilot items from each form in the usual manner, ignoring the multidimensional nature of the data.

Figure 5 displays the linking plan devised for Phase One. This bank consists of 100 items. Form A in time period one consists of 60 operational items, and 20 pilot items. According to this plan, the 20 pilot items from time period one are treated as operational items in form B during time period two.



Item Bank of 100 items

Figure 5. Linking Plan and Assignment of Items to Forms in Phase One

Phase Two

Phase two extended Phase One in a number of important ways. Firstly, in Phase Two, I examined the interaction effects of violations of model assumptions. Secondly, because the overarching purpose of this study was to define the limits of preequating and since preequating was generally robust to violations of assumptions in Phase One, I elected to lower the sample size from 500 to 100 in an effort to force preequating to produce larger standard errors of equating. If preequating worked adequately with small samples as small as 100, then the utility of the method would increase, especially for smaller testing programs. Thirdly, to determine if equating precision and accuracy deteriorated across item calibrations (research question 5d and hypothesis 5), I examined equating error across five forms rather than two.

Phase Two Manipulated Factors

The levels for all manipulated factors were reduced from five to three in Phase Two. Because preequating proved to be quite robust to the violations in Phase One, I focused on the more severe levels of violations in an effort to find the limit of preequating. The *a* parameter was modeled again with a uniform distribution, U(0.50, 1.10), U(0.40,1.20), U(0.30, 1.30). The *c* parameter was modeled with a uniform distribution, U(0, 0.15), U(0, 0.20), U(0, 0.25). Population nonequivalence was modeled at three levels, mean shift of 0, -0.60, and -1.20. (Figure 3 and Figure D1 in Appendix D). Finally, two dimensional response data were simulated using thetas correlated at three levels, $r_{\theta_1\theta_2}$ =.90, .60, and .30.

Phase Two Conditions

Crossing all the levels of four manipulated factors with all other manipulated factors produced a 3 X 3 X 3 X 3 matrix. Table 4 shows the 81 conditions. Each condition consisted of a sample size of 100 examinees. A total number of 20 bootstrap samples were drawn with replacement for each experimental condition. To answer Research Question 5, equating was performed between the base form and the new form for all 81 conditions shown. To answer research question 5d, equating was performed across five forms for a subset of the 81 conditions. A subset of seven conditions was used rather than the entire 81 conditions because substantial redundancy was found in the results across the subset of conditions. This implied that equating five forms for additional conditions would produce little new knowledge. Table 4 provides the number of forms equated per condition.

To summarize and describe the interaction effects of multidimensionality, population nonequivalence, nonequivalent *a* parameters, and guessing on equating error, analysis of variance was conducted. Global measures of equating bias and SEE were used to summarize error across all raw score points. Even though the SEE and bias varied across the score continuum, the pattern of the variation was consistent across conditions. The pattern of preequating bias tended to reach its maximum value at lower raw scores and diminished across the rest of the score continuum. The pattern of the preequating SEE tended to reach its maximum near the mean of the score distribution and its minimum toward the scale extremes. Considering the consistency of the patterns shown in the preequating bias and SEE, it seemed reasonable to use means to summarize the equating error across the scale. Absolute differences between the criterion score and the mean equated score from 20 replications were averaged across 61 raw score points to calculate a global measure of equating bias. Absolute values were used because the direction of bias varied across the raw score scale. The SEE was also averaged across 61 raw score points to produce the mean standard error of equating (MSEE). The mean absolute bias of equating and the MSEE were then subjected to ANOVA to obtain effect size measures of the main and interaction effects of all conditions in Phase Two.

Table 4. Design Matrix for Phase Two

		Violation of the Assumption of Unidimensionality								
		$r_{\theta_1\theta_2} = .90$			$r_{\theta_1\theta_2} = .60$			$r_{\theta_1\theta_2} = .30$		
Violations of the 1PL Model Assumptions		Population Nonequivalence								
a parameter	*c* parameter	0	-0.60	-1.20	0	-0.60	-1.20	0	-0.60	-1.20
U(.50, 1.10)	U(0, .15)	**5**	1	1	1	1	1	1	1	1
	U(0, .20)	1	**5**	1	1	1	1	1	1	1
	U(0, .25)	1	1	1	1	1	1	1	1	1
U(.40, 1.20)	U(0, .15)	1	1	1	**5**	1	1	1	1	1
	U(0, .20)	1	1	1	1	**5**	1	1	1	1
	U(0, .25)	1	1	1	1	1	**5**	1	1	1
U(.30, 1.30)	U(0, .15)	1	1	1	1	1	1	1	1	1
	U(0, .20)	1	1	1	1	1	1	1	**5**	1
	U(0, .25)	1	1	1	1	1	1	1	1	**5**

Note: The values in the cell indicate the number of equatings performed within each condition.

Phase Two Simulation Procedures

In Phase Two, data were simulated in the same manner as Phase One, however, the linking procedure was extended to include five forms to answer question 5d. Figure 6 displays the linking plan used in Phase Two. Each subsequent form utilizes the pilot items from the prior time period. According to this plan, 20 of 60 items in time period two are former pilot items estimated during time period one; at time period three, 40 of 60 items in form C are former pilot items. At time period four, 60 of 60 items in form D are former pilot items. Lastly, at time period five, none of the items in form E were administered in time period one. In this design accumulated item bias and equating error are likely to be detectable across the equated forms. This linking plan was thus designed to permit me to test hypothesis 5, i.e., that equating error will increase across linkings as item parameter error accumulates in the item bank and as the item bank grows in size.

A program in Statistical Analysis Software (SAS) 9.1 was written to perform the simulation procedures (Appendix A). Sections of this code use Fleishman coefficients which were adapted from code originally published by Fan and Fan (2005). Table 5 lists the procedures used to calculate the bootstrap standard errors and bias across the three forms.

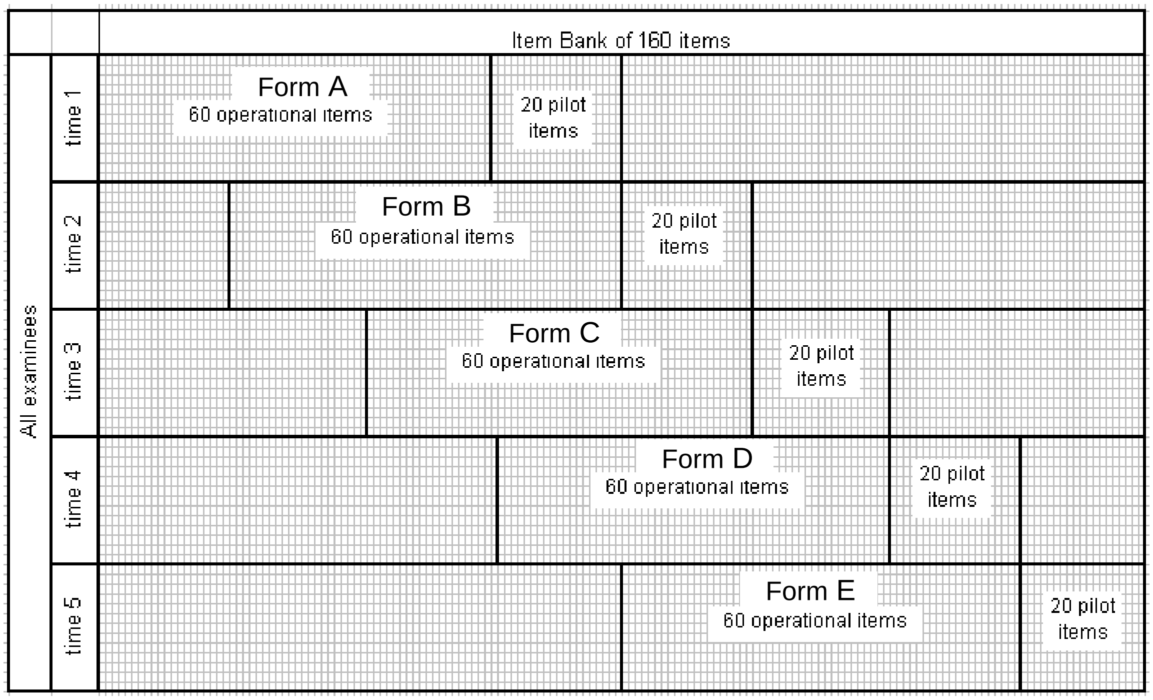


Figure 6. Linking Plan and Assignment of Items to Forms in Phase Two

Analysis of the simulation results consisted of plotting the bootstrap SEE and the bias at 60 points along the raw score scale for all equating methods for all 17 conditions. Standard errors of equating below .10 of a raw score standard deviation were considered sufficiently precise (Kolen & Brennan, 2004). The magnitude of systematic error in equating was evaluated by comparing the bias of preequating with that of identity equating and linear equating all along the raw score scale.

Table 5. Steps to Calculating Bootstrap Standard Error and Bias Across Specified Number of Forms

Order	Step
	Set up simulation
1	Generate 2 populations of 100,000 examinees each
2	Randomly sample 25,000 examinees from population 1
3	Obtain the base form
	Create criterion conversion table
4	Obtain the new form
5	Randomly sample 25,000 examinees from population 2
6	Randomly assign examinees from step 2 and 5 to both forms, producing equivalent Groups
7	Calculate true scores for base and new form using generated parameters and 3PL compensatory 2D model
8	Equate true scores from base and new form using random groups equipercentile equating
	Administer exam with pilot items
9	Randomly sample examinees from population 1
10	Create response strings using generated item parameters from base form and thetas from sample
	Calibrate operational items
11	Estimate operational item parameters for base form using Bigsteps
12	Calibrate operational items in subtest 1 to generated item scale using SCSL
13	Calibrate operational items in subtest 2 to generated item scale using SCSL
	Calibrate pilot items and preequated
14	Calibrate pilot items with the Rasch model using FPC and then SCSL and add pilot items to pool
15	Preequate new form to base form
	Administer new form with pilot items
16	Randomly sample examinees from population 2
17	Create response strings using generated item parameters from new form and thetas from sample
18	Perform Levine true score equating (chain to original form if necessary)
19	Calibrate pilot items from new form using FPC and then SCSL and add pilot items to pool
	Repeat procedures
21	Repeat steps 4 through 8 and steps 4 through 19 for specified number of forms within replication 1
22	Repeat steps 9 - 21 for 20 replications to obtain bias of equating and SEE for specified Forms

CHAPTER FOUR

RESULTS

Phase One

Preequating was first performed under ideal conditions to define a baseline for comparing the performance of Rasch preequating under conditions of violated assumptions. Figure 7 displays summary graphs for an ideal condition. Plot 1 shows four equivalent, normally distributed theta distributions used for generating response data. Plot 2 shows a scree plot illustrating the unidimensional nature of the data. Plots 3 through 5 display the RMSE of the assumed *a*, estimated *b*, and assumed *c* item parameters. These plots display the RMSE of parameters associated with each calibration method (FPC and SCSL). Under this ideal condition the item parameters remain uniformly flat and close to zero for all assumed and estimated parameters. Plot 6 shows the true score distributions derived from the generated theta and item parameters. These true score distributions were used in defining the criterion equating function via random groups equipercentile equating. The difference between these two distributions is caused by form differences, since the two groups for each form attained equivalence via random assignment. Plot 7 and 8 are Test Characteristic Curves derived from item parameter estimates obtained from the FPC method and the SCSL methods, respectively.

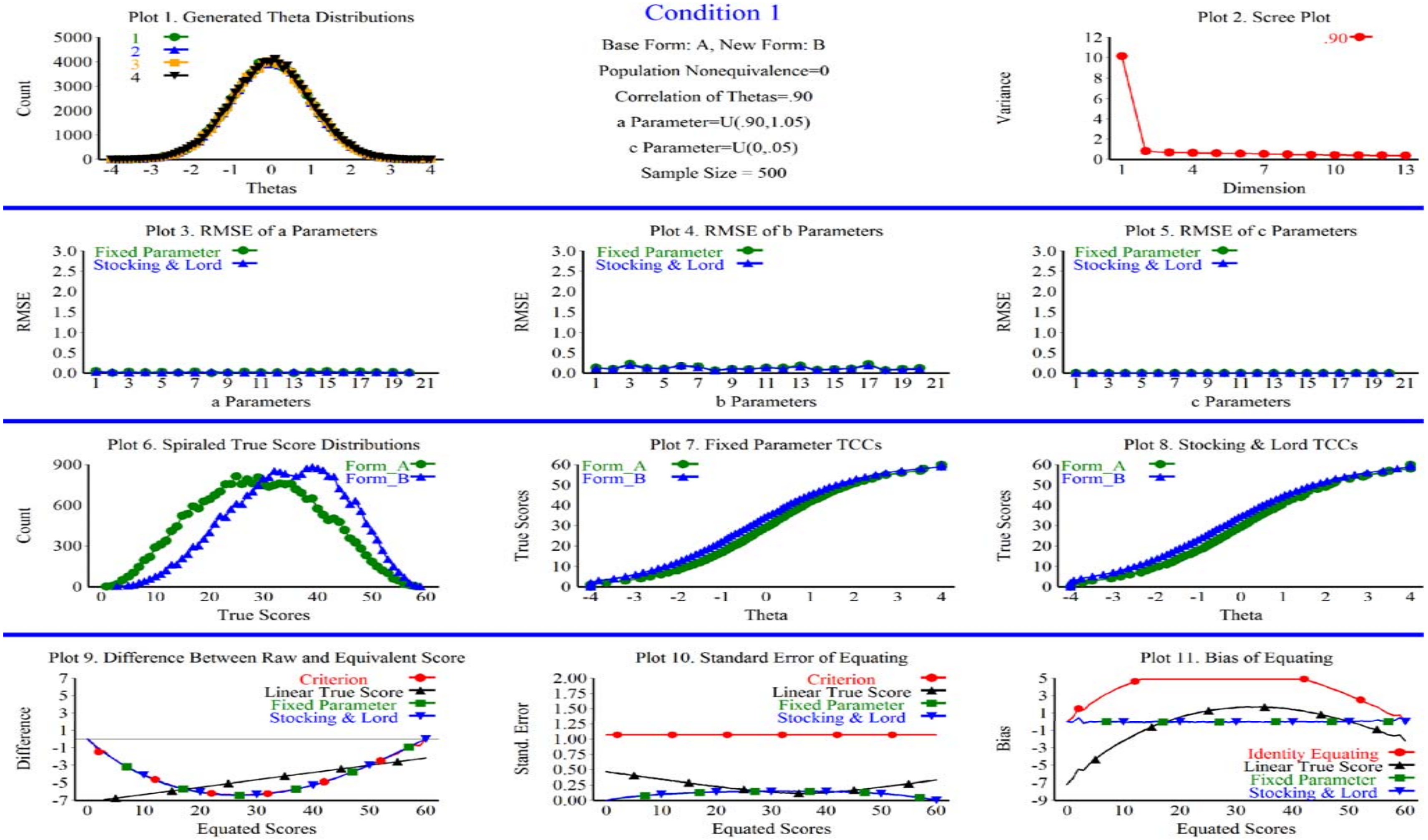


Figure 7. Ideal Conditions and Equating Outcomes. Note: The identity line in Plot 11 extends beyond the scale of the graph. RMSE = Root mean squared error.

equivalent score on the base form according to equating method. The criterion difference was obtained from the equipercentile conversion table. Plot 10 and 11 displays the SEE and bias of equating by method. Research Questions 1 through 4 were answered by comparing the results from the most violated conditions to the results from the ideal condition.

Research Question 1

Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and linear equating) when the IRT assumption of unidimensionality is violated, but all other IRT assumptions are satisfied? As for the preequating methods, does the FPC method perform at least as well as the SCSL method under the same conditions?

Rasch true score preequating produced less equating error than the postequating methods of identity and Levine true score linear equating, when the assumption of unidimensionality was violated with data produced by a two dimensional compensatory model. Rasch true score preequating was unaffected by multidimensionality. The SEE and the bias of preequating under the most severe condition of multidimensionality (Figure 8, plot 10 and 11) remained nearly identical to the SEE and bias of preequating under the ideal condition (Figure 7). FPC performed as well as SCSL under multidimensionality.

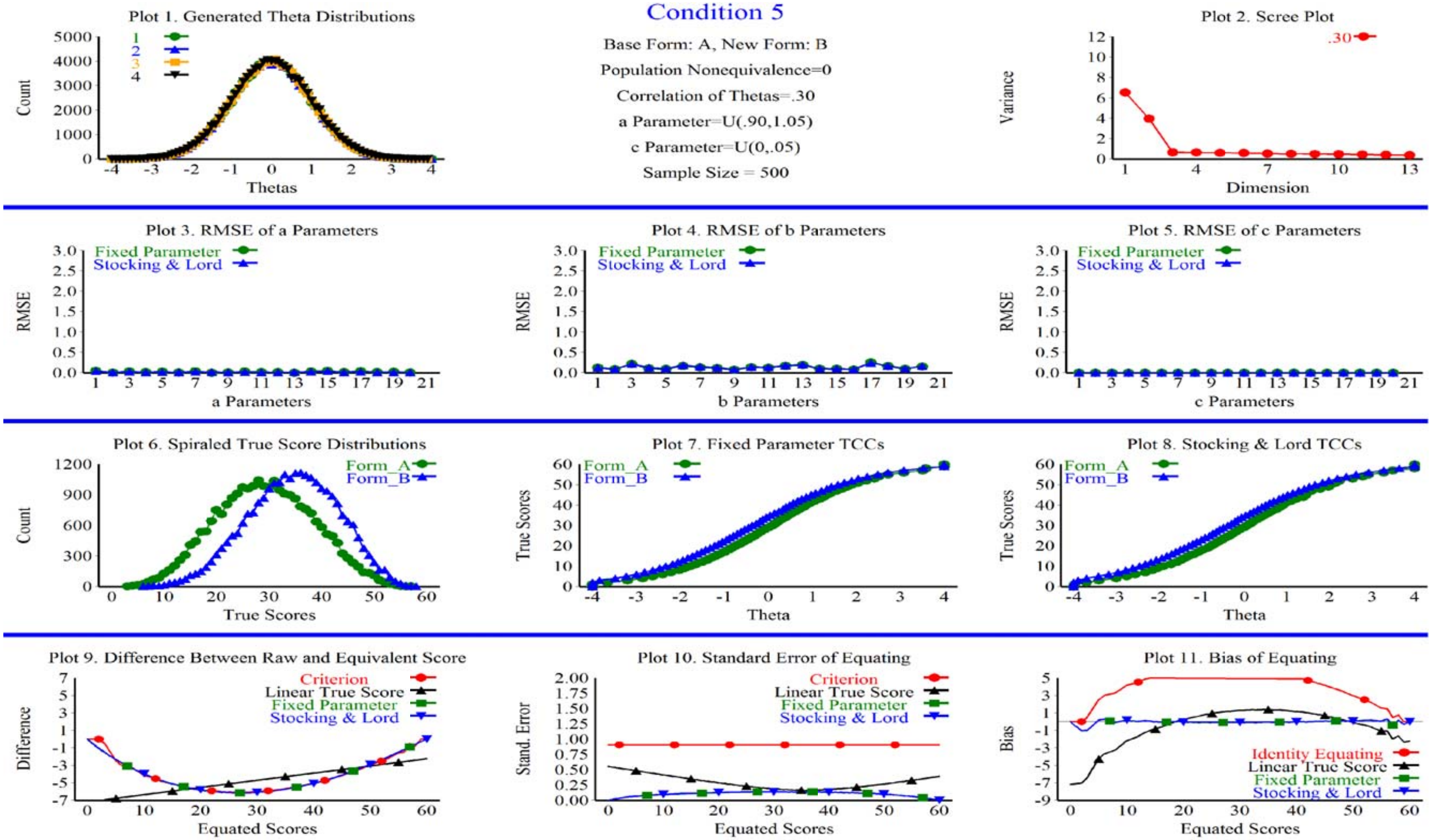


Figure 8. Equating Outcomes under the Severely Violated Assumption of Unidimensionality. Note: The identity line in Plot 11 extends beyond the scale of the graph. RMSE = Root mean squared error.

Research Question 2

Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and Linear equating) when populations are nonequivalent, and IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

Rasch true score preequating produced less equating error than the postequating methods of identity and Levine true score linear equating when populations were nonequivalent and all other IRT assumptions were satisfied. The SEE and the bias of preequating under the most severe condition of nonequivalence (Figure 9, plot 10 and 11) remained nearly identical to the SEE and bias of preequating under the ideal condition (Figure 7). The FPC method performed as well as the SCSL under population nonequivalence.

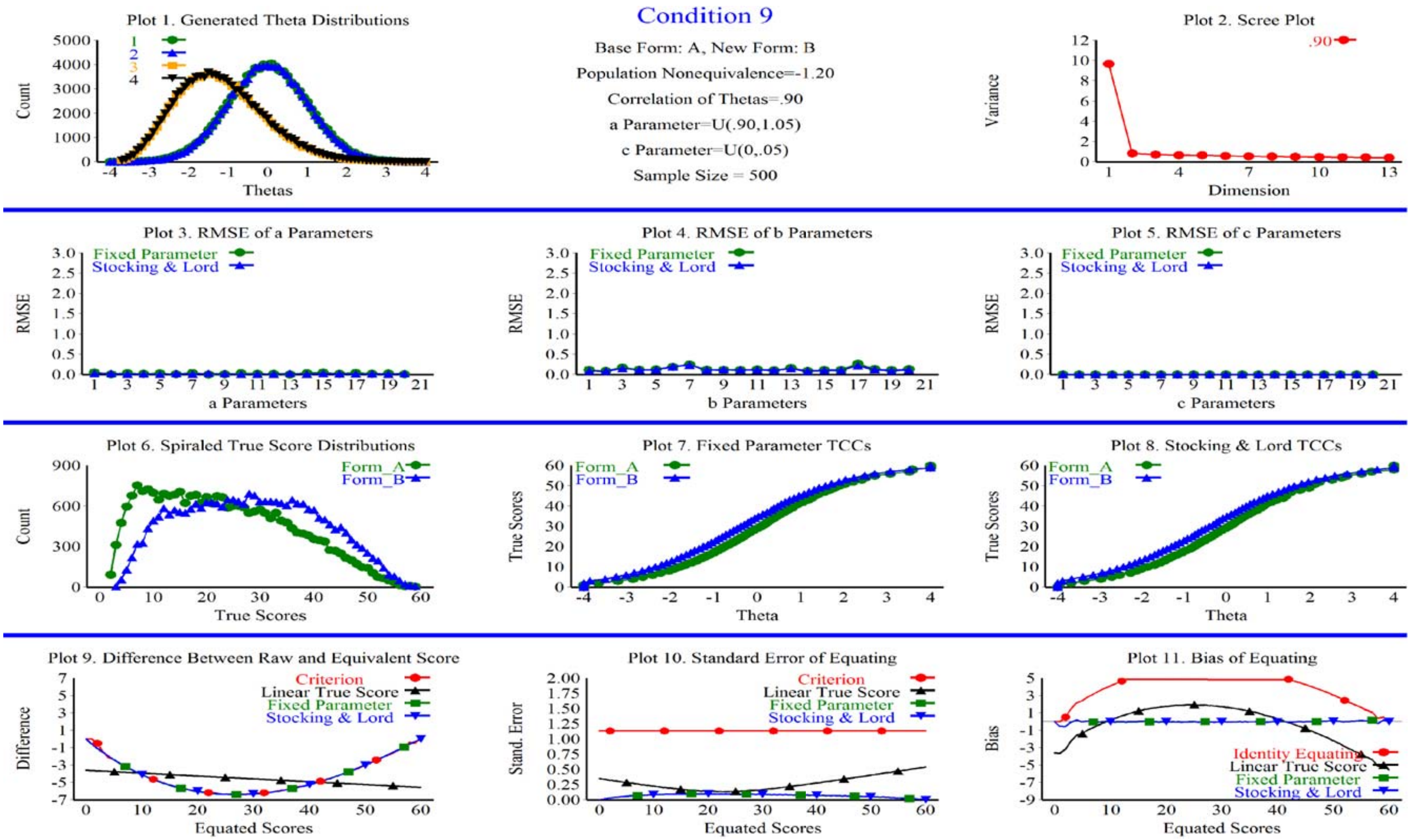
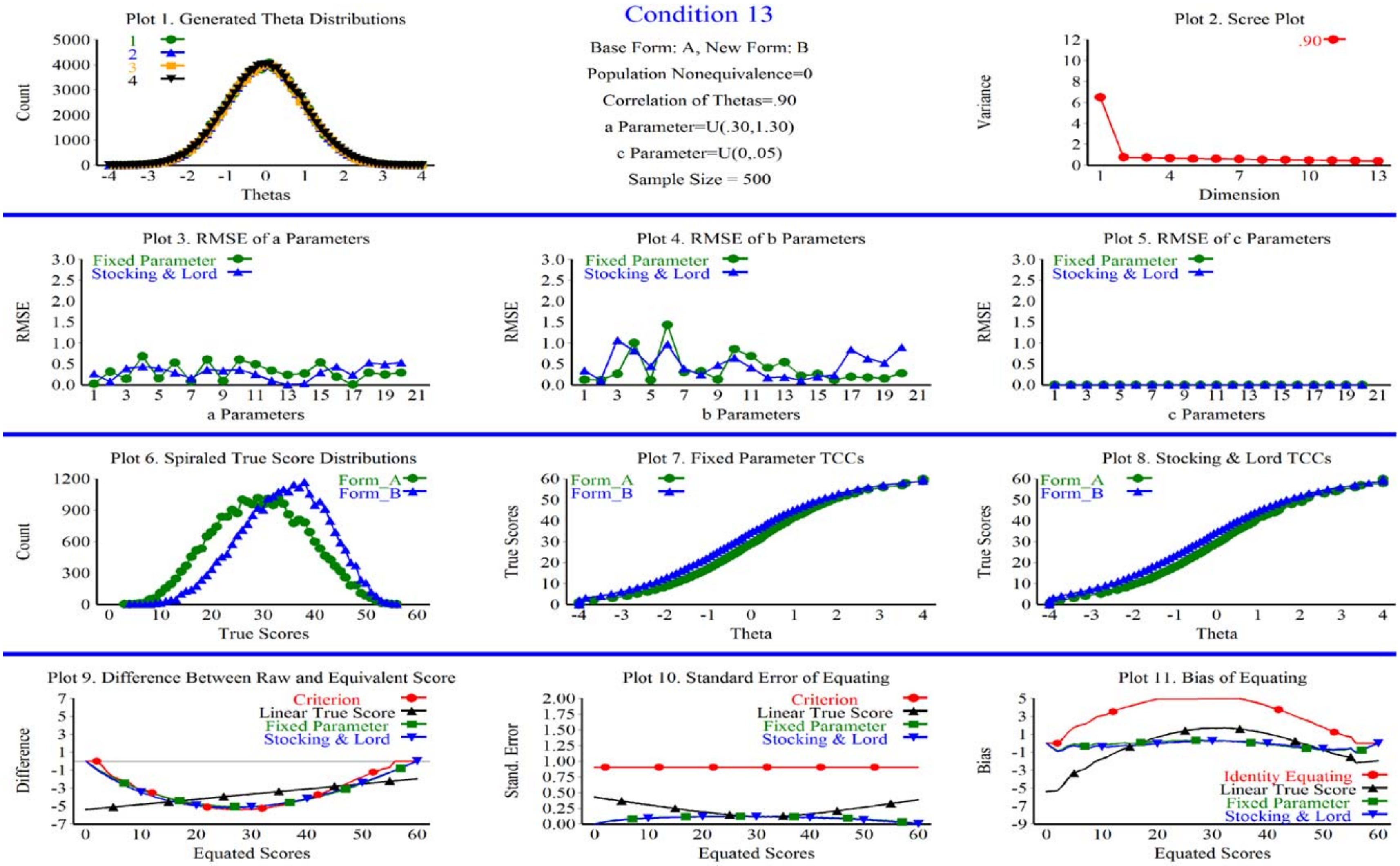


Figure 9. Equating Outcomes Under Severely Nonequivalent Populations. Note: The identity line in Plot 11 extends beyond the scale of the graph. RMSE = Root mean squared error.

Research Question 3

Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and Linear equating) when the Rasch model assumption of equivalent item discriminations is violated, but populations are equivalent and other IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

Rasch true score preequating produced less equating error than identity and Levine true score linear equating when the Rasch model assumption of equivalent item discriminations was violated. The SEE and the bias of preequating under the most severe condition of nonequivalent item discriminations (Figure 10, plot 10 and 11) remained nearly identical to the SEE and bias of preequating under the ideal condition (Figure 7). This robustness to nonequivalent *a* parameters surfaced despite the marked increase in RMSE in the assumed *a* and estimated *b* parameters (plot 4). The FPC method performed as well as the SCSL under population nonequivalence.



Condition 13

Base Form: A, New Form: B

Population Nonequivalence=0

Correlation of Thetas=.90

a Parameter=U(.30,1.30)

c Parameter=U(0,.05)

Sample Size = 500

Plot 1. Generated Theta Distributions

Plot 2. Scree Plot

Plot 3. RMSE of a Parameters

Plot 4. RMSE of b Parameters

Plot 5. RMSE of c Parameters

Plot 6. Spiraled True Score Distributions

Plot 7. Fixed Parameter TCCs

Plot 8. Stocking & Lord TCCs

Plot 9. Difference Between Raw and Equivalent Score

Plot 10. Standard Error of Equating

Plot 11. Bias of Equating

Figure 10. Equating Outcomes Under Severely Nonequivalent Item Discriminations. RMSE = Root mean squared error.

Research Question 4

Do Rasch true score preequating methods (FPC and SCSL) perform better than postequating methods (identity and Linear equating) when the Rasch model assumption of no guessing is violated, but populations are equivalent and other IRT model assumptions are satisfied? Does the FPC method perform at least as well as the SCSL method under the same conditions?

Rasch true score preequating produced less equating error than the postequating methods of identity and Levine true score linear equating when the Rasch model assumption of no guessing was violated, but populations were equivalent and other IRT model assumptions were satisfied. The SEE of preequating under the most severe condition of guessing (Figure 11, plot 10 and 11) remained nearly identical to the SEE of preequating under the ideal condition (Figure 7). Bias increased under the severe condition of guessing. Equating bias was maximum at the lower end of the score scale (plot 11), when the no guessing assumption was severely violated (plot 5). The FPC method performed as well as the SCSL under population nonequivalence.

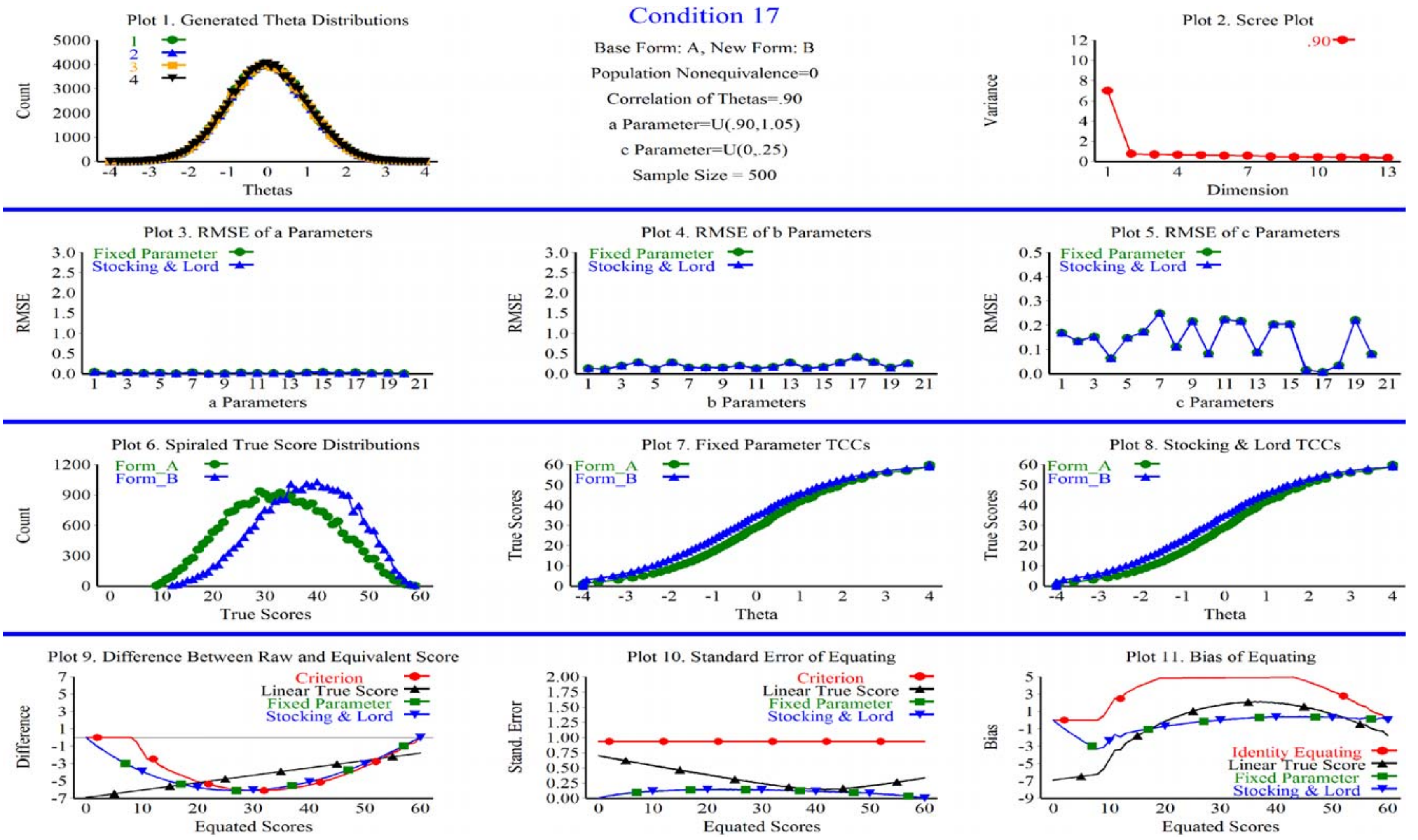


Figure 11. Equating Outcomes Under Severe Guessing. Note: Bias of identity equating extends beyond the bias scale. RMSE = Root mean squared error.

Phase Two

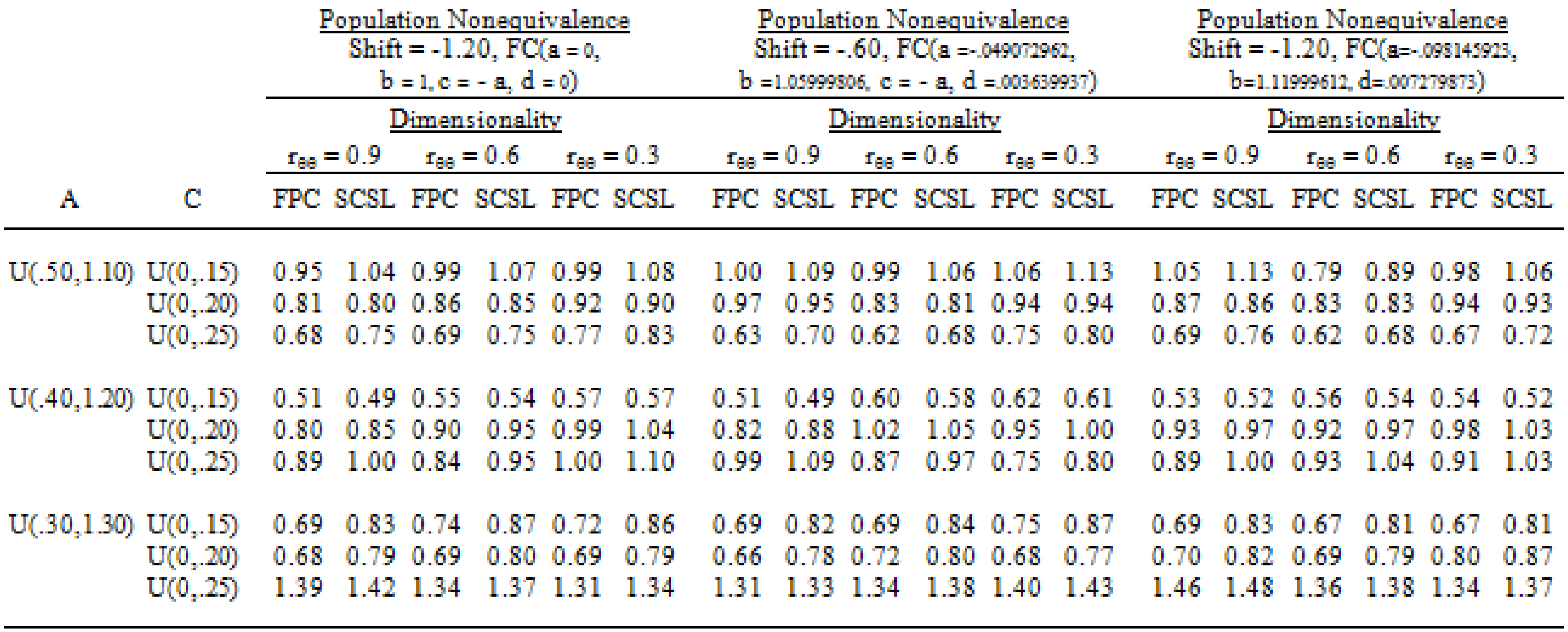
Research Question 5a

What are the interaction effects of multidimensionality, population nonequivalence, nonequivalent item discriminations (*a* parameters), and guessing (*c* parameters) on random and systematic equating error?

Table 6 displays the mean absolute bias for all conditions. The mean absolute bias ranged from 0.51 to 1.48. The absolute bias was least when the *a* parameter ranged from .40 to 1.20 and the *c* parameter ranged from 0 to .15. The absolute bias was greatest when the *a* parameter ranged from .30 to 1.30, the *c* parameter ranged from 0 to .25, and populations nonequivalence was -1.20. Table 7 presents η^2 effect sizes for each main and interaction effect. The interaction effect of nonequivalent *a* parameters and guessing explained 67 percent of the variance in the bias of the SCSL method, and 71 percent of the variance in the bias of the FPC method. The main effect of guessing explained 18 percent of the variance in the bias of the SCSL method, and 18 percent of the variance in the bias of the FPC method. The main effect of nonequivalent *a* parameters explained ten percent of the variance in the bias of the SCSL method, and five percent of the variance in the bias of the FPC method. None of the other factors or interactions had meaningful effects on the bias of preequating.

Table 6

Mean Absolute bias of Equating by Method



		Population Nonequivalence Shift = -1.20, FC(a = 0, b = 1, c = - a, d = 0)						Population Nonequivalence Shift = -.60, FC(a =-.049072962, b =1.05999806, c = - a, d =.003639937)						Population Nonequivalence Shift = -1.20, FC(a=-.098145923, b=1.11999612, d=.007279873)					
		Dimensionality						Dimensionality						Dimensionality					
		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$	
A	C	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL
U(.50,1.10)	U(0,.15)	0.95	1.04	0.99	1.07	0.99	1.08	1.00	1.09	0.99	1.06	1.06	1.13	1.05	1.13	0.79	0.89	0.98	1.06
	U(0,.20)	0.81	0.80	0.86	0.85	0.92	0.90	0.97	0.95	0.83	0.81	0.94	0.94	0.87	0.86	0.83	0.83	0.94	0.93
	U(0,.25)	0.68	0.75	0.69	0.75	0.77	0.83	0.63	0.70	0.62	0.68	0.75	0.80	0.69	0.76	0.62	0.68	0.67	0.72
U(.40,1.20)	U(0,.15)	0.51	0.49	0.55	0.54	0.57	0.57	0.51	0.49	0.60	0.58	0.62	0.61	0.53	0.52	0.56	0.54	0.54	0.52
	U(0,.20)	0.80	0.85	0.90	0.95	0.99	1.04	0.82	0.88	1.02	1.05	0.95	1.00	0.93	0.97	0.92	0.97	0.98	1.03
	U(0,.25)	0.89	1.00	0.84	0.95	1.00	1.10	0.99	1.09	0.87	0.97	0.75	0.80	0.89	1.00	0.93	1.04	0.91	1.03
U(.30,1.30)	U(0,.15)	0.69	0.83	0.74	0.87	0.72	0.86	0.69	0.82	0.69	0.84	0.75	0.87	0.69	0.83	0.67	0.81	0.67	0.81
	U(0,.20)	0.68	0.79	0.69	0.80	0.69	0.79	0.66	0.78	0.72	0.80	0.68	0.77	0.70	0.82	0.69	0.79	0.80	0.87
	U(0,.25)	1.39	1.42	1.34	1.37	1.31	1.34	1.31	1.33	1.34	1.38	1.40	1.43	1.46	1.48	1.36	1.38	1.34	1.37

Note: FC = Fleishman Coefficients. FPC = Fixed Parameter Calibration. SCSL = Separate Calibration with the Stocking and Lord method. The mean absolute bias of equating was calculated by finding the absolute difference between the criterion equated score and the estimated equated score at each score, and averaging across all 61 score points.

Table 7

Variance of Equating Bias

Source	DF	SS	SS Total	η^2	SS	SS Total	η^2
			Stocking & Lord			FPC	
Populations	2	0.00	4.24	0.00	0.00	4.24	0.00
Dimensions	2	0.02	4.24	0.00	0.02	4.24	0.01
Population*Dimensions	4	0.01	4.24	0.00	0.02	4.24	0.00
a	2	0.42	4.24	0.10	0.23	4.24	0.05
Populations*a	4	0.01	4.24	0.00	0.01	4.24	0.00
Dimensions*c	4	0.02	4.24	0.01	0.03	4.24	0.01
Population*Dimensions*a	8	0.03	4.24	0.01	0.03	4.24	0.01
c	2	0.75	4.24	0.18	0.76	4.24	0.18
Populations*c	4	0.02	4.24	0.00	0.02	4.24	0.00
Dimensions*a	4	0.01	4.24	0.00	0.02	4.24	0.00
Population*Dimensions*c	8	0.01	4.24	0.00	0.02	4.24	0.00
a*c	4	2.84	4.24	0.67	3.02	4.24	0.71
Population*a*c	8	0.01	4.24	0.00	0.01	4.24	0.00
Dimensions*a*c	8	0.02	4.24	0.00	0.02	4.24	0.00
Population*Dimensions*a*c	16	0.06	4.24	0.01	0.06	4.24	0.01

Table 8 displays the MSEE for all Phase Two conditions. The MSEE ranged from 0.14 to 0.36. Table 9 presents η^2 effect sizes for each condition. The interaction of population nonequivalence, multidimensionality, nonequivalent item discriminations, and guessing explained the largest portion of the variance at 17 percent. While the interactions of the violated assumptions were present, there was not a substantial amount of total variance to explain. Violations of model assumptions had no meaningful effect on the variance of the MSEE. These results underscore the fact that the SEE for Rasch preequating is primarily a function of sample size.

Table 8

Mean Standard Error of Equating (MSEE) by Method

		Population Nonequivalence Shift = -1.20, FC(a = 0, b = 1, c = - a, d = 0)						Population Nonequivalence Shift = -.60, FC(a =-.049072962, b =1.05999806, c = - a, d =.003639937)						Population Nonequivalence Shift = -1.20, FC(a=-.098145923, b=1.11999612, d=.007279873)					
		Dimensionality						Dimensionality						Dimensionality					
		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$		$r_{\theta\theta} = 0.9$		$r_{\theta\theta} = 0.6$		$r_{\theta\theta} = 0.3$	
A	C	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL	FPC	SCSL
U(.50,1.10)	U(0,.15)	0.23	0.20	0.25	0.23	0.29	0.27	0.27	0.24	0.24	0.22	0.28	0.25	0.24	0.23	0.20	0.20	0.23	0.20
	U(0,.20)	0.21	0.20	0.24	0.22	0.16	0.16	0.27	0.25	0.29	0.27	0.25	0.23	0.26	0.25	0.23	0.21	0.23	0.21
	U(0,.25)	0.26	0.24	0.25	0.23	0.18	0.16	0.24	0.23	0.24	0.22	0.17	0.16	0.27	0.25	0.25	0.23	0.22	0.20
U(.40,1.20)	U(0,.15)	0.23	0.22	0.22	0.21	0.23	0.22	0.21	0.20	0.21	0.19	0.27	0.26	0.25	0.23	0.21	0.19	0.22	0.21
	U(0,.20)	0.20	0.18	0.30	0.27	0.18	0.17	0.29	0.27	0.23	0.21	0.23	0.21	0.36	0.32	0.20	0.19	0.21	0.19
	U(0,.25)	0.27	0.25	0.24	0.22	0.22	0.20	0.27	0.23	0.24	0.22	0.17	0.16	0.24	0.22	0.21	0.18	0.21	0.20
U(.30,1.30)	U(0,.15)	0.24	0.22	0.24	0.22	0.28	0.25	0.28	0.25	0.26	0.24	0.17	0.15	0.25	0.23	0.27	0.24	0.29	0.27
	U(0,.20)	0.23	0.22	0.28	0.26	0.19	0.17	0.25	0.23	0.25	0.23	0.19	0.17	0.24	0.22	0.23	0.22	0.20	0.18
	U(0,.25)	0.24	0.21	0.16	0.14	0.28	0.25	0.22	0.20	0.26	0.24	0.25	0.23	0.28	0.26	0.29	0.26	0.26	0.23

Note: FC = Fleishman Coefficients. FPC = Fixed Parameter Calibration. SCSL = Separate Calibration with the Stocking and Lord method. The MSEE was calculated by averaging the SEE across the raw score scale.

Table 9

Variance of the Standard Error of Equating by Method

Source	DF	SS	SS Total	η^2	SS	SS Total	η^2
			Stocking & Lord			FPC	
Populations	2	0.00	0.13	0.00	0.00	0.16	0.00
Dimensions	2	0.01	0.13	0.07	0.01	0.16	0.07
Population*Dimensions	4	0.01	0.13	0.07	0.01	0.16	0.07
a	2	0.00	0.13	0.01	0.00	0.16	0.01
Populations*a	4	0.01	0.13	0.05	0.01	0.16	0.05
Dimensions*c	4	0.00	0.13	0.02	0.00	0.16	0.02
Population*Dimensions*a	8	0.01	0.13	0.09	0.01	0.16	0.09
c	2	0.00	0.13	0.00	0.00	0.16	0.00
Populations*c	4	0.01	0.13	0.06	0.01	0.16	0.06
Dimensions*a	4	0.02	0.13	0.12	0.02	0.16	0.12
Population*Dimensions*c	8	0.01	0.13	0.08	0.01	0.16	0.08
a*c	4	0.00	0.13	0.03	0.00	0.16	0.03
Population*a*c	8	0.02	0.13	0.13	0.02	0.16	0.12
Dimensions*a*c	8	0.01	0.13	0.11	0.02	0.16	0.11
Population*Dimensions*a*c	16	0.02	0.13	0.17	0.02	0.16	0.16

Research Question 5b

At what levels of interaction does Rasch preequating work less effectively than identity equating or linear equating?

There were no conditions under which Rasch preequating worked less effectively than identity or linear equating (Figures 7 - 18). Rasch preequating produced less bias and SEE than did the identity or Linear equating methods across all conditions (Table 10). Identity equating produced the most equating error, followed by Levine true score linear equating, SCSL, and FPC.

Table 10. Mean Absolute Bias Across All Conditions

Equating Error	Count	Identity	Levine's Linear True Score	Stocking & Lord Calibration	FPC
Mean Absolute Bias	81	2.41	1.61	0.91	0.85
Mean Standard Error	81	N/A	0.78	0.23	0.24

Research Question 5c

How does FPC compare to SCSL in terms of equating error under the interactions?

Preequating with FPC was slightly more accurate than preequating with SCSL, but less precise (Table 10). However, in a practical sense, the magnitudes of the differences were negligible. This can be seen in Figure 11 which displays the mean of the standard errors of equating and bias from all conditions. The error lines for the FPC and the SCSL methods are nearly indistinguishable.

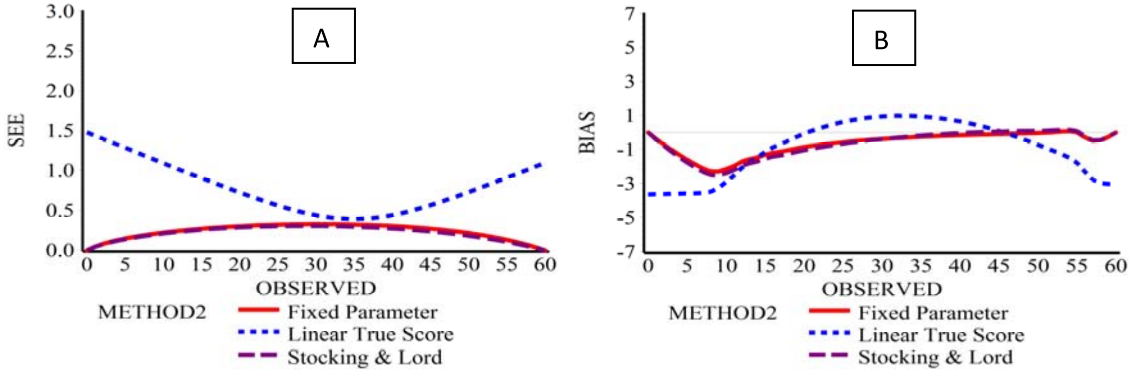


Figure 12. The Mean Standard Error of Equating (SEE) (plot A) and the Mean Bias of Equating (plot B) of All Conditions by Method. The horizontal axis is the observed (raw) score scale.

Research Question 5d

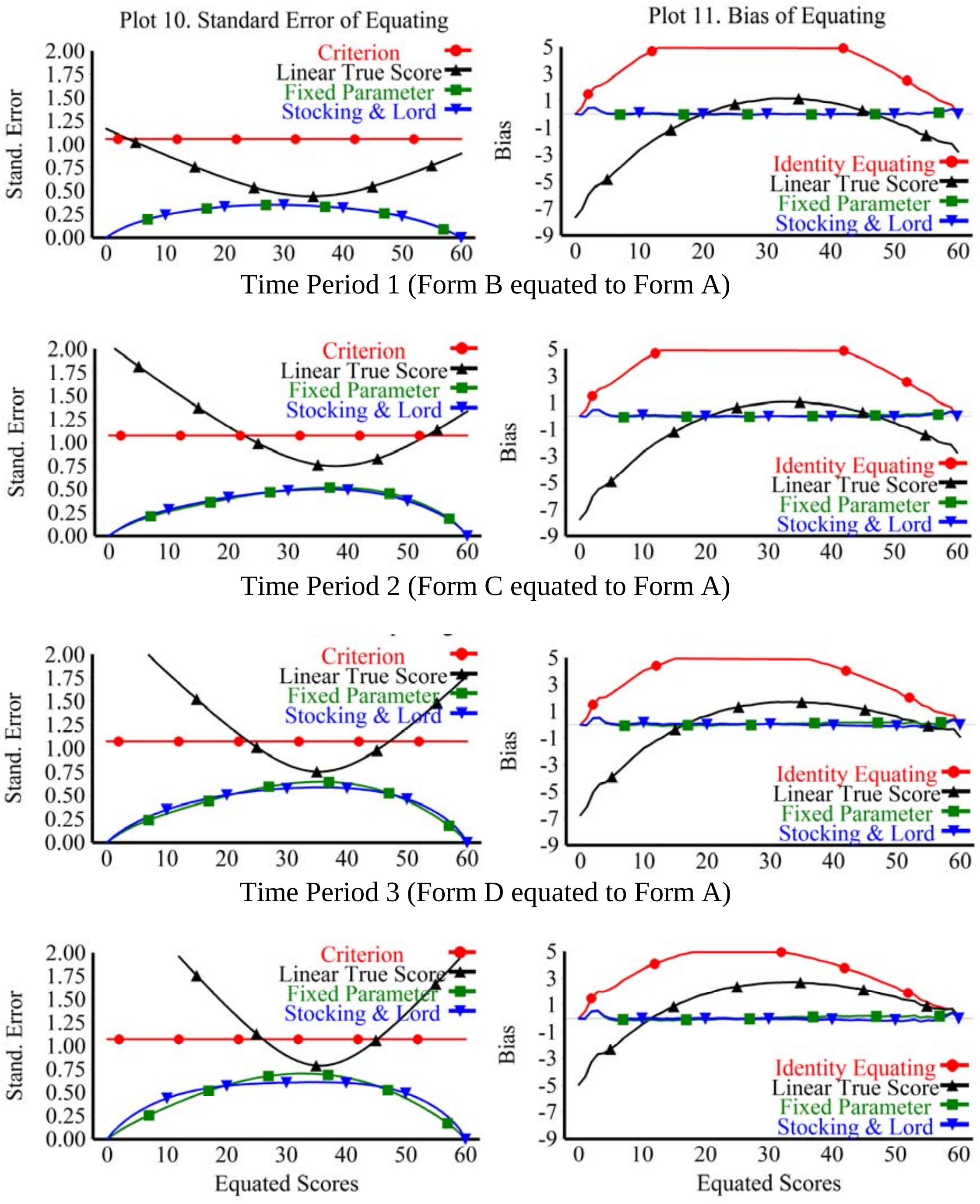
Does equating error accumulate across four equatings under the interactions?

In the ideal condition, depicted in Figure 13, the SEE increased from a maximum of 0.37 in the first equating to a maximum of 0.75 in the fourth equating. While this is a substantial increase in error, the maximum value of the SEE remained below the conservative criterion of 0.10 of a standard deviation of the raw score for this condition. The bias remained small across all equatings.

Under moderately violated conditions, depicted in Figure 14, the SEE increased more substantially from the first equating to the fourth equating. The SEE increased from a maximum of 0.37 in the first equating to 0.80 in the fourth equating. The SEE approached the conservative criterion of 0.10 of a standard deviation of the raw score for this condition. The bias improved across the equatings.

Under severely violated conditions, depicted in Figure 15, the SEE exceeded the criterion at the fourth equating. The SEE increased from a maximum of 0.37 to a maximum of 0.88.

Under the most severely violated conditions, depicted in Figure 16, the SEE exceeded the criterion at the third equating. The SEE increased from a maximum of 0.37 to a maximum of 1.03. The SCSL method appeared to perform better in terms of bias than did the FPC method.



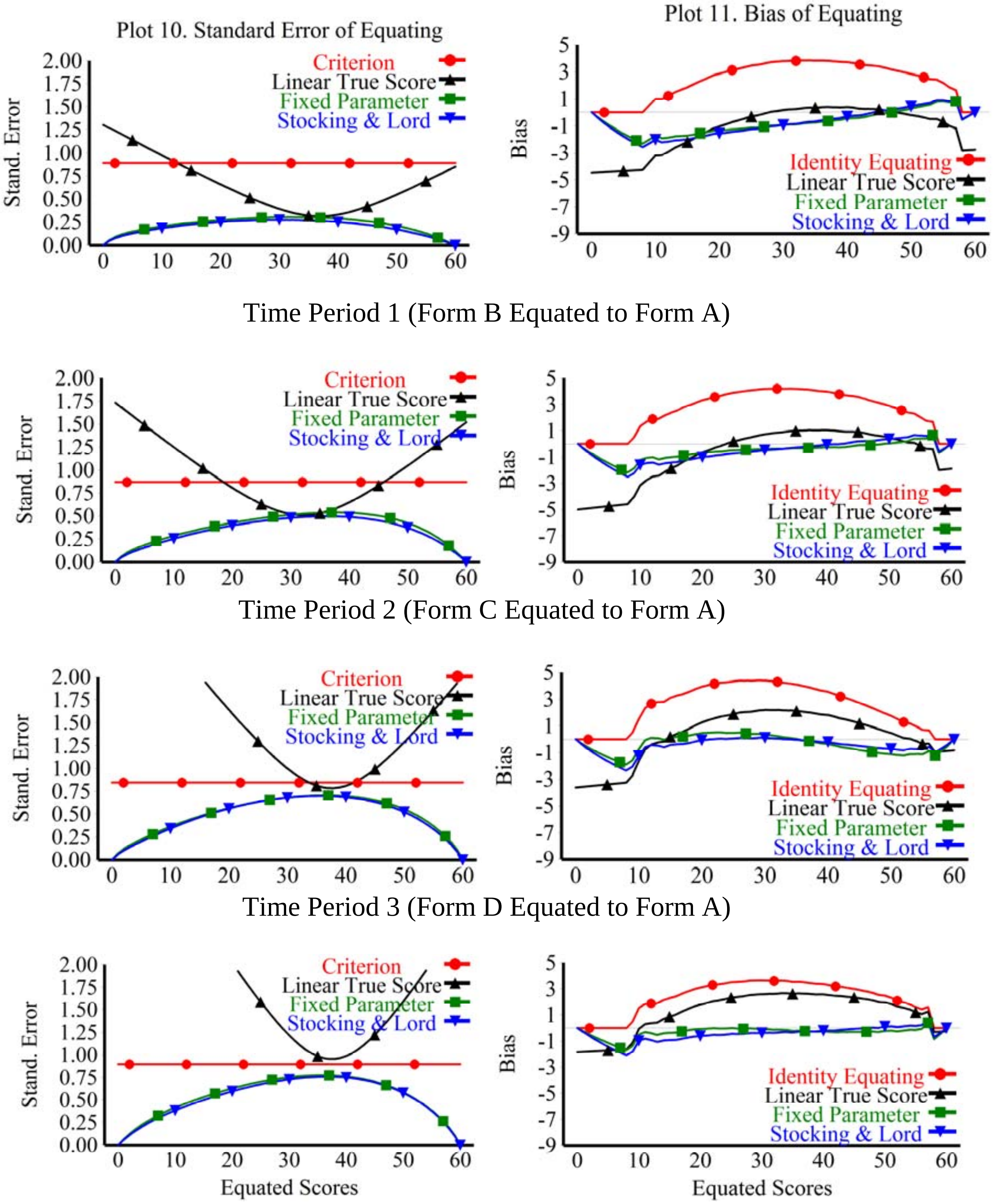
Time Period 1 (Form B equated to Form A)

Time Period 2 (Form C equated to Form A)

Time Period 3 (Form D equated to Form A)

Time Period 4 (Form E equated to Form A)

Figure 13. Standard Errors of Equating and Bias Across Five Forms under Ideal Conditions. (a=(U(.90, 1.05)), c=(U(0,.05)), rθθ=(.90), Shift = 0, FC(a = 0, b = 1, c = - a, d = 0))



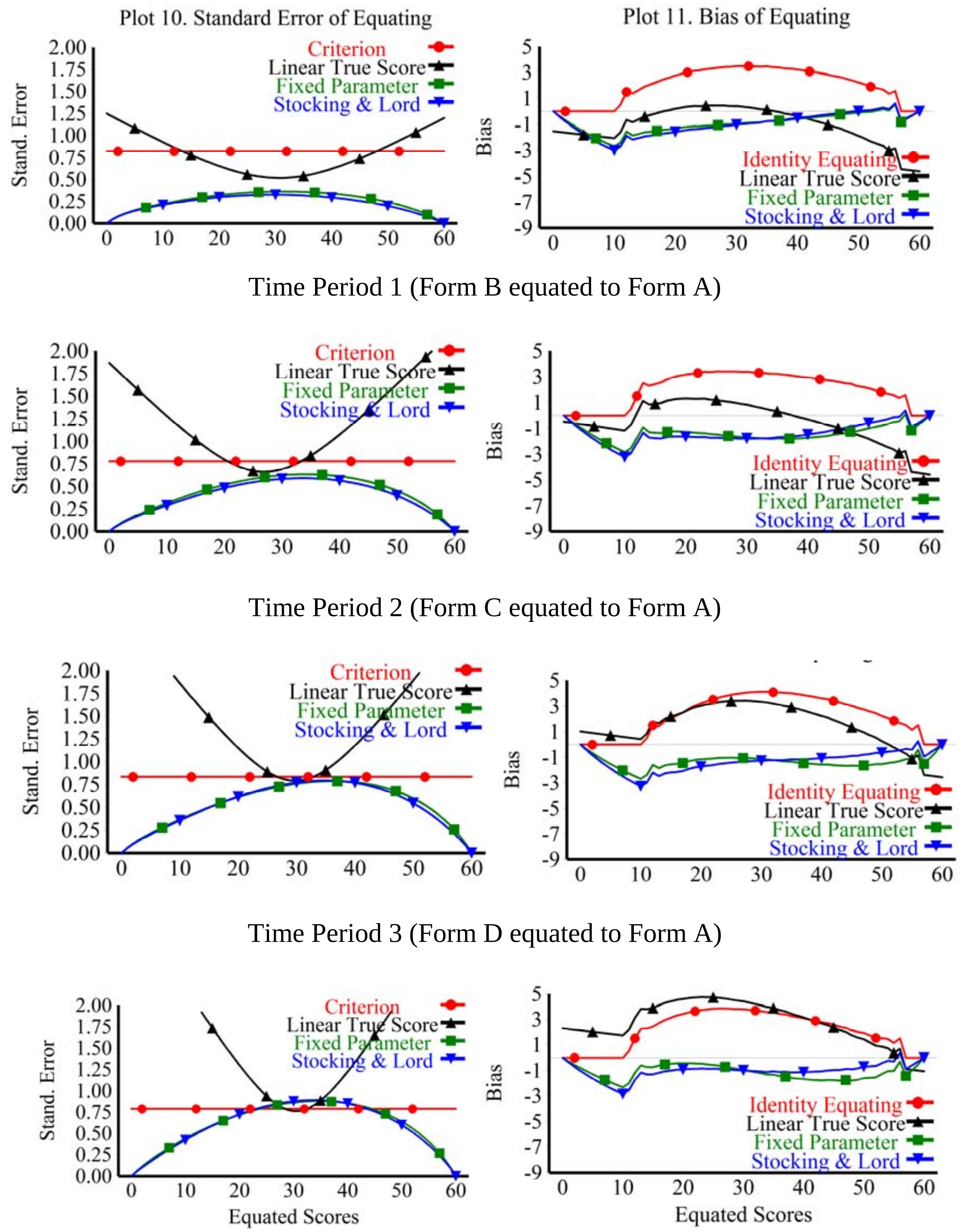
Time Period 1 (Form B Equated to Form A)

Time Period 2 (Form C Equated to Form A)

Time Period 3 (Form D Equated to Form A)

Time Period 4 (Form E Equated to Form A)

Figure 14. Standard Errors of Equating and Bias Across Five Forms under Moderately Violated Assumptions. (a=(U(.40, 1.20)), c=(U(0,.20), r=(.60), Shift = -.60, FC(a = .049072962, b =1.05999806, c = - a, d =.003639937)



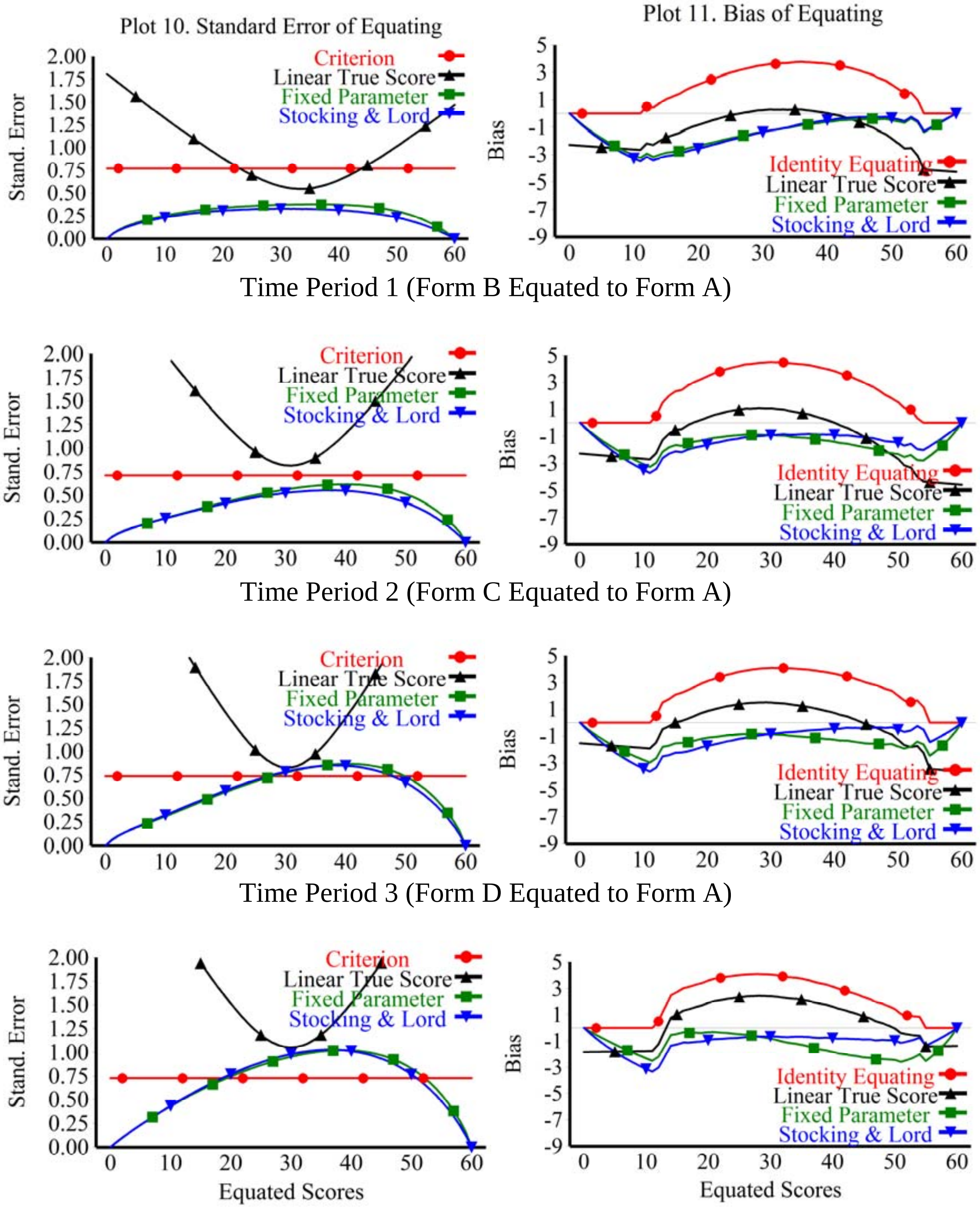
Time Period 1 (Form B equated to Form A)

Time Period 2 (Form C equated to Form A)

Time Period 3 (Form D equated to Form A)

Time Period 4 (Form E equated to Form A)

Figure 15. Standard Errors of Equating and Bias Across Five Forms under Severely Violated Model Assumptions. (a=(U(.40, 1.20)), c=(U(0,.25), r=(.40), Shift = -1.20, FC(a=-.098145923, b=1.11999612, d=.007279873)



Time Period 1 (Form B Equated to Form A)

Time Period 2 (Form C Equated to Form A)

Time Period 3 (Form D Equated to Form A)

Time Period 4 (Form E Equated to Form A)

Figure 16. Standard Errors of Equating and Bias Across Five Forms under the Most Severely Violated Model Assumptions. (a=U(.30, 1.30), c=U(0,.25), r=(.30), Shift = -1.20, FC(a=-.098145923, b=1.11999612, d=.007279873).

CHAPTER FIVE

DISCUSSION

This chapter presents the substantive conclusions and implications of the study. First, the results for Phase One and Phase Two are summarized, followed by a discussion of the four hypotheses presented in the methods section. An explanation is offered for the cause of preequating's sensitivity to violations of the no guessing assumption. Results from an additional condition are then presented that provide support for this explanation. Implications of the results of this study to classification consistency and accuracy are discussed. The limitations of the study and suggestions for future research are then presented.

Phase One

In Phase One, simulation results provide evidence that preequating was robust to multidimensionality, population nonequivalence, and nonequivalent item discriminations. The finding that Rasch true score equating is robust to violations of the assumption of unidimensionality is consistent with studies previously conducted with the 3PL model (Bogan & Yen, 1983; Camili, Wang, & Fesq, 1995; Cook Dorans, Eignor, & Petersen, 1985; Dorans & Kingston, 1985; Wang, 1985; Yen, 1984; Smith, 1996). However, these findings do contradict the studies on preequating under the 3PL model that concluded preequating was not robust to multidimensionality (Eignor, 1985; Kolen & Harris, 1990; Hendrickson & Kolen, 1999). Given the many types of multidimensionality that can be present, perhaps the robustness of IRT true score equating depends on the type of multidimensionality. This study provides evidence that Rasch true score equating is robust to at least one type of multidimensionality: a 2D compensatory model with a simple structure. The likely cause for this result is the fact that the JMLE procedure targets a composite theta (Reckase, Ackerman, & Carlson, 1988). Provided that the test forms are produced consistently according to a blueprint, the same composite measure is targeted during parameter estimation and equating. This produces consistent and accurate equating.

Sample sizes of 500 examinees produced very small SEE. The SEE for all conditions remained well below the conservative criterion of 0.10 standard deviations of the raw score. In fact the SEE remained below 0.25 of a raw score point across all conditions. The SEE for preequating remained smaller than linear equating across all conditions. This outcome was consistent with Kolen and Brennan's recommendation to use a sample of 400 examinees for Rasch true score equating (2004).

The bias of preequating remained less than Levine's true score linear equating method and less than the identity equating for all conditions. This result that an IRT true score preequating method produced less equating error than linear equating is consistent with earlier findings (Bolt, 1995; Kolen & Brennan, 2004).

The accuracy of difficulty parameter estimates in this study were negatively affected by the nonequivalent *a* parameters, however, the error in the assumed *a* and estimated *b* parameters had little effect on preequating. Preequating bias reached its maximum at the low end of the score scale when guessing was most severe. These results were consistent with Du, Lipkins, and Jones's equating study (2002).

The finding that Rasch true score preequating was not robust to violations of the assumption of no guessing was consistent with earlier studies that suggested that the Rasch model does not perform well under guessing (Slinde & Linn, 1978; Loyd & Hoover, 1981; Skaggs & Lissetz, 1986).

Phase Two

In comparison to identity equating and Levine's true score equating, Rasch preequating performed well under the interaction effects of violated assumptions. However, the magnitude of equating bias in some conditions would be unacceptably large for some testing applications. The fact that a substantial interaction between nonequivalent item discriminations and guessing was found in this study, may help explain the contradictory results of some past studies that have examined the feasibility of Rasch true score equating. The results of this study suggest that Rasch true score equating is tolerant of low levels of guessing; however, if low levels of guessing interact with moderate levels of nonequivalent item discriminations, substantial bias can appear.

It is very likely that when highly and positively skewed ability distributions coincide with guessing or with nonequivalent discriminations and guessing, then equating bias at the low end of the score scale would coincide with the large proportion of low scoring examinees. It can be inferred that this condition would represent the worst case scenario for Rasch preequating, in which a large proportion of examinees obtain scores in the area of the score scale where equating bias is most substantial. In the testing situations simulated in this study, equated scores underestimated the actual score. If accuracy of equated scores is important at the low end of the scale, as they often are for the measurement of growth for instance, then the bias would be unacceptably large. For criterion referenced tests, in which cut scores are located near or above the middle of the distribution, the bias caused by violations may be small enough to be acceptable for many applications.

Equating error did accumulate across equatings. In most conditions, the magnitude of the accumulated error was not large enough to exceed the criteria. The bias was inconsistent in the direction in which it changed. In some instances the bias increased, and in other instances it decreased across equatings. In contrast, the SEE consistently increased across linkings.

Hypotheses

Contrary to Hypothesis 1, preequating error did not exceed the criteria when population nonequivalence exceeded .50 standard deviations. Population nonequivalence did have a more substantial affect on linear equating. Rasch true score equating was not affected by nonequivalent populations in this study.

Results of this study confirmed Hypothesis 2. Rasch preequating was more robust to violations of the *a* parameter than the no guessing assumption. Relatively minor violations of the no guessing assumption created substantial bias at the low end of the score scale. In contrast, even the most severe violations of nonequivalent discriminations created very small amounts of bias (Figure 10, plot 11).

Hypothesis 3 stated that preequating error would increase rapidly as assumptions were simultaneously violated. Hypothesis 3 was partially confirmed. Moderate levels of nonequivalent item discriminations increased the negative effects of guessing substantially. Typically this interaction increased the maximum bias slightly, but had a greater effect on the range of bias across the score scale. Guessing alone tended to create bias at the lower end of the score scale in the score range of 0 to 25 scale points (Figure 11, Plot 11), but if moderate levels of nonequivalent item discriminations interacted with guessing, the range of the bias extended toward the middle of the scale (Figure 17, Plot 11). Sometimes this effect on bias was magnified across multiple equatings (Figure 15, Plot 11). In other instances the bias diminished across equatings (Figure 14).

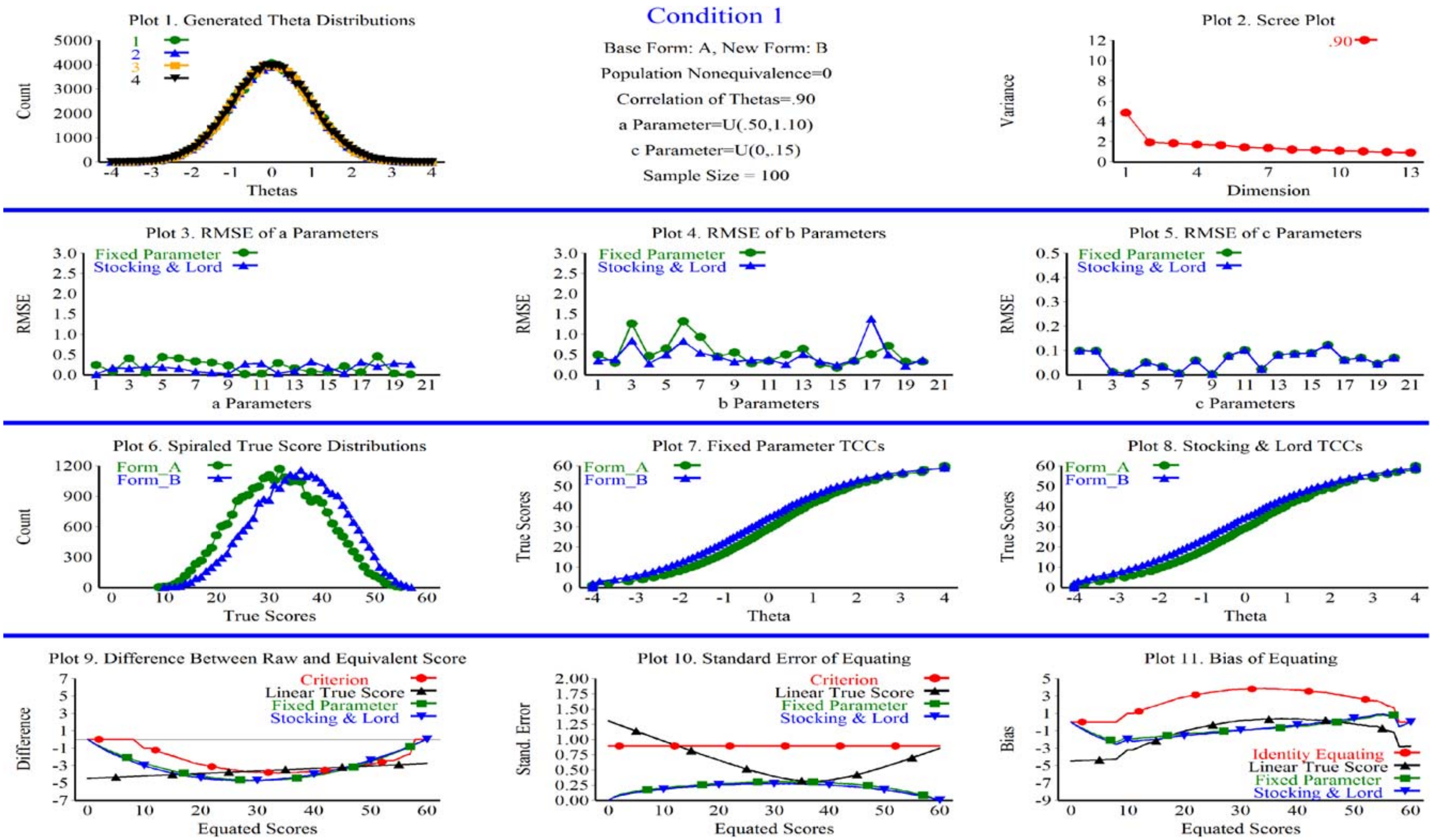


Figure 17. Equating Outcomes Under the Interaction of Moderate Guessing and Moderate Nonequivalent Item Discriminations.

RMSE = Root mean squared error.

Interactions of multidimensionality and population nonequivalence had little direct effect on preequating error. When population nonequivalence and guessing interacted, they tended to shrink the variance of the score distribution (compare plot 6 in Figures 17 and Figure 18). The effect of this interaction was to lower the criterion for the SEE (Plot 10). Otherwise, multidimensionality, population nonequivalence, and their interactions with other factors had no significant negative effect on preequating in this study.

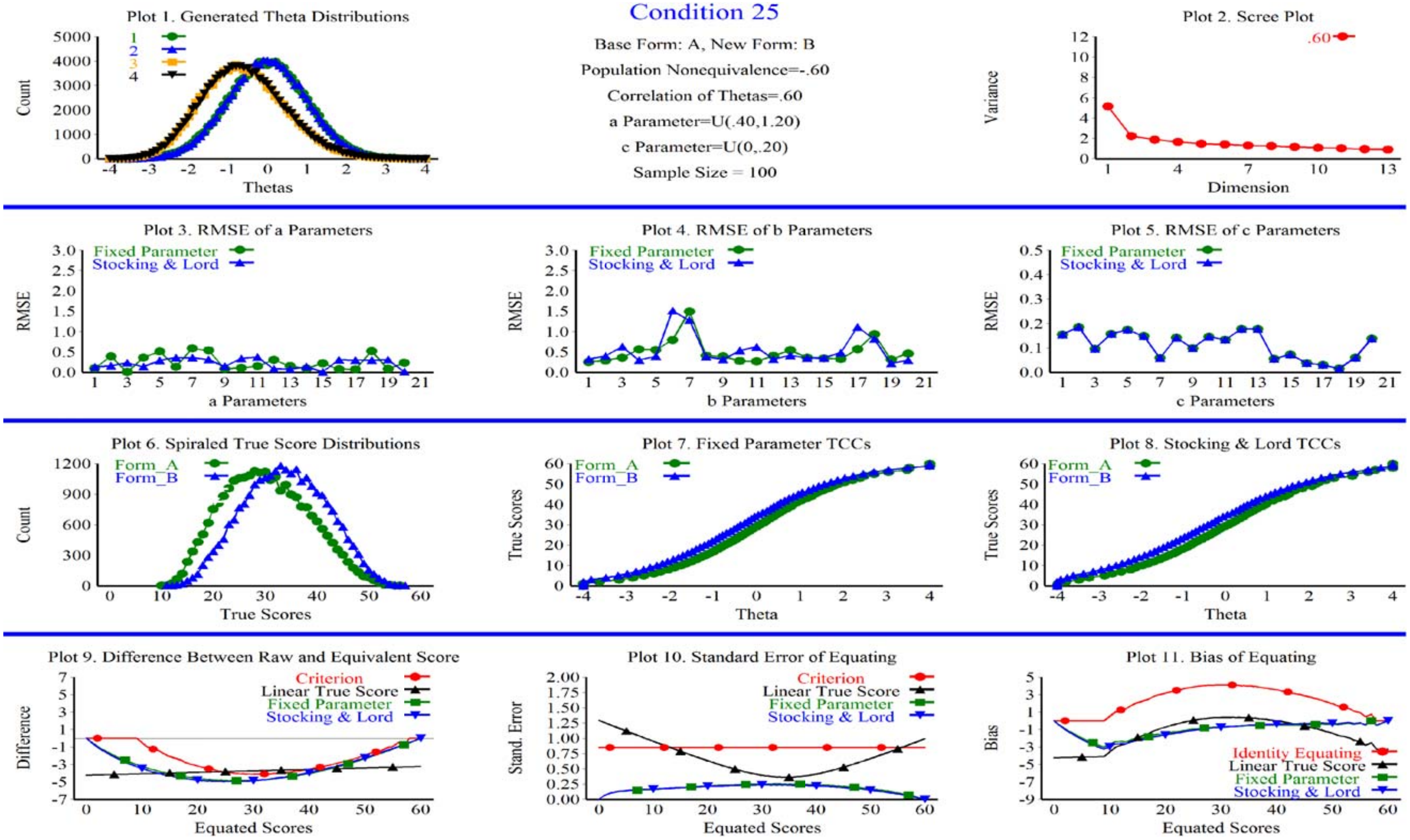


Figure 18. Equating Outcomes Under the Interaction of Severe Guessing and Moderate Levels of Nonequivalent Item Discriminations and Moderate Levels of Population Nonequivalence. RMSE = Root mean squared error.

Hypothesis 4 stated that violations of model assumptions would result in error in the item parameter estimates, which would result in increased error in the SEE and bias via the TCC. Results of this study generally support this hypothesis, but only for violations of the no guessing assumption and its interaction with violations of the nonequivalent discrimination. Compensatory two dimensional data had no visible effect on the RMSE of Bigstep's difficulty parameter estimates (contrast Figure 7 with Figure 8, Plot 2 and Plot 4). Population nonequivalence had no visible effect on the RMSE of Bigstep's difficulty parameter estimates (contrast Figure 7 with Figure 9, Plot 1 and 4). However, violations of the assumption of equivalent discriminations substantially increased the error in Bigstep's difficulty parameter estimates (contrast Figure 7 with Figure 10, Plots 3 and 4). Yet, the error introduced in the difficulty parameters and the assumed *a* parameters had little effect on preequating (Figure 10, Plot 11). Violations of the assumption of no guessing also increased the error in Bigstep's difficulty parameter estimates (contrast Figure 7 and Figure 11, plots 3 and 4). Although error in the difficulty parameters may have had some effect on the equating, the primary cause of the equating error under the conditions with modeled guessing resulted from the Rasch model predicting lower true scores (Figure 11, Plot 7 and 8) than what the generated parameters were capable of producing (Plot 6). Because the Rasch model TCCs predicted the lowest true score to be zero, the Raphson Newton method began its search at a raw score of zero, many points below where it actually should have begun. It appears that as a direct result of starting at the incorrect minimum raw score, the Raphson Newton method produced biased results.

The bias introduced by guessing is a symptom of a more general problem in Rasch true score preequating. Namely, the further away from zero that a raw score distribution begins, the greater the bias. If the minimum raw score is close to zero, then the bias remains local to very low scores; however, if the minimum raw score is distant from zero, then bias spreads across the score continuum.

To investigate this more general problem further, I produced a condition with no violated assumptions, except that the test form was very easy relative to the ability of the population (Figure 19). Using a form so mismatched to the ability of the population is not considered good practice, but in some testing contexts, low scores are not common. Although not shown, the Test Information Function would not be well aligned with the ability distribution of the examinees. This condition produced a negatively skewed score distribution (Plot 6), which resulted in a minimum raw score of ten points. This condition created the same type of equating bias at the low end of the score range (Plot 11) that guessing produced. These results clearly show that it is not guessing alone that can cause equating bias at the extremes of a score scale, but such bias will appear in preequated conversion tables anytime the minimum or maximum raw score does not match the minimum or maximum of the scale.

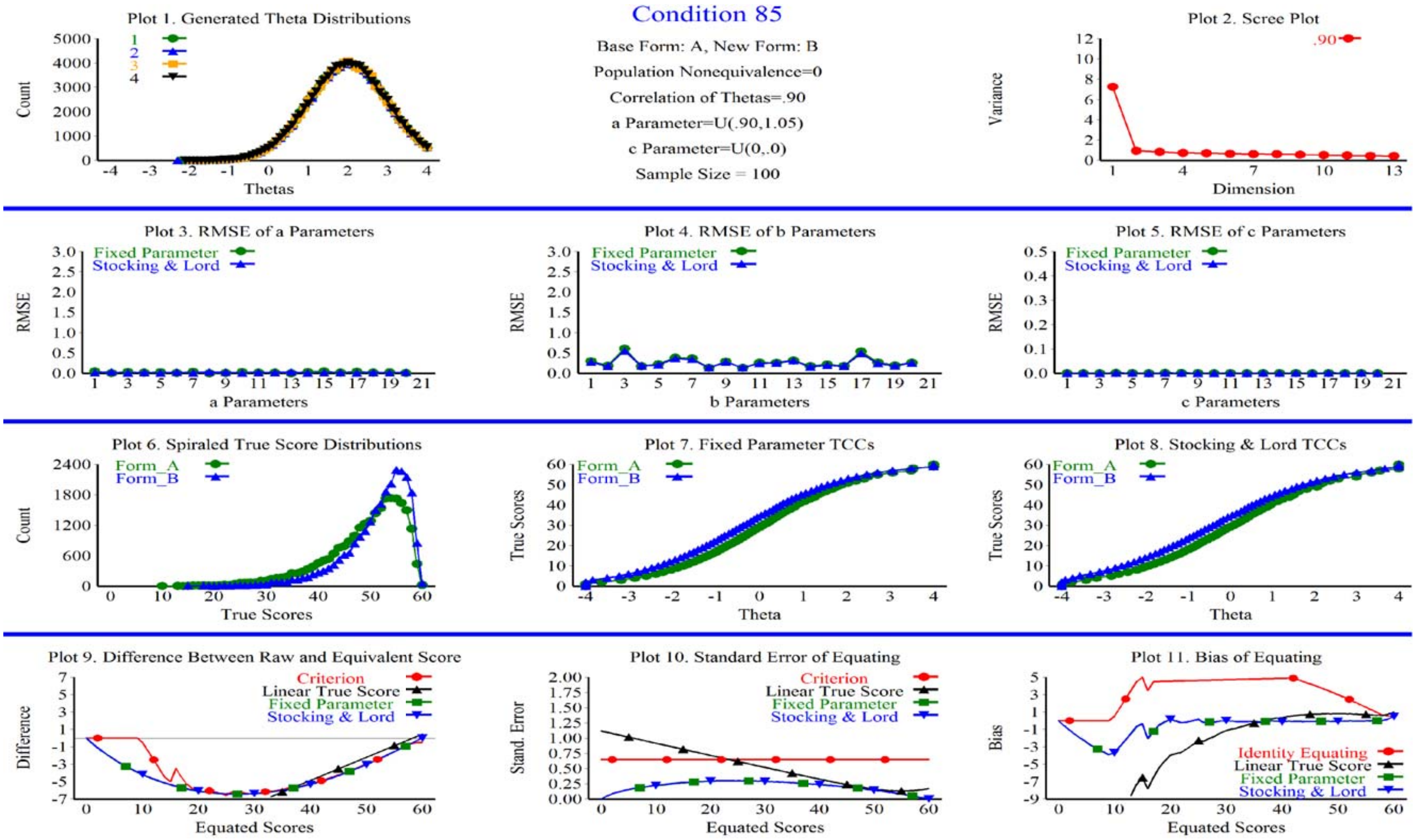


Figure 19. Equating Outcomes When All Assumptions are Satisfied and the Difficulty of the Test is Misaligned with the Ability of the Examinees. RMSE = Root mean squared error.

In Rasch true score postequating, this problem could be addressed by starting the Rapshon Newton procedure at the lowest raw score of the new form and then using Kolen's ad hoc procedure (Kolen & Brennan, 2004) to estimate equivalents between the minimum raw score and all incorrect raw score. However, in a preequating context, the minimum raw score is unknown. Using estimates for the pseudo-guessing parameter would probably be the best approach to this problem. Other solutions to this problem may be possible.

These results have implications for testing programs that use Rasch true score equivalent scores to classify examinees. If guessing is present and/or the test forms are not well matched to the ability of examinees, classification inaccuracy will probably increase under preequating. Classification inaccuracy will probably increase because cut scores for standards are usually defined on the first form produced for a testing program. Bias in the equating would underestimate or overestimate equivalent scores of examinees around the cut score, thereby creating incorrect classification decisions. The magnitude of bias and classification inaccuracy would likely be consistent across forms to the extent that the forms are parallel and the population is stable. Because relatively easier new forms, produce equivalent scores that are negatively biased, easier forms would tend to increase false negative decisions at the cut score.

Consistency of classification would not be affected as much by high minimum raw scores induced by guessing or easy forms as would classification accuracy. It is likely that examinees would all be affected in a similar manner by the bias observed in this study. Relative to large sample equipercentile equating, low ability examinees would receive lower equated scores caused by the bias introduced via high minimum raw scores induced by guessing and easy forms. If a pilot study was conducted for the purpose of defining a cut score, and then classification decisions began with the second form, then all classified examinees would likely be classified consistently, provided test assembly procedures are well defined and consistent. Otherwise, if the cut score is applied to examinees from the first form, examinees around the cut score would likely be affected differently in the first form than subsequent forms.

In general, accumulating item parameter error did increase preequating error across four equatings, confirming hypothesis 5. The SEE increased in magnitude with each new equating, although rarely exceeding the criterion by the fifth form. The bias was less predictable than the SEE. The bias was not constant across multiple equatings, sometimes increasing, and sometimes decreasing.

Recommendations

Based on the results of this study, Rasch true score preequating can be recommended for sample sizes of 100 or more, provided that precision and accuracy is required only around the mean of the score distribution, and provided that only two forms are being equated. As violations of model assumptions increase and the item bank increases, random error can quickly accumulate to produce high levels of SEE. To prevent this, items in the pool could be recalibrated as the sample sizes grow, thereby keeping random equating error in check. Even under violated conditions, Rasch true score preequating generally produced better equating results than identity or linear equating. For instance, criterion referenced tests that have cut scores high in the scale score would be appropriate tests to use with Rasch true score preequating. Results of this study do support the use of measuring growth via true score postequating, provided that Kolen's ad hoc procedure is used to produce equivalent scores between all incorrect and the lowest raw score. Results from this study do not support the use of Rasch true score preequating for tests that do not produce scores at or near zero and that require accuracy at the extremes of the score scale. If accuracy all along the score scale is needed and if raw scores of zero are unlikely, then Rasch true score preequating should not be used. If accuracy and precision is needed all along the score continuum, then one may use the 3PL model if sample sizes permit it. Rasch true score postequating with Kolen's ad hoc procedure is a better alternative to preequating when accuracy is needed all along the score scale.

Although sample size was not manipulated in this study, inferences can be made concerning sample size. If at all possible, sample sizes of 500 should be used in Rasch true score equating, especially if guessing is known to be present. To a limited extent, the effects of violations of IRT assumptions on the RMSE of equating can be offset by increasing the sample size from 100 to 500, thereby reducing the random component of equating error. Not only would the larger sample size offset a small portion of the equating bias, but a larger sample size will help to keep the SEE in check across multiple equatings.

Results of this study support the use of either FPC or SCSL in developing a calibrated item bank. FPC has a cost advantage over SCSL, since SCSL requires the use of additional software and expertise in item linking. In contrast, FPC offers the advantage of using the same software to estimate and calibrate the items in the bank, saving considerable time, effort, and cost. However, this cost savings is lost if DIF analysis is performed during the equating process, since DIF analysis requires two sets of item parameter estimates. DIF analysis is recognized as a best practice, as a means of screening common items during the equating process (Kolen & Brennan, 2004). Also, a limitation of this study was that the TCCs were mostly parallel. If the TCCs were not parallel, the SCSL method may produce better results than the FPC method, since the SCSL accommodates mean differences in the *a* parameter between forms, and the FPC method always assumes the *a* parameter is equal to one, both within and across forms. So, this study demonstrated that FPC is a viable procedure on its own for parallel TCCs, but if TCCs are not parallel, or if DIF analysis is to be performed, separate calibration may be the best alternative, since it provides two sets of estimates for each item.

There are both advantages and disadvantages to implementing preequating. The primary advantage to using preequating is that scores can be released immediately at the end of the test administration. However, a disadvantage to reporting scores immediately, is that no review of the items can be conducted after the test is administered. Therefore, to prevent any unexpected problems with items, careful attention should be given to the appearance of items to ensure that they are presented identically to past presentations of the items. Also, it is advisable to keep items in relatively the same position across forms (Kolen & Brennan, 2004). Moreover items used for scoring and calibration purposes should be carefully selected for the property of population invariance. All of these safeguards should reduce the risk of items performing differently than expected. Even still, it is advisable to implement preequating with a postequating design and inspect the performance of the method for a time period, before replacing postequating with preequating to a calibrated item bank (Kolen & Brennan, 2004).

Limitations

As previously stated, to make this study feasible many factors that would likely affect the performance of preequating have been held constant. Item parameter drift was not an active variable, although in a real world context, items do tend to drift both nonuniformly and uniformly. While studies have suggested that item parameter drift has negligible effects on normal equating (Wells, Subkoviak, & Serlin, 2002), item parameter drift may have a strong negative effect on preequating since preequating depends on precalibrated items. In order for the results of this study to hold, parameter drift may have to be minimal or all together absent. The effects of parameter drift on equating could be the focus of a future study.

This study used 20 items as pilot items during each administration; as a result, a large number of items (60) are shared in common between forms. Having a maximum number of common items is ideal for CINEG equating and in fact was chosen for this reason, but may not be typical. Many linking designs require a minimum of common items between forms so as to minimize item exposure. Researchers should take care not to assume that the results of this study will apply to test forms that share a moderate to minimum number of common items (i.e., 20% to 50%).

Item context effects also pose a major threat to preequating (Kolen & Brennan, 2004). This study did not manipulate item context effects, so, the results generalize to items that are not susceptible to item context effects. In order to use Rasch preequating successfully, practitioners should exclude common items that show any susceptibility to context effects.

In this study unrounded equivalent raw scores were used in calculating random error and systematic error. Standard errors of rounded raw scores or scales scores could also have been used to evaluate preequating. The drawback to using scale scores is that they are very specific to a testing program, and so results do not generalize well to other programs with different scales. However, the SEE of scale scores will be larger than those of unrounded equivalent scores.

Another limitation to the study is the fact that test form similarity was not manipulated. The magnitude of the difference between the forms was held constant. The magnitude of the shift in the difficulty parameters was quite large (-.50 standard deviations), so I suspect that most item banks would be able to produce forms less dissimilar as this. The TCCs were also mostly parallel. If the average discrimination of two forms differed substantially, then the results may not apply. In that situation, the SCSL method may produce better results than the FPC method, since the SCSL accommodates mean differences in item discriminations between forms.

A two dimensional compensatory model was used to simulate violations of unidimensionality. More than three dimensions may produce different results. The use of a noncompensatory model may have resulted in a different outcome as well. This study examined two dimensional tests with a simple structure, in that subtest one scores depended exclusively on dimension one, and subtest two scores depended exclusively on dimension two. However, a test could be multidimensional in other ways, such as when a positive response to an individual item depends on multiple dimensions.

Future research

Because this study used a true experimental design, it attains a high degree of internal validity; however, simulation studies are sometimes criticized for having low external validity, since real data are not used. It could be argued that this study achieved a higher level of realism than most simulation studies, since four factors were manipulated simultaneously to produce multiple, concurrent model violations. Nonetheless, it would be advisable to perform additional research using actual data to validate the feasibility of Rasch true score preequating.

Applying different equating criteria to the simulation results may have produced different interpretations of the outcomes. A follow up study could be performed to investigate the effectiveness of Rasch preequating using Lord's equity criteria. While this study focused on the limitations of Rasch preequating, other studies could focus on strategies to extend the limitations defined by this study. For instance, Kolen and Brennan have suggested the use of double linkings as a strategy to reduce the SEE (Kolen & Brennan, 2004). Another study could examine the effect of using double or triple links on the SEE across multiple equatings.

Another line of inquiry could examine the effect of repeating examinees on Rasch preequating. Repeating examinees would likely alter the score distribution over time and may represent an additional source of error in the item bank.

A logical extension of this study would be to vary the number of common items used across forms, and vary the length of the test. As mentioned in the literature review of this paper, prior studies have suggested that equating results largely depend on the number and quality of common items. Since the current study used a relatively large number of common items, it would be valuable to know if the findings of this study hold true even when operational forms contain as few as 20 percent of the operational items in common. It also would be interesting to see if these results hold true with very short or very long tests.

Since high minimum raw scores induced by guessing or very easy tests, proved to be the biggest threat to the accuracy of true score equating with the Rapshon Newton method, a follow up study could be performed to investigate alternative approaches to dealing with minimum raw scores that are distant from zero. Kolen devised an ad hoc procedure for the 3PL model, using linear interpolation to extend the conversion table to scores between the sum of the *c* parameters and all incorrect raw scores (Kolen & Brennan, 2004). A new procedure needs to be developed that can accommodate score distributions that do not extend to all incorrect raw scores for a preequating context. For instance, would preequating results improve if the Rapshon Newton procedure was set to start at the minimum raw score of the base form distribution, rather than zero? In this same line of thinking, would a constant *c* parameter improve true score equating? Empirical work can be performed on strategies to obtain a good constant *c* parameter estimate under small sample sizes. It appears to me that any improvement to the false assumption that the *c* parameter equals zero, would improve preequating results. This leads me to believe that an IRT model that assumes equivalent *a* parameters, models *b* parameters, and models a constant *c* parameter, may produce better preequating results than Rasch preequating.

Conclusion

For those who use the Rasch model, this study offers insight into the limitations of true score preequating. Rasch preequating will not produce accurate equating at the extremes of the score scale, if the range of the scores do not extend across the entire score continuum. This scenario can be caused by guessing or by forms that are not well matched to the ability of the examinees. The bias at the extremes of a score scale may be irrelevant to testing programs that use scores for pass/fail decisions, especially if the cut score is close to the mean of the distribution. If a program requires accurate equating all along the score scale, Rasch true score postequating with the Rapshon Newton method will likely produce accurate results, provided the Raphson Newton method starts at the minimum raw score rather than zero. The FPC method is a cost efficient and effective approach to building the calibrated item bank, but separate calibration may be the best calibration choice to facilitate DIF analysis in the equating process.

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APPENDIX A: SAS CODE

```
/*********************************************************************/
/*  TRUE SCORE PREEQUATING SIMULATION PROGRAM
/*    THIS PROGRAM CONTAINS MACROS TO SIMULATED THE FOLLOWING:
/*
/*    1. A SIMPLE 2 DIMENSIONAL FACTOR STRUCTURE
/*    2. POPULATION NONEQUIVALENCE, INCLUDING MULTIDIMENSIONAL SKEWNESS
/*    3. 3PL ITEM PARAMETERS FOR OPERATIONAL AND PILOT ITEMS
/*    4. DICHOTOMOUS ITEM RESPONSES
/*    5. PARAMETER ESTIMATION USING BIGSTEPS
/*    6. ITEM CALIBRATION USING FPC IN BIGSTEPS
/*    7. ITEM LINKING USING POLYST (STOCKING AND LORD METHOD)
/*    8. CREATION OF A CALIBRATED ITEM POOL
/*    9. UNLIMITED ADMINISTRATIONS AND UNLIMITED REPLICATIONS
/*    10. ESTIMATION OF ESTIMATED PARAMETER STANDARD ERRORS AND BIAS
/* NOTE: IN ORDER TO RUN THESE MACROS, BIGSTEPS AND POLYST MUST BE
*/
/* STORED IN THE FOLDER DEFINED BY THE '&OUTPATH' MACRO VARIABLE
*/
/*********************************************************************/



DATA A (TYPE=CORR);
_TYPE_='CORR';
INPUT _TYPE_ $ X1 X2 Y1 Y2 ;
CARDS;
MEAN  0 0 0 0
N      500 500 500 500
STD    1 1 1 1
CORR  1 . . .
CORR  .90 1 . .
CORR  .90 .90 1 .
CORR  .90  .90 .90 1
; PROC PRINT;RUN;


%MACRO MAKE_POPULATIONS
(X1A=-0.0, X1B = 1, X1C = 0, X1D =0,
 X2A=-0.0, X2B = 1, X2C = 0, X2D =0,
 Y1A=-0.0, Y1B = 1, Y1C = 0, Y1D =0,
 Y2A=-0.0, Y2B = 1, Y2C = 0, Y2D =0,
OUTPATH = C:\DISSERTATION\SIMULATION, CONDITION= COND1, COR = .90,
SHIFT_P = -0, PRINT = *);

DATA AA(type=corr);
SET A;
IF _N_ = 5 THEN X1 = &COR; /*MANIPULATE THE CORRELATIONS*/
IF _N_ = 6 THEN X2 = &COR; /*MANIPULATE THE CORRELATIONS*/
IF _N_ = 7 THEN X1 = &COR; /*MANIPULATE THE CORRELATIONS*/
IF _N_ = 7 THEN Y1 = &COR; /*MANIPULATE THE CORRELATIONS*/
&PRINT PROC PRINT;
RUN;

PROC PRINT DATA = A;RUN;

PROC FACTOR DATA = AA NFACT = 4 OUTSTAT=FACOUT NOPRINT;
```

```
TITLE1 "CORRELATION = &COR ";
TITLE2 " ";
TITLE3 " ";
RUN;
DATA PATTERN; SET FACOUT;
IF _TYPE_='PATTERN';
DROP _TYPE_ _NAME_;
RUN;

PROC PRINT DATA = FACOUT;
TITLE "FACTOR PATTERN ";
RUN;

DATA N_FACTORS;
SET FACOUT;
IF INDEX(UPCASE(_NAME_),"FACTOR");
CALL SYMPUTX ('N_FACTORS',_N_);
RUN;

/*********************************************************************
Note: This next section of code was adapted from Fan & Fan (2005)
***************************************************************/

PROC IML;
USE PATTERN; * USE THE FACTOR PATTERN MATRIX;
READ ALL VAR _NUM_ INTO F;
F=F`; * DIAGONAL MATRIX CONTAINING STDS FOR 4 VARIABLES;
STD={1 0 0 0,
     0 1 0 0,
     0 0 1 0,
     0 0 0 1};
X=RANNOR(J(100000,4,0)); * GENERATE A DATA MATRIX (100000×N_FACTORS);
X=X`; * TRANSPOSE THE DATA MATRIX (4×100000);
Z=F*X; * TRANSFORM UNCORRELATED VARIABLES TO CORRELATED ONES;
Z=Z`; * TRANSPOSE THE DATA MATRIX BACK (100000×4);
* FLEISHMAN POWER TRANSFORMATION FOR EACH OF 4 VARIABLES;
X1= &X1A + &X1B *Z[,1]+&X1C *Z[,1]##2-&X1D *Z[,1]##3;/*CHANGE THE SHAPE
HERE*/
X2= &X2A +&X2B *Z[,2]+&X2C *Z[,2]##2-&X2D *Z[,2]##3;/*CHANGE THE SHAPE
HERE*/
Y1= &Y1A + &Y1B *Z[,3]+&Y1C *Z[,3]##2-&Y1D *Z[,3]##3;/*CHANGE THE SHAPE
HERE*/
Y2= &Y2A +&Y2B *Z[,4]+&Y2C *Z[,4]##2-&Y2D *Z[,4]##3;/*CHANGE THE SHAPE
HERE*/
Z=X1||X2||Y1||Y2;
Z=Z*STD; *TRANSFORM THE SCALES OF THE VARIABLES TO SPECIFIED STDS;
CREATE DAT FROM Z[COLNAME={X1 X2 Y1 Y2}];
APPEND FROM Z;

/********************************************************************
Note: This indicates the end of the section of code that was adapted
from Fan & Fan (2005)************************************************/

DATA DAT;
SET DAT;
Y1 = Y1 + &SHIFT_P;/*SHIFT THE ENTIRE DISTRIBUTION LEFT*/
Y2 = Y2 + &SHIFT_P;
```

```
CANDID_ID_X =COMPRESS('X'||_N_);
CANDID_ID_Y =COMPRESS('Y'||_N_);
&PRINT PROC PRINT;
RUN;
/*TRUE THETAS FOR EACH GROUP*/
DATA GROUPX;
SET DAT;
KEEP CANDID_ID_X X1 X2;
RUN;

DATA GROUPY;
SET DAT;
KEEP CANDID_ID_Y Y1 Y2;
RUN;

PROC MEANS DATA=DAT N MEAN STD SKEW KURT;
VAR X1 X2 Y1 Y2;
OUTPUT OUT = ALLSTATS
SKEW =SKEW1 SKEW2
KURT=KURT1 KURT2
MEAN =MEAN1 MEAN2
STD = STD1 STD2
;
RUN;
DATA ALLSTATS;
SET ALLSTATS;
 CALL SYMPUTX ('MEAN1',ROUND(MEAN1,.01 ));
 CALL SYMPUTX ('STD1',ROUND(STD1,.01) );
 CALL SYMPUTX ('SKEW1',ROUND(SKEW1,.01));
 CALL SYMPUTX ('KURT1',ROUND(KURT1,.01) );

 CALL SYMPUTX ('MEAN2',ROUND(MEAN2,.01 ));
 CALL SYMPUTX ('STD2',ROUND(STD2,.01) );
 CALL SYMPUTX ('SKEW2',ROUND(SKEW2,.01));
 CALL SYMPUTX ('KURT2',ROUND(KURT2,.01) );
RUN;

%PUT &MEAN1;

PROC CORR DATA =DAT NOSIMPLE;
VAR X1 X2 Y1 Y2 ;
RUN; QUIT;

DATA DAT;
SET DAT;
XX1 = ROUND(X1,.1);
XX2 = ROUND(X2,.1);
YY1 = ROUND(Y1,.1);
YY2 = ROUND(Y2,.1);
&PRINT PROC PRINT;
&PRINT VAR XX1 XX2 YY1 YY2;RUN;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE XX1 / OUT =OUT1;
RUN;
```

```
&PRINT PROC PRINT DATA = OUT1;RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE XX2 / OUT =OUT2;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE YY1 / OUT =OUT3;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE YY2 / OUT =OUT4;
RUN;

DATA OUT1;
SET OUT1;
RENAME XX1 = VALUE;
THETA = 1;
RUN;
DATA OUT2;
SET OUT2;
RENAME XX2 = VALUE;
THETA = 2;
RUN;

DATA OUT3;
SET OUT3;
RENAME YY1 = VALUE;
THETA = 3;
RUN;

DATA OUT4;
SET OUT4;
RENAME YY2 = VALUE;
THETA = 4;
RUN;

DATA BOTH;
SET OUT1 OUT2 OUT3 OUT4;
&PRINT PROC PRINT;RUN;

SYMBOL1 I=J  C=BLUE W=1 H=1;
SYMBOL2 I=J  C=RED  W=1 H=1;
SYMBOL3 I=J  C=BLACK W=1 H=3.5;
SYMBOL4 I=J  C=GREEN  W=1 H=3.5;
SYMBOL5 I=J  C=ORANGE W=2 H=3.5;
SYMBOL6 I=J  C=PURPLE  W=2 H=3.5;
SYMBOL7 I=J  C=YELLOW W=2 H=3.5;

/*MAKE FOLDER FOR OUTPUT*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION");
RUN;

ODS PDF FILE = "&OUTPATH\&CONDITION\POPULATIONS.PDF";
PROC GPLOT DATA = BOTH;
```

```
PLOT COUNT*VALUE=THETA;
TITLE1 "POPULATION ABILITY DISTRIBUTIONS  - CORRELATION = &COR";
TITLE2 "STAT   ABILITY 1  ABILITY 2";
TITLE3 "MEAN      &MEAN1       &MEAN2";
TITLE4 "STD       &STD1        &STD2";
TITLE5 "SKEW      &SKEW1       &SKEW2";
TITLE6 "KURT      &KURT1       &KURT2";
RUN;
QUIT;
ODS PDF CLOSE;

DATA DAT;
SET DAT;
FILE "&OUTPATH\&CONDITION\POPULATION X.TXT " DSD;
PUT CANDID_ID_X X1 X2 ;
RUN;

DATA DAT;
SET DAT;
FILE "&OUTPATH\&CONDITION\POPULATION Y.TXT " DSD;
PUT CANDID_ID_Y Y1 Y2 ;RUN;
QUIT;

DATA _NULL_;
COR = &COR;
CALL SYMPUTX ('COR ', COR );
RUN;
%MEND;
```

```
/*MAKE ITEM PARAMETERS*/
%MACRO MAKE_ITEM_PARAMS(PRINT = *,THETA2 = .10, OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION = COND1, N_OPER_ITEMS = 60,A1
=.30 , A2 =.85, B1=0, B2=1 , C1= .001);
DATA ITEM_PARAMS;
ARRAY A [&N_OPER_ITEMS] A1 - A&N_OPER_ITEMS;
ARRAY B [&N_OPER_ITEMS] B1 - B&N_OPER_ITEMS;
ARRAY C [&N_OPER_ITEMS] C1 - C&N_OPER_ITEMS;
DO I =1 TO &N_OPER_ITEMS;
SEED = 989898989;/* CONSIDER SAVING A SAS GENERATED SEED FOR FUTURE
REPLICATION*/
A[I] = ((RAND('UNIFORM')* &A1) + &A2);
B[I] = RAND('NORMAL',&B1, &B2);
C[I] = RAND('UNIFORM')* &C1;
END;
&PRINT PROC PRINT;
RUN;

PROC TRANSPOSE DATA= ITEM_PARAMS OUT = T_ITEMS;
VAR A1 - A&N_OPER_ITEMS B1-B&N_OPER_ITEMS C1 -C&N_OPER_ITEMS;
RUN;
&PRINT PROC PRINT DATA = T_ITEMS;RUN;
DATA T_ITEMS;
SET T_ITEMS;
IF INDEX(_NAME_,'A')> 0 THEN PARAM = 'A';
IF INDEX(_NAME_,'B')> 0 THEN PARAM = 'B';
IF INDEX(_NAME_,'C')> 0 THEN PARAM = 'C';
SEQUENCE = COMPRESS(_NAME_, 'A,B,C') ;
RUN;

PROC SORT DATA = T_ITEMS;
BY SEQUENCE;
RUN;
PROC TRANSPOSE DATA = T_ITEMS  OUT= TT_ITEMS;
ID PARAM;
VAR COL1;
BY SEQUENCE;
RUN;

DATA TT_ITEMS;
SET TT_ITEMS;
ITEMID = COMPRESS("ITEM"||SEQUENCE);
RUN;

DATA TRUE_ITEM_PARAMETERS;
RETAIN ITEMID SEQUENCE A B C;
SET TT_ITEMS;
ORDER = INPUT(SEQUENCE, 8.);
DROP _NAME_;
PROC SORT;
BY ORDER;
&PRINT PROC PRINT;
RUN;

&PRINT PROC PRINT DATA = TRUE_ITEM_PARAMETERS;RUN;
```

```
PROC MEANS DATA = TRUE_ITEM_PARAMETERS;
VAR A B C;
RUN;

/*ADD THE OPERATIONAL ITEMS TO THE POOL OF GENERATED ITEMS */
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\REP1\ITEMS");
RUN;
DATA BASE_FORM_ITEMS;
SET TRUE_ITEM_PARAMETERS;
IF _N_ =< 30 THEN ABILITY = 1;
IF _N_ > 30 THEN ABILITY = 2;
IF ABILITY = 2 THEN B = B - &THETA2;

FORM = "A"; ADMIN_EVENT = 1; CAL_METHOD = 'GENERATED';
FILE "&OUTPATH\&CONDITION\REP1\ITEMS\GENERATED_POOL.TXT" DSD;
PUT FORM $ ADMIN_EVENT CAL_METHOD $ ITEMID $ SEQUENCE A B C ABILITY;
&PRINT PROC PRINT;
RUN;

%MEND;
```

```
%MACRO ASSEMBLE_FORM (PRINT = , THETA2 = 0, OUTPATH=, CONDITION=COND1,
REPLICATION=REP1, ADMIN_EVENT =1, N_PILOT_ITEMS= 20,FORM = A,PILOT_FORM
= B,  SHIFT = 1, START_ITEM_ID = 61, REPLACE = N );

DATA TRUE_ITEM_PARAMETERS;
INFILE "&OUTPATH\&CONDITION\REP1\ITEMS\GENERATED_POOL.TXT" DSD;
INPUT FORM $ ADMIN_EVENT CAL_METHOD $  ITEMID $ ORDER A B C ABILITY;
&PRINT PROC PRINT;
RUN;
PROC PRINT DATA = TRUE_ITEM_PARAMETERS;RUN;
DATA PILOT_ITEMS;
SET TRUE_ITEM_PARAMETERS;
IF _N_ < 61;
RUN;

DATA PILOT_ITEMS;
SET PILOT_ITEMS;
R = RAND('NORMAL',0,1);
PROC SORT;
BY ORDER;
&PRINT PROC PRINT;
RUN;

DATA PILOT_ITEMS;
SET PILOT_ITEMS;
ITEMID = COMPRESS('ITEM'||_N_+&START_ITEM_ID - 1 );
ORDER2 = _N_+ &START_ITEM_ID - 1 ;
IF _N_ <= &N_PILOT_ITEMS;
NEW_B =B + &SHIFT ;
*NEW_B = RAND('NORMAL', &SHIFT, 1) + B;
DROP B SEQUENCE R ORDER ;
&PRINT PROC PRINT;
RUN;

DATA PILOT_ITEMS;
SET PILOT_ITEMS;
IF _N_ =<10 THEN ABILITY = 1;
IF _N_ >10 THEN ABILITY = 2;
IF ABILITY = 2 THEN B = B - &THETA2;

FORM = "&PILOT_FORM";
RENAME NEW_B = B ORDER2 =ORDER;
&PRINT PROC PRINT;
RUN;

DATA SET1 SET2;
SET TRUE_ITEM_PARAMETERS;
IF ABILITY =1 THEN OUTPUT SET1;
IF ABILITY = 2 THEN OUTPUT SET2;
RUN;
PROC SORT DATA = SET1;
BY DESCENDING ORDER;
PROC PRINT;RUN;
PROC SORT DATA = SET2;
BY DESCENDING ORDER;
PROC PRINT;RUN;
DATA SET1;
```

```
SET SET1;
IF _N_ =<30;
RUN;

DATA SET2;
SET SET2;
IF _N_ =<30;
RUN;

DATA TRUE_ITEM_PARAMETERS;
SET SET1 SET2 PILOT_ITEMS;
PROC SORT;
BY ORDER;
RUN;

DATA TRUE_ITEM_PARAMETERS;
SET TRUE_ITEM_PARAMETERS;
SEQUENCE = ORDER;
RUN;

PROC PRINT DATA = TRUE_ITEM_PARAMETERS;
TITLE "FORM = &FORM ";
RUN;
/*MAKE FOLDER FOR ITEMS*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\&REPLICATION\ITEMS");
RUN;

/*MAKE FOLDER FOR FORMS*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\&REPLICATION\FORMS");
RUN;
DATA TRUE_ITEMS;
SET TRUE_ITEM_PARAMETERS;
FILE "&OUTPATH\&CONDITION\&REPLICATION\FORMS\FORM_&FORM..TXT " DSD;
PUT ORDER ITEMID A B C ABILITY;
RUN;

/*ADD JUST THE PILOT ITEMS TO THE POOL OF GENERATED ITEMS */
DATA BASE_FORM_ITEMS;
SET TRUE_ITEM_PARAMETERS;
IF _N_ >60;
ADMIN_EVENT = &ADMIN_EVENT; CAL_METHOD = 'GENERATED';
FILE "&OUTPATH\&CONDITION\&REPLICATION\ITEMS\GENERATED_POOL.TXT" DSD
MOD;
PUT FORM $ ADMIN_EVENT CAL_METHOD $ ITEMID $ SEQUENCE A B C ABILITY;
&PRINT PROC PRINT;
RUN;

%MEND;
```

```
%MACRO SPIRAL (PRINT = *, OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION = COND1, SAMPLE_SIZE = 50000);
DATA POPX;
INFILE "&OUTPATH\&CONDITION\POPULATION X.TXT " DSD;
INPUT CANDID_ID_X $ THETA1 THETA2 ;
GROUP ='X';
RUN;
DATA POPX;
SET POPX;
R = RAND('NORMAL',0,1);
PROC SORT;
BY R;
RUN;
DATA POPX;
SET POPX;
IF _N_ =< &SAMPLE_SIZE;
RUN;

DATA POPX;
SET POPX;
COUNT +1;
IF COUNT =5 THEN DO;
COUNT = 1;
END;
RUN;

DATA GRPX1 GRPX2 GRPX3 GRPX4;
SET POPX;
IF COUNT = 1 THEN OUTPUT GRPX1;
IF COUNT = 2 THEN OUTPUT GRPX2;
RUN;

DATA POPY;
INFILE "&OUTPATH\&CONDITION\POPULATION Y.TXT " DSD;
INPUT CANDID_ID_X $ THETA1 THETA2 ;
GROUP ='Y';
RUN;
DATA POPY;
SET POPY;
R = RAND('NORMAL',0,1);
PROC SORT;
BY R;
RUN;
DATA POPY;
SET POPY;
IF _N_ =< &SAMPLE_SIZE;
RUN;

DATA POPY;
SET POPY;
COUNT +1;
IF COUNT =5 THEN DO;
COUNT = 1;
END;
RUN;

DATA GRPY1 GRPY2 GRPY3 GRPY4;
```

```
SET POPY;
IF COUNT = 1 THEN OUTPUT GRPY1;
IF COUNT = 2 THEN OUTPUT GRPY2;
RUN;

DATA GRP1XY;
SET GRPX1 GRPY1;
PROC SORT;
BY GROUP;
RUN;

DATA GRP2XY;
SET GRPX2 GRPY2;
PROC SORT;
BY GROUP;
RUN;
DATA GRP1XY;
SET GRP1XY;
FILE "&OUTPATH\&CONDITION\GRP1XY.TXT " ; /*RETRIEVE FORM FROM FIRST
REPLICATION*/
PUT CANDID_ID_X THETA1 THETA2 GROUP;
RUN;

DATA GRP2XY;
SET GRP2XY;
FILE "&OUTPATH\&CONDITION\GRP2XY.TXT " ; /*RETRIEVE FORM FROM FIRST
REPLICATION*/
PUT CANDID_ID_X THETA1 THETA2 GROUP;
RUN;

PROC MEANS DATA = GRP1XY;
VAR THETA1 THETA2;
OUTPUT OUT = MN_GRP1XY;
RUN;
DATA MN_GRP1XY;
SET MN_GRP1XY;
FILE "&OUTPATH\&CONDITION\MOMENTS_GRP1XY.TXT " ;
PUT _STAT_ THETA1 THETA2;
RUN;
PROC MEANS DATA = GRP2XY;
VAR THETA1 THETA2;
OUTPUT OUT = MN_GRP2XY;
RUN;

DATA MN_GRP2XY;
SET MN_GRP2XY;
FILE "&OUTPATH\&CONDITION\MOMENTS_GRP2XY.TXT " ;
PUT _STAT_ THETA1 THETA2;
RUN;

%MEND;
```

```
%MACRO GET_POP_TRUE_SCORES(PRINT =* , EXCLUDE_FORM = ,POOL =YES ,POP =,
LIMIT_POOL = 300,GROUP = 1, SAMPLE_SIZE= 100, OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =COND1, REPLICATION = REP1, FORM
= A, ADMIN_EVENT = 1, START_THETA1 = 1, NITEMS= 80, N_OPER_ITEMS=60,
END_THETA1 = 30, START_THETA2 = 31,
END_THETA2 = 60, CAL_METHOD = STOCK_LORD, START_PILOT_THETA1 =
61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 = 71,END_PILOT_THETA2 =
80);

/*GET THE ITEM IDS FOR THE SPECIFIED FORM FROM THE GENERATED FORMS*/
%IF &POOL = YES %THEN %DO;
DATA FORM&FORM;
INFILE "&OUTPATH\&CONDITION\REP1\ITEMS\GENERATED_POOL.TXT " DSD;
/*RETRIEVE FORM FROM FIRST REPLICATION*/
INPUT FORM $ ADMIN METHOD $ ITEMID $ ORDER A B C ABILITY;
RUN;

DATA FORM&FORM;
SET FORM&FORM;
*IF FORM NE "&EXCLUDE_FORM";
IF FORM EQ "&FORM";
RUN;

%END;
%IF &POOL NE YES %THEN %DO;
DATA FORM&FORM;
INFILE "&OUTPATH\&CONDITION\REP1\FORMS\FORM_&FORM..TXT " DSD;
/*RETRIEVE FORM FROM FIRST REPLICATION*/
INPUT ORDER ITEMID $ A B C ABILITY;
RUN;
DATA FORM&FORM;
SET FORM&FORM;
IF _N_ =<60;
RUN;
%END;

DATA _NULL_;
SET FORM&FORM;
CALL SYMPUTX ('N_IN_FORM', _N_ );
RUN;

/*GET THE POPULATION*/
DATA RESPONSES;
INFILE "&OUTPATH\&CONDITION\GRP&GROUP.XY.TXT " ; /*RETRIEVE FORM FROM
FIRST REPLICATION*/
INPUT CANDID_ID_X $ THETA1 THETA2 GROUP $;
RUN;

%DO I = 1 %TO &N_IN_FORM;
DATA TEST&I;
SET FORM&FORM;
IF _N_ = &I;
CALL SYMPUTX ('A',A );
CALL SYMPUTX ('B',B );
CALL SYMPUTX ('C',C );
CALL SYMPUTX ('ABILITY',ABILITY);
RUN;


/*MODEL RESPONSES TO SUBTEST 1 OPERATIONAL TEST*/
%IF &ABILITY = 1 %THEN %DO;
DATA RESPONSES;
SET RESPONSES;
P&I = &C + (1-&C)*(EXP(&A*1*(THETA1- &B))/(1 +EXP(&A*1*(THETA1 -
&B))));
R&I = RAND('UNIFORM');
X&I = 0;
IF P&I > R&I THEN X&I = 1;
RUN;
%END;
%IF &ABILITY = 2 %THEN %DO;
DATA RESPONSES;
SET RESPONSES;
P&I = &C + (1-&C)*(EXP(&A*1*(THETA2- &B))/(1 +EXP(&A*1*(THETA2 -
&B))));
R&I = RAND('UNIFORM');
X&I = 0;
IF P&I > R&I THEN X&I = 1;
RUN;
%END;

DATA RESPONSES;
SET RESPONSES;
TRUE_SCORE = SUM(OF P1 - P&N_IN_FORM);/*FIRST X N ITEMS ARE
OPERATIONAL*/
PERCENT_TRUE_SCORE = TRUE_SCORE/&N_IN_FORM;
EXP_TRUE_SCORE = PERCENT_TRUE_SCORE* 60;
RUN;


%END;
DATA RESPONSES&GROUP._&FORM;
SET RESPONSES;
EXP_TRUE_SCORE = ROUND(EXP_TRUE_SCORE,1);
&PRINT PROC PRINT;
RUN;
PROC FREQ DATA = RESPONSES&GROUP._&FORM NOPRINT;
TABLE EXP_TRUE_SCORE/ OUT  = FREQ_&FORM;
RUN;


DATA FREQ_&FORM;
SET FREQ_&FORM;
COUNT_&FORM = COUNT;
RUN;
PROC PRINT DATA = FREQ_&FORM;
TITLE "FREQUENCY OF ROUNDED EXPECTED TRUE SCORES FOR FORM &FORM AND
GROUP &GROUP ";
RUN;
```

```
DATA FREQ_&FORM;
SET FREQ_&FORM;
N_ITEMS =&N_IN_FORM ;
FILE "&OUTPATH\&CONDITION\FREQ_&FORM..TXT " DSD;
PUT EXP_TRUE_SCORE COUNT_&FORM PERCENT N_ITEMS;
RUN;


%MEND;
```

```
%MACRO EQUIPERCENTILE_EQUATE (PRINT =*, OUTPATH =
C:\DISSERTATION\SIMULATION, BASE = , NEWFORM = , CONDITION = COND1 );

DATA FREQ_&BASE;
INFILE "&OUTPATH\&CONDITION\FREQ_&BASE..TXT " DSD;
INPUT EXP_TRUE_SCORE COUNT_&BASE PERCENT N_ITEMS ;
&PRINT PROC PRINT;
RUN;

DATA FREQ_&NEWFORM;
INFILE "&OUTPATH\&CONDITION\FREQ_&NEWFORM..TXT " DSD;
INPUT EXP_TRUE_SCORE COUNT_&NEWFORM PERCENT N_ITEMS ;
&PRINT PROC PRINT;
RUN;

DATA DISTRIB;
DO EXP_TRUE_SCORE =0 TO 60 BY 1;
OUTPUT;END;
&PRINT PROC PRINT;
RUN;

DATA DISTRIB2;
MERGE DISTRIB FREQ_&BASE FREQ_&NEWFORM;
BY EXP_TRUE_SCORE;
IF COUNT_&BASE    = . THEN COUNT_&BASE    = 0;
IF COUNT_&NEWFORM = . THEN COUNT_&NEWFORM = 0;

CONVERSION = EXP_TRUE_SCORE;
DROP COUNT PERCENT;
RUN;

OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
RUN;

OPTIONS NOXWAIT ;
Data _null_;
call system ("CD &OUTPATH\EQUIPERCENTILE");
CALL SYSTEM ("COPY RAGE.EXE
&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY TEMPLATE_PRE_EQ.SAS
&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY TEMPLATE_PRE.SAS
&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY TEMPLATE_POST.SAS
&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY WIN.CTL &OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY BAT.BAT &OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
CALL SYSTEM ("COPY CONTROL.TXT
&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
RUN;

DATA DISTRIB2;
SET DISTRIB2;
FILE "&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM\EQUIP.TXT ";
PUT EXP_TRUE_SCORE COUNT_&NEWFORM COUNT_&BASE CONVERSION;
```

```
RUN;

OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
RUN;


OPTIONS NOXWAIT ;
Data _null_;
call system ("CD &OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM");
call system ("BAT.BAT");
RUN;

DATA EQUATING_RESULTS;
INFILE "&OUTPATH\&CONDITION\POP_EQUATING\&NEWFORM\OUT.TXT ";
INPUT @1 WORDS $80. @1 SCORE 11. @12 SE 11. @23 NOSMOOTH 11.;
IF INDEX(UPCASE(WORDS),"RAW SCORE MOMENTS FOR POSTSMOOTHING:") >0 THEN
STOP = 1;
IF STOP = 1 THEN CALL SYMPUTX ('STOP', _N_);
RUN;%PUT &STOP;
DATA EQUATING_RESULTS;
SET EQUATING_RESULTS;
IF _N_ < &STOP;
IF SCORE NE .;
DROP WORDS STOP;
RUN;

DATA FORMA;
DO SCORE =0 TO 60 BY 1;
OUTPUT; END;RUN;

DATA EQUATING_RESULTS;
SET EQUATING_RESULTS;
A= NOSMOOTH;
KEEP SCORE A;
RUN;
&PRINT PROC PRINT DATA = EQUATING_RESULTS;RUN;

DATA EQUATING_RESULTS2;
MERGE FORMA EQUATING_RESULTS;
BY SCORE;
&PRINT PROC PRINT;
RUN;
DATA EQUATING_RESULTS2;
SET EQUATING_RESULTS2;
NEWFORM = "&NEWFORM";
FILE "&OUTPATH\&CONDITION\EQUIPERCENTILE_CONV_TABLE.TXT " MOD;
PUT NEWFORM SCORE A  ; /*NEWFORM FORMA FORM_NEW*/
RUN;
%MEND;
```

```
%MACRO MAKE_RESPONSES (PRINT =* ,SAMPLE_SIZE= 100, OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =COND1, REPLICATION = REP1, GROUP
= X, FORM = A, ADMIN_EVENT = 1, START_THETA1 = 1, NITEMS= 80,
N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
END_THETA2 = 60, START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70,
START_PILOT_THETA2 = 71,END_PILOT_THETA2 = 80);



/*MODEL RESPONSES*/
DATA DAT;
INFILE "&OUTPATH\&CONDITION\POPULATION &GROUP..TXT " DSD ; /*RETRIEVE
FORM FROM FIRST REPLICATION*/
INPUT CANDID_ID_&GROUP $ THETA1 THETA2 ;
RUN;


DATA THETAS;
SET DAT;
R = RAND('NORMAL',0,1);  /*RANDOMLY ORDER EXAMINEES*/
PROC SORT;
BY R;
RUN;

DATA RESPONSES;
RETAIN CANDID_ID_&GROUP THETA1 THETA2;
SET THETAS;
IF _N_ <= &SAMPLE_SIZE;/*SELECT FIRST 100 EXAMINEES*/
DROP R;
&PRINT PROC PRINT;
RUN;


/*MAKE FOLDER FOR OUTPUT*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\&REPLICATION\ABILITIES");
RUN;

/*PLACE EXAMINEES IN FOLDER*/
DATA RESPONSES;
SET RESPONSES;
ADMIN_EVENT = &ADMIN_EVENT;
METHOD = "GENERATED";
FORM = "&FORM";
FILE "&OUTPATH\&CONDITION\&REPLICATION\ABILITIES\GENERATED_THETAS.TXT "
DSD MOD;
PUT FORM ADMIN_EVENT METHOD CANDID_ID_&GROUP THETA1 THETA2;
RUN;

/*END*/
/*GET THE TRUE ITEM PARAMETERS*/
DATA TRUE_IT_PARAMS;
INFILE "&OUTPATH\&CONDITION\REP1\FORMS\FORM_&FORM..TXT " DSD;
/*RETRIEVE FORM FROM FIRST REPLICATION*/
INPUT ORDER ITEMID $ A B C ABILITY;
&PRINT PROC PRINT;
```

```
RUN;

%DO I = 1 %TO &NITEMS;
DATA TEST&I;
SET TRUE_IT_PARAMS;
IF _N_ = &I;
CALL SYMPUTX ('A',A );
CALL SYMPUTX ('B',B );
CALL SYMPUTX ('C',C );
CALL SYMPUTX ('ABILITY', ABILITY);
RUN;

/*MODEL RESPONSES TO SUBTEST 1 OPERATIONAL TEST*/
%IF &ABILITY = 1 %THEN %DO;/*MAKE SUBTEST ONE CORRESPONDING TO THETA1*/
DATA RESPONSES;
SET RESPONSES;
P&I = &C + (1-&C)*(EXP(&A*1*(THETA1- &B))/(1 +EXP(&A*1*(THETA1 -
&B))));
R&I = RAND('UNIFORM');
X&I = 0;
IF P&I > R&I THEN X&I = 1;
RUN;
%END;

/*MODEL RESPONSES TO SUBTEST 2 OPERATIONAL TEST*/
%IF &ABILITY = 2 %THEN %DO;/*MAKE SUBTEST TWO CORRESPONDING TO THETA2*/
DATA RESPONSES;
SET RESPONSES;
P&I = &C + (1-&C)*(EXP(&A*1*(THETA2- &B))/(1 +EXP(&A*1*(THETA2 -
&B))));
R&I = RAND('UNIFORM');
X&I = 0;
IF P&I > R&I THEN X&I = 1;
RUN;
%END;

DATA RESPONSES;
SET RESPONSES;
SUB1 = SUM(OF X&START_THETA1 - X&END_THETA1);
SUB2 = SUM(OF X&START_THETA2 - X&END_THETA2);
COMPOSITE = (THETA1 + THETA2)/2;
TRUE_SCORE = SUM(OF P1 - P&N_OPER_ITEMS);/*FIRST X N ITEMS ARE
OPERATIONAL*/
PERCENT_TRUE_SCORE = TRUE_SCORE/&N_OPER_ITEMS;
OBSERVED_SCORE = SUB1 + SUB2;
RUN;
%END;

&PRINT PROC PRINT DATA= RESPONSES;
&PRINT VAR CANDID_ID_&GROUP TRUE_SCORE PERCENT_TRUE_SCORE THETA1 THETA2
SUB1 SUB2 X1 - X50;
RUN;
DATA RESPONSES;
SET RESPONSES;
LENGTH STRING $ 100.;
ARRAY C[&NITEMS] X1 - X&NITEMS;
DO J =1 TO &NITEMS;
```

```
STRING = COMPRESS(STRING||C[J]);
END;
&PRINT PROC PRINT;
RUN;

&PRINT PROC PRINT data = responses;run;

PROC CORR DATA= RESPONSES;
VAR SUB1 SUB2 THETA1 THETA2 TRUE_SCORE OBSERVED_SCORE ;
RUN;
/*MAKE A PERMANENT RECORD OF THE CRITERION TRUE SCORES AND THETAS*/

DATA CRITERION_MEASURES;
RETAIN FORM REPLICATION CANDID_ID_&GROUP THETA1 THETA2 COMPOSITE SUB1
SUB2 TRUE_SCORE PERCENT_TRUE_SCORE OBSERVED_SCORE;
SET RESPONSES;
FORM = "&FORM";
CONDITION = "&CONDITION";
REPLICATION = "&REPLICATION";
KEEP FORM REPLICATION CANDID_ID_&GROUP THETA1 THETA2 COMPOSITE SUB1
SUB2 TRUE_SCORE PERCENT_TRUE_SCORE OBSERVED_SCORE;
FILE "&OUTPATH\&CONDITION\CRITERION_SCORES.TXT " DSD MOD;
PUT FORM REPLICATION CANDID_ID_&GROUP THETA1 THETA2 COMPOSITE SUB1 SUB2
TRUE_SCORE PERCENT_TRUE_SCORE OBSERVED_SCORE ;
RUN;


/*SEND THE RESPONSE MATRIX OUT FOR LINEAR EQUATING*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\LINEAR");
RUN;

DATA LINEAR_DATA;
SET RESPONSES;
FORM = "&FORM";
KEEP FORM CANDID_ID_&GROUP X1 - X&N_OPER_ITEMS;
RUN;

proc export data=LINEAR_DATA
outfile="&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\LINEAR\EXAM
.DAT" dbms=dlm replace;
delimiter=",";
run;

%MEND;
```

```
%MACRO COPY_FORMS(CONDITION = COND,OUTPATH =C:\DISSERTATION\SIMULATION,
FILE = FORMS);

OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\REP1\FORMS");
RUN;

OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\REP1\ITEMS");
RUN;

OPTIONS NOXWAIT;
Data _null_;
call system ("CD &OUTPATH\&FILE");
CALL SYSTEM ("COPY FORM_A.TXT &OUTPATH\&CONDITION\REP1\FORMS");
CALL SYSTEM ("COPY FORM_B.TXT &OUTPATH\&CONDITION\REP1\FORMS");
CALL SYSTEM ("COPY FORM_C.TXT &OUTPATH\&CONDITION\REP1\FORMS");
CALL SYSTEM ("COPY FORM_D.TXT &OUTPATH\&CONDITION\REP1\FORMS");
CALL SYSTEM ("COPY FORM_E.TXT &OUTPATH\&CONDITION\REP1\FORMS");
CALL SYSTEM ("COPY GENERATED_POOL.TXT &OUTPATH\&CONDITION\REP1\ITEMS");
RUN;

%MEND;
```

```
%MACRO CALIBRATE (PRINT = *, LINK_METH=STOCKING, ESTIMATE = Y,
ADMIN_EVENT = 1, LINK_START=1, LINK_STOP=60, N_LINK_ITEMS=60, FORM=A,
BASE_FORM = A, GROUP = X, BASE_POOL = GENERATED, BASE_CAL_METHOD =
GENERATED, OUTPATH =C:\DISSERTATION\SIMULATION , CONDITION =COND1 ,
REPLICATION = REP1, CAL_METHOD = SEPARATE, SEPARATE=, N_SELECTED = 80,
FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_REPLACED= 0,
CALIBRATE_PILOTS = , FPC = );
              OPTION MLOGIC SYMBOLGEN;
 %IF &ESTIMATE = Y %THEN %DO;
                  OPTIONS NOXWAIT ;
                  Data _null_;
                  call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD");
                  RUN;

                  DATA RESPONSES2;
                  SET RESPONSES;
                  FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\EXAM.DA
T ";
                  PUT @1 CANDID_ID_&GROUP @11 STRING ;
                  RUN;

            %IF &REPLICATION NE 1 %THEN %DO;
                  OPTIONS NOXWAIT ;
                  Data _null_;
                  call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ITEMS");
                  RUN;
              OPTIONS NOXWAIT ;
                  Data _null_;
                  call system ("CD
C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ITEMS");
                  CALL SYSTEM ("COPY GENERATED_POOL.TXT
&OUTPATH\&CONDITION\&REPLICATION\ITEMS");
                  RUN;
                  %END;

              OPTIONS NOXWAIT ;
                  Data _null_;
                  call system ("CD C:\DISSERTATION\SIMULATION");
                  CALL SYSTEM ("COPY BIGSTEPS.EXE
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD");
                  RUN;

                  DATA TEMP_;
                  LINE14 = "DFILE=DEL.TXT";
                  BLANK = " ";
                  LINE13 = "PFILE = EXAMIN.TXT";
                  LINE10 = "IAFILE= ANCHOR.IAF";
                  LINE15= "MUCON=100";
                  %IF &SEPARATE = Y %THEN %DO;
              /*SEPARATE CALIBRATION WITH LINKING*/
                  CALL SYMPUTX ('LINE14', LINE14) ;
                  CALL SYMPUTX ('LINE13', LINE13) ;
                  CALL SYMPUTX ('LINE10', BLANK);
                  %END;
                  RUN;
                  %IF &CALIBRATE_PILOTS = Y %THEN %DO;
                  DATA TEMP_;
                  SET TEMP_;
            CALL SYMPUTX ('LINE14', BLANK) ;/*REMOVE THE COMMAND TO
DELETE THE PILOT ITEMS*/
                  CALL SYMPUTX ('LINE13', LINE13) ;/*  */
                  CALL SYMPUTX ('LINE10', BLANK);
                  %END;

                  %IF &FPC = Y %THEN %DO;
                  DATA TEMP_;
                  SET TEMP_;
            CALL SYMPUTX ('LINE14', LINE13) ;
                  CALL SYMPUTX ('LINE13', LINE15);/*MUCON COMMAND TO
LIMIT ITERATIONS TO 100*/
                  CALL SYMPUTX ('LINE10', LINE10);
                  %END;

                  RUN;
                  /*CREATE WINSTEPS SYNTAX FILE FOR */
                  data rasch;
                  LINE1 = "&INST";
                  LINE2 = " TITLE='&CAL_METHOD FORM=&FORM'  ";
                  LINE3 = " NI=&N_SELECTED";
                  LINE4 = " ITEM1=11";
                  LINE5 = " NAME1=1";
                  LINE6 = " PERSON=EXAMINEE";
                  LINE7 = " ITEM=ITEM";
                  LINE8 = "CODES=10 ";
                  LINE9 = " DATA=EXAM.DAT";
                  LINE10 = "&line10";
                  LINE11 = "IFILE=ITEMS.TXT";
                  LINE12 ="GRFILE=GRFILE.TXT";
                  LINE13 = "&LINE13";
                  LINE14 = "&LINE14 "; /*PRCOMP=S*/
                  LINE15 = " ";
                  LINE16 = " &END";
                  run;

                  PROC TRANSPOSE DATA = RASCH OUT = T_RASCH;
                  VAR _ALL_;
                  RUN;
                  /*BUILD THE COMMAND PAGES FOR BIGSTEPS*/
                  DATA T_RASCH;
                  SET T_RASCH;
                  FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\BIG_IN.
CON ";
                  PUT @ 1 COL1;
                  RUN;

                  /*INCREMENT THE ITEM ID LIST*/
                  DATA _NULL_;
                  STOP = &N_SELECTED + &FIRST_OPER_ITEMID -1;
                  START = &FIRST_OPER_ITEMID;
                  CALL SYMPUTX ('START', START );
                  CALL SYMPUTX ('STOP', STOP );
                  RUN;
                  /*PRINT THE ITEM ID LIST*/
                  DATA FORM&FORM;
                  INFILE
"&OUTPATH\&CONDITION\REP1\FORMS\FORM_&FORM..TXT" DSD;
                  INPUT SEQUENCE ITEMID $ A B C;&PRINT PROC PRINT;
                  RUN;

                  DATA FORM&FORM;;
                  SET FORM&FORM;
                  FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\BIG_IN.
CON" MOD;
                  PUT @ 1 ITEMID;
                  RUN;

                  DATA CCCC;
                  FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\BIG_IN.
CON" MOD;
                  PUT @ 1 "END NAMES";
                  RUN;
               /*MAKE THE DELETE FILE*/
                      data PILOT;
                        file
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\DEL.TXT
" ;
                        run;
                      %DO I = 61 %TO 80;
                        data PILOT;
                        file
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\DEL.TXT
" MOD;
                        put @1 "&I";
                        run;
                        %END;

                %IF &CAL_METHOD = FPC %THEN %DO;


                        /*RETRIEVE THE ITEM POOL*/
                        DATA FIXED2;
                        SEQUENCE = _N_;
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ITEMS\FPC_POOL.TXT" DSD  ;
                        INPUT  FORM $ ADMIN CAL_METHOD $ ITEMID $ ORDER
A B C ;
                        RUN;

                        /*RETRIEVE THE NEW FORM ITEM IDS*/
                        DATA FORM_ITEMIDS;
                        INFILE
"&OUTPATH\&CONDITION\REP1\FORMS\FORM_&FORM..TXT" DSD;/*USE FORM IN
FIRST REPLICATION*/
                        INPUT SEQUENCE ITEMID $ A B C;
                        KEEP ITEMID;
                        &PRINT PROC PRINT;RUN;
                        PROC SORT DATA = FORM_ITEMIDS; BY ITEMID;RUN;
                        PROC SORT DATA = FIXED2;       BY ITEMID;RUN;

                        DATA FIXED3;
                        MERGE FIXED2 (IN =H) FORM_ITEMIDS (IN =J);
                        BY ITEMID;
                        IF H; IF J;
                        ORIG_ORDER = INPUT(COMPRESS(ITEMID,'ITEM'),8.);
                        PROC SORT;
                        BY ORIG_ORDER;
                        &PRINT PROC PRINT;RUN;

                        DATA FIXED3;
                        SET FIXED3;
                        NEW_FORM_SEQ = _N_;
                FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\ANCHOR.
IAF";
                        PUT NEW_FORM_SEQ +1 B   +10 ITEMID;
                        RUN;
                        %END;

                  /*control Bigsteps*/
                        data big_bat;
                        lines = "bigsteps BIG_IN.con BIG_OUT.txt";
                        run;
                        data big_bat;
                        set big_bat;
                        file
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\BIG.BAT
";
                        put @1 lines;
                        run;

                        OPTIONS noXWAIT ; /*command stops SAS and gives
DOS and CIPE control until they are finished.*/
                        Data _null_;/*frequently used trick to perform
a process reserved for data steps.*/
                        call system ("CD
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\ ");
/*trigger the batch file*/
                        call system ("BIG.BAT "); /*trigger the batch
file*/
                        run; QUIT;


                        DATA BIGIN;
                        RUN;
                        %LET NOBS = 1;*SET NOBS TO 1;
                        %LET CNTR =0;
                        %DO %UNTIL(&NOBS>1 OR &CNTR =20);

                              DATA _NULL_;
                        CNTR = &CNTR +1;
                        CALL SYMPUTX ('CNTR', CNTR);
                        RUN;
                        DATA BIGIN;
                        CAL_METHOD = "&CAL_METHOD     ";
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\ITEMS.T
XT " TRUNCOVER;
                        INPUT
                        @2 SEQUENCE $6. @8 MEASURE $7. @19 COUNT $6.
                        @26 SCORE $5. @33 ERROR $ 6.
                        @39 IMNSQ $ 6.   @46 IZSTD $7.    @54 OMNSQ $6.
                        @61 OZSTD $8.   @70 DISPL $5.     @76 PTBS $4.
                        @85 ITEMID $12.;
                        RUN;
                        DATA THETIN;
                        TIME = 1;
                        CAL_METHOD = "&CAL_METHOD     ";
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\EXAMIN.
TXT " TRUNCOVER;
                        INPUT
                        @2 SEQUENCE 6. @8 MEASURE 7.  @19 COUNT 6.
                        @26 SCORE 5. @33 ERROR  8.
                        @39 IMNSQ 8.   @46 IZSTD 6.    @54 OMNSQ 6.
                        @61 OZSTD 6.   @69 DISPL 5.     @76 PTBS 5.
                        @81 RECORD $ 7.;
                        RUN;

                        DATA THETIN;
                        SET THETIN;
                        IF ERROR NE .;
                        &PRINT PROC PRINT;
                        RUN;

                        PROC CONTENTS DATA = BIGIN OUT=CHECK;
                        RUN;
                        DATA _NULL_;
                        SET CHECK;
                        CALL SYMPUTX ('NOBS',NOBS );RUN;
                        %END;

                  DATA BIGSTEPS_N ;
                  set BIGIN;
                  IF error ne " ";

                  &PRINT PROC PRINT;
                  &PRINT TITLE "&N_SELECTED ";
                  &PRINT TITLE2 " ";
                  run;

                  *CONVERT ALL OF THE CHARACTER VARIABLES TO NUMERIC
VARIABLES;
                  DATA BIGSTEPS_N;
                  SET  BIGSTEPS_N;
            ARRAY CHAR [11 ] SEQUENCE MEASURE COUNT SCORE ERROR IMNSQ
IZSTD OMNSQ OZSTD DISPL pTBS ;
            ARRAY NUM [11 ] SEQUENCE_ MEASURE_ COUNT_ SCORE_ ERROR_
IMNSQ_ IZSTD_ OMNSQ_ OZSTD_ DISPL_ pTBS_ ;
                  DO I = 1 TO 11;
            NUM[I] = INPUT(CHAR[I],8.);
                  END; DROP SEQUENCE MEASURE COUNT SCORE ERROR IMNSQ
IZSTD OMNSQ OZSTD DISPL pTBS ;
                  RUN;

                  DATA BIGSTEPS_N;
                  SET BIGSTEPS_N;
                  KEEP ITEMID MEASURE_;
                  IF MEASURE_ NE .;
                  PROC SORT;
                  BY ITEMID;
                  &PRINT PROC PRINT;
                  RUN;

                        /*PLACE EXAMINEES IN FOLDER*/
                        DATA THETIN;
                        SET THETIN;
                        ADMIN_EVENT = &ADMIN_EVENT;
                        LINKED = "UNLINKED";
                        METHOD = "&CAL_METHOD";
                        FORM = "&FORM";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ABILITIES\UNLINKED_THETAS.TXT " DSD
MOD;
                        PUT FORM ADMIN_EVENT METHOD LINKED RECORD
MEASURE;
                        RUN;

                        /*PLACE EXAMINEES IN FOLDER*/

                        OPTIONS NOXWAIT ;
                        Data _null_;
                        call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ITEMS");
                        RUN;

                        DATA BIGSTEPS_N;
                        SET BIGSTEPS_N;
                        A_E =1;
                        C_E =0;
                        ADMIN_EVENT = &ADMIN_EVENT;
                        LINKED = "UNLINKED";
                        METHOD = "&CAL_METHOD";
                        FORM = "&FORM";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ITEMS\UNLINKED_ITEMS.TXT " DSD MOD;
                        PUT FORM ADMIN_EVENT METHOD LINKED ITEMID A_E
MEASURE_ C_E;
                        RUN;

%END; /*END THE ESTIMATION STEP*/
                        /*PERFORM LINKING*/
                        /*MAKE FILE FOR POLYST*/

                        %IF &CAL_METHOD NE FPC %THEN %DO;/*NO LINKING
IS DONE UNDER FPC*/
```

```
                        %IF &CALIBRATE_PILOTS = N %THEN %DO;
                        DATA BIGSTEPS_N;
                        SET BIGSTEPS_N;
                        ORDER = INPUT(COMPRESS(ITEMID,'ITEM'), 8.);
                        IF ORDER >60 AND ORDER <81 THEN DELETE;/*DROP
THE PILOT ITEMS*/
                        PROC SORT;
                        BY ITEMID;
                        RUN;
                        %END;

                        /*GET THE BASE FORM ITEMS*/
                        DATA BASE_FORM_ITEMS;
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ITEMS\&BASE_CAL_METHOD._POOL.TXT"
DSD;
                        INPUT FORM $ ADMIN_EVENT CAL_METHOD $ ITEMID $
SEQUENCE A B C;
                        &PRINT PROC PRINT;
                        RUN;

                        %IF &REPLICATION NE REP1 AND &BASE_CAL_METHOD =
GENERATED %THEN %DO;
                        DATA BASE_FORM_ITEMS;
                        SET BASE_FORM_ITEMS;
                        IF FORM = 'A';
                        RUN;
                        %END;

                        /*INCLUDE OR EXCLUDE PILOT ITEMS*/
                        %IF &CALIBRATE_PILOTS = N %THEN %DO;
                        DATA BASE_FORM_ITEMS2;
                        SET BASE_FORM_ITEMS;
                        ORDER = INPUT(COMPRESS(ITEMID,'ITEM'), 8.);
                        /*EXCLUDE PILOT ITEMS*/
                        IF ORDER >60 THEN DELETE;
                        PROC SORT NODUP;
                        BY ITEMID;
                        RUN;
                        %END;

                        %IF &BASE_CAL_METHOD = GENERATED %THEN %DO;
                        DATA BASE_FORM_ITEMS2;
                        SET BASE_FORM_ITEMS;
                        C= 0;/*SET C TO 0*/
                        ORDER = INPUT(COMPRESS(ITEMID,'ITEM'), 8.);
                        /*SELECT EITHER SUBTEST 1 OR SUBTEST 2*/
                        PROC SORT NODUP;
                        BY ORDER;
                        RUN;

                        DATA BASE_FORM_ITEMS2;
                        SET BASE_FORM_ITEMS2;
                        IF ORDER => &LINK_START AND ORDER =<
&LINK_STOP;
                        PROC SORT NODUP;
                        BY ITEMID;
                        RUN;

                        %END;

                        %IF &CALIBRATE_PILOTS = Y %THEN %DO;
                      DATA BASE_FORM_ITEMS2;
                SET BASE_FORM_ITEMS;
                        ORDER = INPUT(COMPRESS(ITEMID,'ITEM'), 8.);
                        *IF ORDER >80 THEN DELETE;/*INCLUDE PILOT ITEMS
ALONG WITH THE OTHER ITEMS*/
                        PROC SORT NODUP;
                        BY ITEMID;
                        RUN;
                        &PRINT PROC PRINT  DATA =
BASE_FORM_ITEMS2;RUN;
                        %END;

                        DATA COMMON_ITEMS;
                        SET BASE_FORM_ITEMS2;
                        LENGTH I $12.;
                        I = ITEMID;
                        KEEP I;
                        &PRINT PROC PRINT;
                        RUN;
                        DATA COMMON_ITEMS;
                        SET COMMON_ITEMS;
                        RENAME I = ITEMID;
                        RUN;
                        PROC SORT DATA = COMMON_ITEMS NODUP;
                        BY ITEMID;RUN;

                        %IF &BASE_CAL_METHOD = GENERATED %THEN %DO;
                        PROC SORT DATA= BIGSTEPS_N;
                        BY ORDER;
                        RUN;

                        DATA BIGSTEPS_NN;
                        SET BIGSTEPS_N;
                        IF ORDER => &LINK_START AND ORDER =<
                        &LINK_STOP;
                        RUN;
                        %END;

                        %IF &BASE_CAL_METHOD NE GENERATED %THEN %DO;

                        DATA BIGSTEPS_NN;
                        SET BIGSTEPS_N;
                        RUN;
                        %END;

                        PROC SORT DATA = BIGSTEPS_NN ;
                        BY ITEMID;
                        RUN;

                        DATA BIGSTEPS_N2;
                        MERGE COMMON_ITEMS (IN =H ) BIGSTEPS_NN (IN=K);
                        BY ITEMID;
                        IF H; IF K;
                        &PRINT PROC PRINT;
                        RUN;

                        DATA _NULL_;
                        SET BIGSTEPS_N2;
                        CALL SYMPUTX ( 'N_OPER_ITEMS',_N_ );
                        RUN;

                        DATA COMMON_ITEMS;/*RESTRICT THE BASE FORM TO
COMMON ITEMS*/
                        SET BIGSTEPS_N2;
                        KEEP ITEMID;
                        RUN;
                        PROC SORT DATA = BASE_FORM_ITEMS2 NODUP;
                        BY ITEMID;RUN;

                        DATA BASE_FORM_ITEMS2;
                        MERGE COMMON_ITEMS (IN =H ) BASE_FORM_ITEMS2
(IN =K);
                        BY ITEMID;
                        IF H; IF K;
                        RUN;


                        DATA T;
                        SET THETIN;
                        T = ROUND(MEASURE,.01);
                        PROC FREQ DATA = T NOPRINT;
                        TABLE T/ OUT = T_P;RUN;
                        DATA _NULL_; SET T_P; CALL SYMPUTX
('NN',_N_);RUN;

                        DATA T_P; /*NEWLY ESTIMATED PARAMETERS*/
                        SET T_P;
                        P = PERCENT/100;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 T +1 P ;
                        RUN;

                        %IF &BASE_CAL_METHOD = GENERATED %THEN %DO;
                        DATA BASE_ABILITIES;
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ABILITIES\&BASE_CAL_METHOD._THETAS.TX
T " DSD;
                        INPUT FORM $ ADMIN_EVENT METHOD $ CANDID_ID $
THETA1 THETA2;
                        IF INDEX(FORM,"&BASE_FORM")>0;
                        RUN;

                        DATA BASE_ABILITIES;/*DATA SET CONTAINING
THETAS FROM BASE FORM*/
                        SET BASE_ABILITIES;
                        KEEP THETA1 THETA2 T;
                        THETA = (THETA1 + THETA2 )/2;/*USE COMPOSITE
THETA*/
                        T = ROUND(THETA,.01);
                        PROC FREQ NOPRINT;
                        TABLE T/ OUT = T_P_BASE;RUN;
                        DATA _NULL_; SET T_P_BASE; CALL SYMPUTX
('NB',_N_);RUN;

                        %END;
                        %IF &BASE_CAL_METHOD NE GENERATED %THEN %DO;
                        DATA BASE_ABILITIES;
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ABILITIES\&BASE_CAL_METHOD._THETAS.TX
T " DSD;
                        INPUT FORM $ ADMIN_EVENT METHOD $ TT $
CANDID_ID $ THETA;
                        IF INDEX(FORM,"&BASE_FORM")>0;
                        RUN;

                        DATA BASE_ABILITIES;/*DATA SET CONTAINING
THETAS FROM BASE FORM*/
                        SET BASE_ABILITIES
                        KEEP THETA T;
                        T = ROUND(THETA,.01);
                        PROC FREQ NOPRINT;
                        TABLE T/ OUT = T_P_BASE;RUN;
                        DATA _NULL_; SET T_P_BASE; CALL SYMPUTX
('NB',_N_);RUN;
                        %END;

                        %END;/*END OF GETTING PARAMS FROM POOL AND
ESTIMATED ABILITIES*/

                        /*PRINT THE POLYST COMMAND FILE TO A TXT FILE*/
                        DATA P;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT";
                        PUT @1 "MO DR";
                        PUT @1 "NI &N_LINK_ITEMS";
                        PUT @1 "NE DI";
                        RUN;
                        /*OUTPUT THE THE A,B, AND C ESTIMATES FOR THE
NEW FORM*/
                        DATA BIGSTEPS_N2;
                        SET BIGSTEPS_N2;
                        A_E = 1;
                        C_E = 0;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 A_E +1 MEASURE_ +1 C_E;
                        RUN;

                        DATA LINE;
                        LINE = "OL DI";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 LINE;
                        RUN;
                        /*OUTPUT THE THE A,B, AND C PARAMS. FOR THE
BASE FORM*/
                        DATA BASE_FORM_ITEMS2;
                        SET BASE_FORM_ITEMS2;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 A +1 B +1 C;
                        RUN;
                        /*POLYST LINES FOR THE NEW DISTRIBUTION*/
                        DATA _NULL_;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                        PUT @1 "ND &NN SE DI";
                        RUN;

                     /*T_P = FREQUENCIES FROM ABILITY DISTRIBUTIONS*/
                        DATA T_P; /*NEW PARAMETERS*/
                SET T_P;
                        P = PERCENT/100;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 T +1 P ;
                        RUN;

                        /*POLYST LINES FOR THE BASE FORM DISTRIBUTION*/
                        DATA _NULL_;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                        PUT @1 "OD &NB SE DI";
                        RUN;

                        DATA T_P_BASE; /*NEW PARAMETERS*/
                SET T_P_BASE;
                        P = PERCENT/100;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                PUT @1 T +1 P ;
                        RUN;

                        /*FINAL LINES FOR POLYST*/
                        DATA _NULL_;
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLYST_
IN.TXT" MOD;
                        PUT @1 "FS NO NO";
                        PUT @1 "SC 1.00";
                        PUT @1 "BY";
                        RUN;
                        /*CONTROL POLYST TO PRODUCE TRANSFORMATION
CONSTANTS*/
                  OPTIONS NOXWAIT ;
                        Data _null_;
                        call system ("CD C:\DISSERTATION\SIMULATION");
                        CALL SYSTEM ("COPY POLYST.EXE
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD");
                        RUN;

                        DATA POLY;
                        LINE = "polyst.exe<control.txt";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\POLY.BA
T";
                        PUT @1 LINE;
                        RUN;

                        DATA CONTROL;
                        LINE1 = "POLYST_IN.txt";
                        LINE2 = "out.txt ";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\CONTROL
.TXT";
                        PUT @1 LINE1;
                        PUT @1 LINE2;
                        RUN;

                        OPTIONS noXWAIT ;
                        Data _null_;
                        call system ("CD
&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD ");
                        call system ("poly.bat ");
                        run; QUIT;

                        DATA CONSTANTS;
                        INFILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\OUT.TXT
";
                        INPUT @1 CAL_METHOD  $ 10. @16 SLOPE 9. @28
INTERCEPT 9.;
                        CAL_METHOD = TRANSLATE(CAL_METHOD,"_","/");
                        IF INDEX(UPCASE(CAL_METHOD),"&LINK_METH") > 0;
                        CALL SYMPUTX ('SLOPE ' ,SLOPE );
                        CALL SYMPUTX ('INTERCEPT ',INTERCEPT );
                        &PRINT PROC PRINT;RUN;


            /*APPLY THE TRANSFORMATIONS TO THE PARAMETERS*/
                  DATA BIGSTEPS_NN;
                  SET BIGSTEPS_NN;
                  A_E = 1/&SLOPE;
            B_E = &SLOPE*MEASURE_ + &INTERCEPT;
                  C_E = 0;
                  &PRINT PROC PRINT;
                  RUN;
```

```
%IF CAL_METHOD = FPC %THEN %DO;
DATA BIGSTEPS_NN;
SET BIGSTEPS_NN;
A_E = 1;/*ASSUME A = 1 FOR ALL FPC LINKS*/
RUN;
%END;

                  DATA THETIN;
                  SET THETIN;
            LINKED_THETA = &SLOPE*MEASURE + &INTERCEPT;
                  RUN;
                  /*STORE THE LINKED THETAS*/
                        DATA THETIN;
                        SET THETIN;
                        ADMIN_EVENT = &ADMIN_EVENT;
                        LINKED = "LINKED";
                        METHOD = "&CAL_METHOD";
                        FORM = "&FORM";
                        FILE
"&OUTPATH\&CONDITION\&REPLICATION\ABILITIES\&CAL_METHOD._THETAS.TXT "
DSD MOD;
                        PUT FORM ADMIN_EVENT METHOD LINKED RECORD
LINKED_THETA;
                        RUN;

                  %END;/*END LINKING PROCESS*/
                  /*COMPARE GENERATING PARAMETERS TO ESTIMATED
PARAMETERS*/
                  DATA TRUE_IT_PARAMS;
                  LENGTH ITEMID $12.;
                  INFILE
"&OUTPATH\&CONDITION\REP1\FORMS\FORM_&FORM..TXT" DSD;/*FORM IN FIRST
REPLICATION*/
                  INPUT SEQUENCE ITEMID $ A B C;
                  &PRINT PROC PRINT;RUN;

                  PROC SORT DATA = TRUE_IT_PARAMS;
                  BY ITEMID;RUN;

                  PROC SORT DATA = BIGSTEPS_NN;
                  BY ITEMID;RUN;

                  %IF &CAL_METHOD = FPC %THEN %DO;/*ADD THE A AND C
PARAMS TO THE FPC B ESTIMATES*/
                  DATA BIGSTEPS_NN;
                  SET BIGSTEPS_N;
                  A_E = 1; B_E = MEASURE_; C_E = 0;
                  RUN;
                  DATA THETIN;
                  SET THETIN;
                  LINKED_THETA = MEASURE;
                  RUN;
                  %END;
                  DATA BOTH_I_PARAMS;
                  MERGE TRUE_IT_PARAMS BIGSTEPS_NN;
                  BY ITEMID;
                  IF MEASURE_ = . THEN DELETE;
                  UNLINKED_ABS_DIF = ABS(MEASURE_ - B);
                  LINKED_ABS_DIF= ABS(B_E - B);
                  ORIG_SEQ = INPUT(COMPRESS(ITEMID,'ITEM'),8.);
                  PROC SORT;
                  BY ORIG_SEQ;&PRINT PROC PRINT;
                  RUN;


                  DATA EST_THETA;
                  SET THETIN;
                  KEEP RECORD MEASURE LINKED_THETA;
                  RENAME RECORD = CANDID_ID_&GROUP;
                  &PRINT PROC PRINT;
                  PROC SORT;
                  BY CANDID_ID_&GROUP;
                  RUN;
                  PROC SORT DATA = GROUP&GROUP;
                  BY CANDID_ID_&GROUP;
                  RUN;

/*incorporate the true scores into this merge*/

                  DATA THETAS;
                  MERGE GROUP&GROUP EST_THETA (IN =H);
                  BY CANDID_ID_&GROUP;
                  IF H;
                  COMPOSITE = (&GROUP.1 + &GROUP.2)/2;
                  UNLINKED_ABS_DIF = ABS(MEASURE-COMPOSITE);
                  LINKED_ABS_DIF = ABS(LINKED_THETA-COMPOSITE);
                  RUN;

                  /*REPORT PARAMETER RECOVERY*/
                  ODS PDF FILE =
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\PARAM_R
ECOVERY.PDF ";
                  PROC MEANS DATA = BOTH_I_PARAMS SUM;
                  VAR UNLINKED_ABS_DIF LINKED_ABS_DIF;
                  TITLE "UNLINKED VERSUS LINKED ITEM PARAMETERS ";
                  RUN;
                  PROC MEANS DATA = THETAS SUM;
                  VAR UNLINKED_ABS_DIF LINKED_ABS_DIF; OUTPUT OUT = ALL
SUM=;
                  TITLE "UNLINKED VERSUS LINKED THETAS ";
                  RUN;&PRINT PROC PRINT DATA = ALL;RUN;
                  ODS PDF CLOSE;

                  PROC SORT DATA = BOTH_I_PARAMS; BY SEQUENCE; RUN;

                  DATA FINAL_ITEMS;
                  SET BOTH_I_PARAMS;
                  SEQ = INPUT (COMPRESS(ITEMID,'ITEM' ),8.);
                  PROC SORT;
                  BY SEQ;
                  &PRINT PROC PRINT;
                  RUN;

                  DATA FINAL_ITEMS;
                  SET FINAL_ITEMS;
                  SEQUENCE = _N_;
                  FILE
"&OUTPATH\&CONDITION\&REPLICATION\ADMIN&ADMIN_EVENT\&CAL_METHOD\FINAL_I
TEMS.TXT " DSD;
                  PUT ITEMID SEQUENCE A B C MEASURE_ A_E B_E C_E
UNLINKED_ABS_DIF LINKED_ABS_DIF ; RUN;

                  /*ACCUMULATE ALL ITEM ESTIMATES IN A CUMULATIVE
FILE*/
                  DATA FINAL_CUM;
                  SET FINAL_ITEMS;
                  IF _N_>60; /*ACCUMULATE ONLY THE PILOT ITEMS*/
                  CONDITION = "&CONDITION";
                  REPLICATION = "&REPLICATION";
                  ADMIN= "&ADMIN_EVENT";
                  CAL_METHOD = "&CAL_METHOD";
                  FILE
"C:\DISSERTATION\SIMULATION\&CONDITION\FINAL_ITEMS.TXT" DSD MOD;
                  PUT ITEMID CONDITION REPLICATION CAL_METHOD ADMIN
ITEMID  SEQUENCE A B C MEASURE_ A_E B_E C_E UNLINKED_ABS_DIF
LINKED_ABS_DIF ;
                  RUN;
%IF &BASE_CAL_METHOD NE GENERATED %THEN %DO;
                  /*ACCUMULATE ALL ITEM ESTIMATES IN A CUMULATIVE
FILE*/
                  DATA FINAL_THETAS;
                  SET THETAS;
                  CONDITION = "&CONDITION";
                  REPLICATION = "&REPLICATION";
                  ADMIN= "&ADMIN_EVENT";
                  CAL_METHOD = "&CAL_METHOD";
                  FILE
"C:\DISSERTATION\SIMULATION\&CONDITION\FINAL_THETAS.TXT" DSD MOD;
                  PUT  ADMIN CONDITION REPLICATION CAL_METHOD COMPOSITE
MEASURE LINKED_THETA UNLINKED_ABS_DIF LINKED_ABS_DIF;
                  RUN;
%END;
                  /*PLACE ITEM PARAMETERS IN POOL*/
                  %IF &CALIBRATE_PILOTS = Y %THEN %DO;
                  DATA FINAL_ITEMS;
                  SET  FINAL_ITEMS;
                  IF SEQUENCE <61 THEN DELETE;
                  RUN;
                  &PRINT PROC PRINT DATA= FINAL_ITEMS;RUN;
                  %END;
                  /*MAKE FOLDER FOR OUTPUT*/
                  OPTIONS NOXWAIT ;
                  Data _null_;
                  call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ITEMS");
                  RUN;

                  DATA FINAL_ITEMS;
                  SET FINAL_ITEMS;
                  LENGTH CAL_METHOD $ 20.;
                  CAL_METHOD = "&CAL_METHOD";
                  FORM = "&FORM";
                  ADMIN_EVENT = "&ADMIN_EVENT";
                  FILE
"C:\DISSERTATION\SIMULATION\&CONDITION\&REPLICATION\ITEMS\&CAL_METHOD._
POOL.TXT" DSD MOD;
                  PUT FORM ADMIN_EVENT CAL_METHOD ITEMID SEQUENCE A_E
B_E C_E;
                  RUN;

                  %IF &CAL_METHOD = SEPARATE %THEN %DO; /*PUT THE VERY
FIRST ITEMS PARAMS. IN EACH POOL*/
                  DATA FINAL_ITEMS;
                  SET FINAL_ITEMS;
                  LENGTH CAL_METHOD $ 20.;
                  CAL_METHOD = "&CAL_METHOD";
                  FORM = "&FORM";
                  ADMIN_EVENT = "&ADMIN_EVENT";
                  FILE
"C:\DISSERTATION\SIMULATION\&CONDITION\&REPLICATION\ITEMS\STOCK_LORD_PO
OL.TXT" DSD MOD;
                  PUT FORM ADMIN_EVENT CAL_METHOD ITEMID SEQUENCE A_E
B_E C_E;
                  RUN;

                  DATA FINAL_ITEMS;
                  SET FINAL_ITEMS;
                  LENGTH CAL_METHOD $ 20.;
                  A_E = 1;
                  CAL_METHOD = "&CAL_METHOD";
                  FORM = "&FORM";
                  ADMIN_EVENT = "&ADMIN_EVENT";
                  FILE
"C:\DISSERTATION\SIMULATION\&CONDITION\&REPLICATION\ITEMS\FPC_POOL.TXT"
DSD MOD;
                  PUT FORM ADMIN_EVENT CAL_METHOD ITEMID SEQUENCE A_E
B_E C_E;
                  RUN;

                        /*SAVE COPIES*/
                        OPTIONS NOXWAIT ;
                        Data _null_;
                        call system ("mkdir
&OUTPATH\&CONDITION\&REPLICATION\ADMIN1\SEPARATE\SET&LINK_START.TO&LINK
_STOP");
                        RUN;

                        OPTIONS NOXWAIT ;
                        Data _null_;
                        call system ("CD
&OUTPATH\&CONDITION\&REPLICATION\ADMIN1\SEPARATE");
                        CALL SYSTEM ("COPY POLYST_IN.TXT
&OUTPATH\&CONDITION\&REPLICATION\ADMIN1\SEPARATE\SET&LINK_START.TO&LINK
_STOP");
                        CALL SYSTEM ("COPY OUT.TXT
&OUTPATH\&CONDITION\&REPLICATION\ADMIN1\SEPARATE\SET&LINK_START.TO&LINK
_STOP");
```

```
                        CALL SYSTEM ("COPY FINAL_ITEMS.TXT
&OUTPATH\&CONDITION\&REPLICATION\ADMIN1\SEPARATE\SET&LINK_START.TO&LINK
_STOP");
                        RUN;

                  %END;

                  %MEND;

%GLOBAL T F TS;
```

```
%MACRO EQUATE_TRUE_SCORES (PRINT = *, D=1, OUTPATH = , CONDITION=,
REPLICATION = ,CAL_METHOD =  , NEW_FORM =B);

/*NOTE: THIS CODE WILL WORK WITH A 1PL MODEL, NOT A 2 OR 3PL MODEL*/
DATA OPER_BASE_FORM;
INFILE "&OUTPATH\&CONDITION\REP1\FORMS\FORM_A.TXT" DSD;
INPUT SEQUENCE ITEMID $ A B C ABILITY;
KEEP ITEMID;

IF _N_ =<60;
&PRINT PROC PRINT;
PROC SORT;
BY ITEMID;
RUN;

DATA OPER_NEW_FORM;
INFILE "&OUTPATH\&CONDITION\REP1\FORMS\FORM_&NEW_FORM..TXT" DSD;
INPUT SEQUENCE ITEMID $ A B C ABILITY;

KEEP ITEMID;
IF _N_ =<60;
&PRINT PROC PRINT;
PROC SORT;
BY ITEMID;
RUN;

DATA POOL;
D = &D;
INFILE "&OUTPATH\&CONDITION\&REPLICATION\ITEMS\&CAL_METHOD._POOL.TXT"
DSD;
INPUT FORM $ ADMIN METHOD $ ITEMID $ SEQUENCE A B C;
&PRINT PROC PRINT;
PROC SORT;
BY ITEMID;
RUN;


DATA PARAMS1;
MERGE POOL OPER_BASE_FORM (IN =H);
BY ITEMID;
IF H;
&PRINT PROC PRINT;
TITLE "BASE FORM";
PROC SORT;
BY SEQUENCE;
RUN;

DATA PARAMS2;
MERGE POOL OPER_NEW_FORM (IN =H);
BY ITEMID;
IF H;
&PRINT PROC PRINT;
TITLE "NEW FORM";
PROC SORT;
BY SEQUENCE;
RUN;
```

```
OPTIONS SYMBOLGEN MLOGIC;

DATA CONV_TABLE;/*START THE CONVERSION TABLE BY DEFINING SOME INITIAL
VALUES*/
TRUESCORE_2 = 0;
PERCENT_2 = 0;
THETA = -99;
PERCENT_1 = 0;
TRUESCORE_1 = 0;
RUN;
DATA _NULL_;/*OBTAIN THE N OF ITEMS IN THE NEW FORM*/
SET PARAMS2;
CALL SYMPUTX('N',_N_);
RUN;


DATA _NULL_;/*OBTAIN THE N OF ITEMS IN THE POOL*/
SET PARAMS1;
CALL SYMPUTX ('NN',_N_ );
RUN;


%LET PRINT = *;/*TURN PRINTING ON ( ) FOR DEBUGGING OR OFF (*) */
%LET T = -3;/*STARTING GUESS OF THETA*/
%LET F = 1;/*ASSIGN A VALUE GREATER THAN 0 TO THE FUNCTION*/
%DO TS=1 %TO &N; /*DEFINE A LOOP THAT WILL REPEAT N TIMES (N=LENGTH OF
THE NEW FORM)*/

            %LET F = 1; /*RESET THE FUNCTION BEFORE EACH RUN OF THE
RAPHSON NEWTON METHOD*/
            %DO %WHILE (&F >0.0001);/*PERFORM RAPHSON NEWTON METHOD
WHILE THE FUNCTION IS GREATER THAN CRITERION*/
            DATA D&TS;
            SET PARAMS2;
            TARGET=&TS/&N;/*DEFINE THE TARGET VALUE AS THE PERCENT
CORRECT TRUE SCORE*/
            T=&T; /*STARTING VALUE (GUESS) FOR THETA*/

            PROB =C + (1-C)*(EXP(D*A*(T - B))/(1 +EXP(D*A*(T -
B))));/*PROBABILITY OF 1*/
            DERIVATIVE = (D*A*(1-PROB)*(PROB-C))/(1-C);/*DERIVATIVE*/
            SUM_P + PROB;/*EXPECTED NUMBER CORRECT TRUE SCORE FOR THETA
&T*/
            SUM_D + DERIVATIVE; /*SUM OF DERIVATIVES FOR THETA &T*/

            MN_P = SUM_P/&N;/*EXPECTED PERCENT CORRECT TRUE SCORE FOR
THETA &T*/
            MN_D = SUM_D/&N;/*AVERAGE DERIVATIVES FOR THETA &T*/

            FUNCTION = MN_P-TARGET;/*FUNCTION TO MINIMIZE*/
            NUM=-1*MN_D;
            T_TEMP = T-(TARGET-MN_P)/(-1*MN_D);/*OBTAIN A TEMPORARY
THETA ESTIMATE THAT MINIMIZES THE FUNCTION*/
            IF ABS(T_TEMP - TARGET)>.00001 THEN T = T_TEMP;
OUTPUT;/*TEST THE THETA AGAINST THE CRITERION*/
            /*REPLACE THE PRIOR THETA WITH THE NEW TEMPORARY THETA,
STORE THE FUNCTION, AND THE EXPECTED PERCENT CORRECT TRUE SCORE*/
```

```
            IF _N_ = &N THEN CALL SYMPUTX('T',T );
            IF _N_ = &N THEN CALL
SYMPUTX('F',ROUND(ABS(FUNCTION),.0000001));
            IF _N_ = &N THEN CALL SYMPUTX('MN_p2',MN_p );
            &PRINT PROC PRINT;
            &PRINT TITLE "&TS ";
            RUN;

            DATA DD&TS;
            SET PARAMS1;/*ENTIRE POOL OR FORM*/
            PROB =C + (1-C)*(EXP(D*A*(&T - B))/(1 +EXP(D*A*(&T -
B))));/*PROBABILITY OF 1 FOR EACH ITEM IN POOL*/
            SUM_P + PROB;/*SUM OF PROBABILITIES*/
            MN_P=SUM_P/&N; /*DIVIDE THE SUM OF PROBABILITIES BY THE N
OF THE NEW FORM */
            IF _N_ = &N THEN CALL SYMPUTX('MN_p1',MN_p );/*STORE THE
EXPECTED PERCENT CORRECT TRUE SCORE*/
            &PRINT PROC PRINT;
            &PRINT TITLE "A true score of &MN_p2 on form 2 is
equivalent to a true score of &MN_p1 on form 1";
            &PRINT TITLE2 "&TS";
            RUN;
            %END;/*END OF RAPHSON NEWTON LOOP*/


DATA RESULT&ts;/*SAVE RESULTS*/
TRUESCORE_2 = &TS;/*NEW FORM INTEGER TRUE SCORE*/
PERCENT_2 = &MN_P2;
THETA = &T;
PERCENT_1 = &MN_P1;
TRUESCORE_1 = &MN_P1*&N; /*EXPECTED NUMBER CORRECT TRUE SCORE*/
RUN;

PROC APPEND BASE = CONV_TABLE DATA = RESULT&TS;RUN;/*APPEND RESULTS*/
&PRINT PROC PRINT DATA = CONV_TABLE;
&PRINT TITLE "CONVERSION TABLE";
RUN;
%END;
&PRINT PROC PRINT DATA = CONV_TABLE;
TITLE "CONVERSION TABLE";
RUN;
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\&REPLICATION\CONV_TABLES");
RUN;

DATA CONV_TABLE;
SET CONV_TABLE;
EST_A = TRUESCORE_1;
FORM = "&NEW_FORM ";
RENAME PERCENT_2 = PTS_&NEW_FORM  PERCENT_1 = PTS_BASE;
RUN;
proc export data=CONV_TABLE
outfile="&OUTPATH\&CONDITION\&REPLICATION\CONV_TABLES\&CAL_METHOD._CONV
_TABLE_&NEW_FORM..TXT" dbms=dlm replace;
delimiter=",";
run;
```

```
DATA CUM_CONV_TABLE;
SET CONV_TABLE;
FORM = "&NEW_FORM";
REPLICATION = "&REPLICATION";
FILE "&OUTPATH\&CONDITION\&CAL_METHOD._CONV_TABLE.TXT " MOD;
PUT FORM REPLICATION TRUESCORE_2  THETA EST_A;
RUN;

/*COMPARE TO CRITERION CONV. TABLE*/

DATA CRITERION_CONV_TABLE;
INFILE "&OUTPATH\&CONDITION\EQUIPERCENTILE_CONV_TABLE.TXT " MOD;
INPUT FORM $ TRUESCORE_2 A ;
RUN;

DATA CONV_TABLE;
MERGE CRITERION_CONV_TABLE  CONV_TABLE (IN =H);
BY FORM TRUESCORE_2;
IF H;
RUN;

DATA CUM_CONV_TABLE;
SET CONV_TABLE;
METHOD = "&CAL_METHOD";
REPLICATION = "&REPLICATION";
FILE "&OUTPATH\&CONDITION\DIFFERENCE.TXT " MOD DSD;
PUT METHOD FORM REPLICATION TRUESCORE_2 A EST_A;
RUN;
&PRINT PROC PRINT DATA  = CUM_CONV_TABLE;RUN;
/*EMPTY THE CONV. TABLE */
DATA CONV_TABLE;
RUN;

%MEND;
```

```
/******************************************************************/
/*    PURPOSE OF MACRO IS TO PERFORM LINEAR EQUATING              */
/*    PERFORMS:                                                   */
/*                      1. TUCKER LINEAR EQUATING                 */
/*                      2. LEVINE LINEAR EQUATING                 */
/*                      3. LEVINE TRUE SCORE EQUATING             */
/*                                                                */
/*    PROGRAM ALSO IMPLEMENTS MANTEL HAENZEL DELTA DIF AND REMOVES*/
/*    ITEMS FLAGGED WITH SEVERE DIF                               */
/*                                                                */
/*    NITEMS = NUMBER OF ITEMS ON TEST                            */
/*    CUT = NUMBER CORRECT RAW CUT SCORE                          */
/*    REMOVE_C =  Y =YES, REMOVE ITEMS FLAGGED WITH DIF AT LEVEL 'C'
      */
/*    PASSFAIL = Y =YES, CALCULATE PASS/FAIL                      */
/*    ROUND_BUF = AMOUNT TO ADJUST SCALE, MAY BE USED TO ADJUST SCALE
      */
/*    ODSOUT =                                                    */
/*    BASE = NAME OF BASE FORM                                    */
/*    NEWFORM = NAME OF NEW FORM                                  */
/*    _A_ = SLOPE OF LINEAR SCALE CONVERSION                      */
/*    _B_ = INTERCEPT FOR LINEAR SCALE CONVERSION                 */
/*    CIPE = Y = , SEND DATA OUT FOR CIPE                         */
/*    PRINT = IF * THE DO NOT PRINT ALL DATA SETS                 */
/*    ROUND_SCALE = IF Y THEN ROUND THE SCORE SCALE TO NEAREST WHOLE N
      */
/*                                                                */
/******************************************************************/


%MACRO LINEAR_EQUATE (folder_path= C:\EHT\,  CONDITION =
COND1,REPLICATION = REP1,ADMIN_EVENT = 1, NITEMS =60, CUT = 55,
REMOVE_C = ,
PASSFAIL =, ROUND_BUF = ,ODSOUT =, OUTPATH =, BASE =, NEWFORM = ,
_A_ = 1, _B_ = 1, CIPE = N, PRINT = *,ROUND_SCALE=,
NEW_ADMIN =2, BASE_ADMIN = 1, MONTH = );

libname l "&folder_path";

/*GET THE BASE FORM*/
DATA BASE;
infile "c:\eht\xeaa.txt " truncover dsd delimiter='09'x;
INPUT AN606  AN69  AN250  AN476  AN94  AN216  AN701  AN687  AN37  AN309
AN412  AN361  AN6  AN697  AN471  AN237  AN225  AN387  AN550  AN296
AN209  AN544  AN441  AN299  AN671  AN614  AN626  AN206  AN398  AN386
AN593  AN462  AN561  AN820  AN194  AN494  AN819  AN396  AN113  AN263
AN290  AN584  AN49  AN201  AN124  AN463  AN813  AN224  AN435  AN700
AN182  AN668  AN633  AN326  AN664  AN578  AN198  AN456  AN465  AN622
AN538  AN654  AN159  AN43  AN353  AN684  AN647  AN586  AN514  AN355
AN481  AN52  AN308  AN336  AN103  AN251  AN590  AN63  AN812  AN411;
rscore = sum (of _NUMERIC_);
proc print;run;

data BASE;
set base;
RAW_SCORE2 = RSCORE;
run;
```

```
PROC FREQ DATA = BASE NOPRINT;
TABLE RAW_SCORE2/ OUT= BASEFREQ;
RUN;
DATA BASEFREQ;
SET BASEFREQ;
RENAME COUNT = BASE_COUNT PERCENT = BASE_PERCENT;
RUN;


/*GET NEW ITEMS*/
DATA NEWFORM;
SET L.MATRIX&NEWFORM;
RUN;

/*SAVE COPIES*/
OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&NEWFORM");
RUN;

            DATA DELETED;
                  SET NEWFORM;
                  IF RAW_SCORE2 = 0;
                  PROC PRINT;
                  RUN;

proc export data=DELETED outfile="&OUTPATH\&NEWFORM\DELETED.TXT"
dbms=dlm replace;
delimiter=",";
run;

/*REMOVE ANY SCORES OF 0*/
DATA NEWFORM;
SET NEWFORM;
IF RAW_SCORE2 = 0 THEN DELETE;
RUN;

PROC FREQ DATA = NEWFORM NOPRINT;
TABLE RAW_SCORE2/ OUT= NEWFREQ;
RUN;

data freqs;
retain raw_score2 base_count count base_percent percent;
merge basefreq newfreq;
by raw_score2;
rename count = new_count percent = new_percent;
proc print;run;


proc export data=freqs outfile="&OUTPATH\&NEWFORM\FREQUENCIES.TXT"
dbms=dlm replace;
delimiter=",";
run;

PROC CONTENTS DATA = NEWFORM OUT = ITEMIDS;RUN;
```

```
DATA T_N;
SET ITEMIDS;
CALL SYMPUTX ('N_OBS', NOBS );

IF SUBSTRN(NAME,1,2)= "AN";
RENAME NAME =ITEMID1 ;
NEWFORM =1;
KEEP NAME NEWFORM;
PROC SORT;
BY ITEMID1;
PROC PRINT;RUN;
PROC SORT DATA = T_B;
BY ITEMID1;RUN;

PROC SQL NOPRINT;
SELECT DISTINCT ITEMID1
INTO: NEW_ITEMS SEPARATED BY " "
FROM T_N
ORDER BY ITEMID1;
QUIT;
%PUT &NEW_ITEMS;

/*NOW BASE ITEMS*/


PROC CONTENTS DATA = BASE OUT = ITEMIDSB;RUN;

DATA T_B;
SET ITEMIDSB;
IF SUBSTRN(NAME,1,2)= "AN";
RENAME NAME =ITEMID1 ;
NEWFORM =1;
KEEP NAME NEWFORM;
PROC SORT;
BY ITEMID1;
PROC PRINT;RUN;

PROC SORT DATA = T_B;
BY ITEMID1;RUN;

PROC SQL NOPRINT;
SELECT DISTINCT ITEMID1
INTO: BASE_ITEMS SEPARATED BY " "
FROM T_B
ORDER BY ITEMID1;
QUIT;
%PUT &BASE_ITEMS;

/*COMBINE THEM TO ISOLATE THE COMMON ITEMS*/
DATA ITEMLIST;
MERGE T_N (IN=U) T_B (IN=Y);
BY ITEMID1;
IF U; IF Y;
&PRINT PROC PRINT;
RUN;

PROC SQL NOPRINT;
```

```
SELECT DISTINCT ITEMID1
INTO: COMMON_ITEMS SEPARATED BY " "
FROM ITEMLIST
ORDER BY ITEMID1;
QUIT;
%PUT &COMMON_ITEMS;


/*OBTAIN P VALUES*/
PROC MEANS DATA =  BASE;
VAR &BASE_ITEMS;
OUTPUT OUT = BASE_P
MEAN =
;
RUN;
&PRINT PROC PRINT DATA =BASE_P;RUN;

PROC TRANSPOSE DATA = BASE_P OUT = T_BASE_P (RENAME=(COL1 = BASE_P ));
VAR &BASE_ITEMS;
RUN;
&PRINT PROC PRINT DATA = T_BASE_P;RUN;

PROC MEANS DATA =  NEWFORM;
VAR &NEW_ITEMS;
OUTPUT OUT = NEW_P
MEAN =
;
RUN;
&PRINT PROC PRINT DATA =NEW_P;RUN;
PROC TRANSPOSE DATA = NEW_P OUT = T_NEW_P (RENAME=(COL1 = NEW_P ) );
VAR &NEW_ITEMS;
RUN;
&PRINT PROC PRINT DATA = T_NEW_P;RUN;

PROC SORT DATA =T_NEW_P;
BY _NAME_;RUN;


/*MERGE ALL PVALUES BY ITEMIDS*/
PROC SORT DATA = T_BASE_P;
BY _NAME_;
RUN;

DATA ALLPVALUES;
MERGE T_BASE_P (IN=Y) T_NEW_P (IN = U);
BY _NAME_;
ITEMID1 = _NAME_;
RUN;

DATA ALLPVALUES NEW_UNIQUE BASE_UNIQUE;
SET ALLPVALUES;
IF BASE_P NE . AND NEW_P NE . THEN OUTPUT ALLPVALUES;
IF BASE_P NE . AND NEW_P = . THEN OUTPUT BASE_UNIQUE;
IF BASE_P = . AND NEW_P NE . THEN OUTPUT NEW_UNIQUE;
RUN;
PROC MEANS DATA = NEW_UNIQUE NOPRINT;
VAR NEW_P;
```

```
OUTPUT OUT = MEAN_NEW_UNIQUE
MEAN=;
RUN;

DATA MEAN_NEW_UNIQUE;
SET MEAN_NEW_UNIQUE;
CALL SYMPUTX ( 'M_NEW_P_UNIQUE', NEW_P);
RUN;

PROC MEANS DATA = BASE_UNIQUE NOPRINT;
VAR BASE_P;
OUTPUT OUT = MEAN_BASE_UNIQUE
MEAN=;
RUN;
DATA MEAN_BASE_UNIQUE;
SET MEAN_BASE_UNIQUE;
CALL SYMPUTX ( 'M_BASE_P_UNIQUE', BASE_P);
RUN;

PROC MEANS DATA = ALLPVALUES NOPRINT;
VAR BASE_P;
OUTPUT OUT = MEAN_BASE_COMMON
MEAN=;
RUN;
DATA MEAN_BASE_COMMON;
SET MEAN_BASE_COMMON;
CALL SYMPUTX ( 'M_BASE_P_COMMON', BASE_P);
RUN; %PUT &M_BASE_P_COMMON;

PROC MEANS DATA = ALLPVALUES NOPRINT;
VAR NEW_P;
OUTPUT OUT = MEAN_NEW_COMMON
MEAN=;
RUN;
DATA  MEAN_NEW_COMMON;
SET  MEAN_NEW_COMMON;
CALL SYMPUTX ( 'M_NEW_P_COMMON', NEW_P);
RUN;
%PUT &M_NEW_P_COMMON ;

DATA ALLPVALUES;
SET ALLPVALUES;
DIFF =  NEW_P- BASE_P;
PROC SORT;
BY DIFF;
&PRINT PROC PRINT;
TITLE "DIFFICULTY OF COMMON ITEMS BETWEEN BASE AND NEWFORM ";
RUN;


proc export data=ALLPVALUES outfile="&OUTPATH\&NEWFORM\ALLPVALUES.TXT"
dbms=dlm replace;
delimiter=",";
run;

/*DIF ANALYSIS STARTS HERE*/
/*APPEND THE ITEMS IDS TO THE MATRIX OF RESPONSES FOR THE NEWFORM*/
```

```
PROC TRANSPOSE DATA = BASE11 OUT = T_BASE_ITEMS;
VAR X1 - X&NITEMS;
RUN;
DATA T_BASE_ITEMS;
SET T_BASE_ITEMS;
RENAME COL1 = ITEMID ;
RUN;
&PRINT PROC PRINT DATA = T_BASE_ITEMS;RUN;

DATA BASE_FORM2;
SET BASE;
GROUP = 1;
KEEP &COMMON_ITEMS GROUP;
proc print;
RUN;

DATA NEW_FORM2;
SET NEWFORM;
GROUP = 2;
KEEP &COMMON_ITEMS GROUP;
RUN;


DATA BOTH;
SET BASE_FORM2 NEW_FORM2;
TOTRIGHT = SUM(OF &COMMON_ITEMS);
IF TOTRIGHT NE .;
PROC PRINT;
RUN;


ODS OUTPUT CMH=THREE COMMONRELRISKS =RR;
PROC FREQ DATA = BOTH;
TABLES TOTRIGHT*GROUP*(&COMMON_ITEMS)/CMH NOPRINT;
TITLE1 "BASE (REF) VS. NEWFORM(FOCAL)";
RUN;


DATA CHISQ;
SET THREE;
IF UPCASE(ALTHYPOTHESIS) = 'NONZERO CORRELATION';
RENAME VALUE = CHISQ;
IF PROB < '.0001' THEN PROB = '.0001';
&PRINT PROC PRINT;
RUN;

DATA RELRISK;
SET RR;
IF UPCASE(STUDYTYPE) = 'CASE-CONTROL';
RENAME VALUE = ALPHA;
RUN;


DATA BOTH2;
MERGE CHISQ RELRISK;
&PRINT PROC PRINT;
RUN;
```

```
DATA DIF_RESULTS;
SET BOTH2;
DELTA = LOG(ALPHA) * (-2.35);
LEVEL = 'B';

IF (ABS(DELTA) < 1.0) OR (PROB > 0.05) THEN LEVEL = 'A';

IF (ABS(DELTA) > 1.5) AND ((LOWERCL > 1.0) AND (UPPERCL > 1.0))
 THEN LEVEL = 'C';

IF (ABS(DELTA) > 1.5) AND ((LOWERCL < 1.0) AND (UPPERCL < 1.0))
 THEN LEVEL = 'C';

 ITEMID = SUBSTRN(TABLE,20,10);
IF LEVEL = 'A' THEN LEVEL1 = '3';
IF LEVEL = 'B' THEN LEVEL1 = '2';
IF LEVEL = 'C' THEN LEVEL1 = '1';
LENGTH ITEMID1 $32.;
ITEMID1 = COMPRESS(ITEMID);
PROC SORT;
BY ITEMID1;
&PRINT PROC PRINT;
RUN;

PROC SORT DATA = ALLPVALUES;
BY ITEMID1;RUN;

DATA ALLPVALUES2;
MERGE ALLPVALUES DIF_RESULTS;
BY ITEMID1;
ABS_DELTA = ABS(0 - DELTA);
PROC SORT;
BY LEVEL1 DESCENDING ABS_DELTA;
;PROC PRINT;
RUN;


PROC CONTENTS DATA = ALLPVALUES2 OUT = CNTS NOPRINT;
DATA _NULL_;
SET CNTS;
CALL SYMPUTX('CNT', NOBS);
RUN; %PUT &CNT;


*SEE CAMILLI & SHEPARD, P. 121 OR CLAUSEN NCME PAPER;

/*END OF DIF ANALYSIS, BEGIN EQUATING*/

data allpvalues2;
set allpvalues2;
rename _name_ = itemid1;
run;

PROC FREQ DATA= ALLPVALUES2 NOPRINT;
TABLE LEVEL/OUT = CNTS_DIF;
RUN;
```

```
%LET A_DIF = 0;
%LET B_DIF = 0;
%LET C_DIF = 0;

DATA CNTS_DIF;
SET CNTS_DIF;
IF LEVEL = "A" THEN CALL SYMPUTX ('A_DIF', COUNT );
IF LEVEL = "B" THEN CALL SYMPUTX ('B_DIF', COUNT );
IF LEVEL = "C" THEN CALL SYMPUTX ('C_DIF', COUNT );
PROC PRINT;
RUN;


DATA TEMP;

MAX_DIF_REMOVE = (&CNT - 20);
CALL SYMPUTX ( 'MAX_DIF_REMOVE',MAX_DIF_REMOVE ) ;
RUN;
%PUT &MAX_DIF_REMOVE;

DATA ALLPVALUES2;
SET ALLPVALUES2;
DELETE_ITEM = 'N';
/*
R = RAND('NORMAL',0,1);
PROC SORT;
BY R; */
&PRINT PROC PRINT;
RUN;

%IF &REMOVE_C = Y %THEN %DO;
DATA ALLPVALUES2;
SET ALLPVALUES2;
DELETE_ITEM = 'N';
IF LEVEL = 'C' AND _N_ <= &MAX_DIF_REMOVE THEN DELETE_ITEM = 'Y';
PROC PRINT;
RUN;
%END;

PROC SORT DATA = ALLPVALUES2;
BY DESCENDING DELETE_ITEM LEVEL1;
PROC PRINT;
RUN;

proc export data=ALLPVALUES2 outfile="&OUTPATH\&NEWFORM\DIF.TXT"
dbms=dlm replace;
delimiter=",";
run;

DATA ALLPVALUES2;
SET ALLPVALUES2;
IF DELETE_ITEM = 'N';
RUN;


/* LIMIT TO 50 COMMON ITEMS IF YOU WANT TO SEND OUT TO CIPE*/
```

```
%IF &CIPE = Y %THEN %DO;
DATA ALLPVALUES2;
SET ALLPVALUES2;
IF _N_ <51;
RUN;
%END;


%IF &CNT <20 %THEN %DO;

DATA MESSAGE;
MESSAGE = "THERE ARE ONLY &CNT COMMON ITEMS ON FORM &NEWFORM.  EQUATING
CANNOT BE PERFORMED.";
PROC PRINT NOBS;
RUN;

proc export data=MESSAGE outfile="&OUTPATH\&NEWFORM\MESSAGE.TXT"
dbms=dlm replace;
delimiter=",";
run;

PROC APPEND BASE = NO_EQUATE NEW = MESSAGE;RUN;

%END;


%IF &CNT >=20 %THEN %DO;/*IF 20 OR MORE COMMON ITEMS THEN EQUATE*/


PROC SQL NOPRINT;
SELECT DISTINCT ITEMID1
INTO: COMMON1 SEPARATED BY ' '
FROM ALLPVALUES2
ORDER BY ITEMID1;
RUN; QUIT; %PUT &COMMON1;

PROC SQL NOPRINT;
SELECT DISTINCT ITEMID1
INTO: COMMON2 SEPARATED BY ' '
FROM ALLPVALUES2
ORDER BY ITEMID1;
RUN; QUIT; %PUT &COMMON2;

FILENAME ODSOUT "&ODSOUT";

OPTIONS ORIENTATION = LANDSCAPE;

/*DO SOME WORK ON THE BASE FORM*/
DATA BASE;
SET BASE;
COMMON = SUM(OF &COMMON1);/*COMMON ITEMS AFTER REMOVAL OF DIF ITEMS*/
RAW_BASE = SUM(OF &BASE_ITEMS);
RUN;

PROC CORR OUTP = BASE_CORR DATA = BASE COV NOPRINT;
VAR RAW_BASE COMMON;
RUN;
```

```
DATA _NULL_;
SET BASE_CORR;
IF UPCASE(_TYPE_) = 'MEAN' THEN CALL SYMPUTX ('B_MN_R',RAW_BASE );
IF UPCASE(_TYPE_) = 'MEAN' THEN CALL SYMPUTX ('B_MN_C',COMMON );
IF UPCASE(_TYPE_) = 'STD' THEN CALL SYMPUTX ('B_STD_R',RAW_BASE );
IF UPCASE(_TYPE_) = 'STD' THEN CALL SYMPUTX ('B_STD_C',COMMON );
IF UPCASE(_TYPE_) = 'N' THEN CALL SYMPUTX ('B_N_R',RAW_BASE );
IF UPCASE(_TYPE_) = 'N' THEN CALL SYMPUTX ('B_N_C',COMMON );
IF UPCASE(_TYPE_) = 'COV' AND UPCASE(_NAME_) = 'COMMON' THEN CALL
SYMPUTX ('B_COV',RAW_BASE );
IF UPCASE(_TYPE_) = 'CORR' AND UPCASE(_NAME_)= 'COMMON' THEN CALL
SYMPUTX ('B_COR',RAW_BASE );
RUN;
%PUT &B_MN_R &B_MN_C &B_STD_R &B_STD_C &B_N_R &B_N_C &B_COR &B_COV;
/*NOW THE NEW FORM*/
DATA NEWFORM;
SET NEWFORM;
COMMON = SUM(OF &COMMON2);
RAW_NEW = SUM(OF &NEW_ITEMS);
&PRINT PROC PRINT;
RUN;
PROC CORR OUTP = NEW_CORR DATA = NEWFORM NOPRINT COV;
VAR RAW_NEW COMMON;
RUN;

DATA _NULL_;
SET NEW_CORR;
IF UPCASE(_TYPE_) = 'MEAN' THEN CALL SYMPUTX ('N_MN_R',RAW_NEW );
IF UPCASE(_TYPE_) = 'MEAN' THEN CALL SYMPUTX ('N_MN_C',COMMON );
IF UPCASE(_TYPE_) = 'STD' THEN CALL SYMPUTX ('N_STD_R',RAW_NEW );
IF UPCASE(_TYPE_) = 'STD' THEN CALL SYMPUTX ('N_STD_C',COMMON );
IF UPCASE(_TYPE_) = 'N' THEN CALL SYMPUTX ('N_N_R',RAW_NEW );
IF UPCASE(_TYPE_) = 'N' THEN CALL SYMPUTX ('N_N_C',COMMON );
IF UPCASE(_TYPE_) = 'COV' AND UPCASE(_NAME_) = 'COMMON' THEN CALL
SYMPUTX ('N_COV',RAW_NEW );
IF UPCASE(_TYPE_) = 'CORR' AND UPCASE(_NAME_)= 'COMMON' THEN CALL
SYMPUTX ('N_COR',RAW_NEW );
RUN;
%PUT &N_COR &N_N_C &N_N_R &N_STD_R &N_STD_C &N_MN_R &N_MN_C &N_COV;RUN;

/*THESE VALUES COME FROM THE EXAMPLE IN KOLEN AND BRENNAN 2004, AND
WERE USED TO VALIDATE THE ACCURACY OF THIS CODE WITH THE COMMON ITEM
PROGRAM FOR EQUATING (CIPE).
/*X*//*
%LET N_MN_R =15.8205;
%LET N_MN_C =5.1063;
%LET N_STD_R =6.5278;
%LET N_STD_C =2.3760;
%LET N_COV = 13.4088;
%LET N_COR = .8645;

/*Y*//*
%LET B_MN_R =18.6728;
%LET B_MN_C =5.862;
%LET B_STD_R =6.8784;
%LET B_STD_C =2.4515;
```

```
%LET B_COV = 14.7603;
%LET B_COR =.8753 ;
*/
OPTIONS MLOGIC SYMBOLGEN;

DATA EQUATE;
TUCKER_SLOPE = &B_COV/(&B_STD_C**2);
LEVINE_SLOPE = (&B_STD_R**2)/&B_COV;
TRUE_SCORE_SLOPE1 = (&B_STD_R**2)/&B_COV;
TRUE_SCORE_SLOPE2 = (&N_STD_R**2)/&N_COV;
W1 = 1;
W2 = 1-W1;
Y1 =&N_COV/(&N_STD_C**2) ;
Y2 =&B_COV/(&B_STD_C**2) ;
MS =&N_MN_R-W2*Y1*(&N_MN_C - &B_MN_C);

SS = SQRT((&N_STD_R**2-W2*Y1**2*(&N_STD_C**2-
&B_STD_C**2))+(W1*W2*Y1**2*(&N_MN_C-&B_MN_C)**2));
MSY =&B_MN_R+TUCKER_SLOPE*(&N_MN_C-&B_MN_C);

SSY = SQRT(&B_STD_R**2+TUCKER_SLOPE**2*(&N_STD_C**2-&B_STD_C**2)  );

/*DEFINE THE LINEAR TUCKER EQUIVALENTS*/
T_EQUIV = (SSY/SS)*(0-&N_MN_R)+MSY;
TE1=0*(SSY/SS);
TUCK_INT=T_EQUIV-TE1;
TUCK_SLOPE= SSY/SS;
T_EQ = TUCK_INT+(TUCK_SLOPE*0);

/*DEFINE THE MEAN TUCKER EQUIVALENTS*/
M_T_EQUIV = (1)*(0-&N_MN_R)+MSY;
M_TE1=0*(1);
M_TUCK_INT=T_EQUIV-TE1;
M_TUCK_SLOPE= 1;
M_T_EQ = TUCK_INT+(TUCK_SLOPE*0);


/*DEFINE THE LEVINE LINEAR EQUIVALENTS*/
LMSY=&B_MN_R+LEVINE_SLOPE*(&N_MN_C-&B_MN_C);
LSSY =SQRT(&B_STD_R**2+LEVINE_SLOPE**2*(&N_STD_C**2-&B_STD_C**2));
L_EQUIV =(LSSY/SS)*(0-&N_MN_R)+LMSY;
LE1=0*(LSSY/SS);
LEVINE_INT=L_EQUIV-LE1;
LIVE_SLOPE= LSSY/SS;
L_EQ = LEVINE_INT+(LIVE_SLOPE*0);



/*DEFINE THE LEVINE MEAN EQUIVALENTS*/
M_L_EQUIV =(1)*(0-&N_MN_R)+LMSY;
M_LE1=0*(1);
M_LEVINE_INT=L_EQUIV-LE1;
M_LIVE_SLOPE= 1;
M_L_EQ = LEVINE_INT+(LIVE_SLOPE*0);


/*DEFINE THE LEVINE TRUE SCORE EQUIVALENT*/
```

```
LTS_EQUIV=(TRUE_SCORE_SLOPE1/TRUE_SCORE_SLOPE2)*(0-
&N_MN_R)+&B_MN_R+TRUE_SCORE_SLOPE1*(&N_MN_C-&B_MN_C);
TSCORE_SLOPE=TRUE_SCORE_SLOPE1/TRUE_SCORE_SLOPE2;
LTS2= TSCORE_SLOPE*0;
TSCORE_INT =LTS_EQUIV - LTS2 ;

CALL SYMPUTX ('TUCK_SLOPE',TUCK_SLOPE);
CALL SYMPUTX ('TUCK_INT',TUCK_INT);


CALL SYMPUTX ('M_TUCK_SLOPE',M_TUCK_SLOPE);
CALL SYMPUTX ('M_TUCK_INT',M_TUCK_INT);

CALL SYMPUTX ('LIVE_SLOPE',LIVE_SLOPE);
CALL SYMPUTX ('LIVE_INT',LEVINE_INT);


CALL SYMPUTX ('M_LIVE_SLOPE',M_LIVE_SLOPE);
CALL SYMPUTX ('M_LIVE_INT',M_LEVINE_INT);

CALL SYMPUTX ('TSCORE_SLOPE',TSCORE_SLOPE);
CALL SYMPUTX ('TSCORE_INT',TSCORE_INT);
RUN;
&PRINT PROC PRINT DATA = EQUATE;
&PRINT TITLE1 "EQUATING RESULTS";
&PRINT TITLE2 "TUCKER_EQUATED = &TUCK_INT + &TUCK_SLOPE * X ";
&PRINT TITLE3 "LEVINE_EQUATED = &LIVE_INT + &LIVE_SLOPE * X  ";
&PRINT TITLE4 "TRUE_SCORE_EQUATED = &TSCORE_INT + &TSCORE_SLOPE * X  ";
&PRINT TITLE5 "TUCKER_MEAN_EQUATED = &M_TUCK_INT + &M_TUCK_SLOPE * X ";
&PRINT TITLE6 "LEVINE_MEAN_EQUATED = &M_LIVE_INT + &M_LIVE_SLOPE * X
";
RUN;


proc export data=EQUATE
outfile="&OUTPATH\&NEWFORM\EQUATING_STATISTICS.TXT" dbms=dlm replace;
delimiter=",";
run;

DATA RAW_SCORES;
NAME = "SCORES";
X0 = 0;
ARRAY X[80] X1 - X80;
X_RAW=0;
DO I =1 TO 80;
X_RAW =X_RAW + 1;
X[I] =X_RAW;

END;
DROP X_RAW I;
&PRINT PROC PRINT;RUN;

PROC TRANSPOSE DATA = RAW_SCORES OUT = CONV_TABLE PREFIX = X;
VAR X0 - X80;
RUN;
```

```
/*CREATE THE LINEAR FORMULAS FOR THE CONVERSION TABLE*/
DATA CONV_TABLE;
SET CONV_TABLE;
TUCK_SCALE_INT=(&_B_+&_A_*(&TUCK_INT));
TUCK_SCALE_SLOPE=((&_A_*&TUCK_SLOPE));

M_TUCK_SCALE_INT=(&_B_+&_A_*(&M_TUCK_INT));
M_TUCK_SCALE_SLOPE=((&_A_*&M_TUCK_SLOPE));

LIVE_SCALE_INT=(&_B_+&_A_*(&LIVE_INT));
LIVE_SCALE_SLOPE=((&_A_*&LIVE_SLOPE));

M_LIVE_SCALE_INT=(&_B_+&_A_*(&M_LIVE_INT));
M_LIVE_SCALE_SLOPE=((&_A_*&M_LIVE_SLOPE));

TSCORE_SCALE_INT=(&_B_+&_A_*(&TSCORE_INT));
TSCORE_SCALE_SLOPE=((&_A_*&TSCORE_SLOPE));

TUCK_SCALE_SCORE=(X1*TUCK_SCALE_SLOPE)+TUCK_SCALE_INT;
LIVE_SCALE_SCORE=(X1*LIVE_SCALE_SLOPE)+LIVE_SCALE_INT;
TSCORE_SCALE_SCORE=(X1*TSCORE_SCALE_SLOPE)+TSCORE_SCALE_INT;
&print proc print;
&print WHERE X1 = 1;
&print VAR TUCK_SCALE_INT TUCK_SCALE_SLOPE LIVE_SCALE_INT
LIVE_SCALE_SLOPE TSCORE_SCALE_INT TSCORE_SCALE_SLOPE;
RUN;



/*CREATE THE LINEAR FORMULAS FOR THE CONVERSION TABLE*/
DATA CONV_TABLE;
SET CONV_TABLE;

RENAME X1 =&NEWFORM;/*THE EQUIVALENT IS THE ESTIMATED BASE*/
TUCK_SCALE_INT=(&_B_+&_A_*(&TUCK_INT));
TUCK_SCALE_SLOPE=((&_A_*&TUCK_SLOPE));

M_TUCK_SCALE_INT=(&_B_+&_A_*(&M_TUCK_INT));
M_TUCK_SCALE_SLOPE=((&_A_*&M_TUCK_SLOPE));

LIVE_SCALE_INT=(&_B_+&_A_*(&LIVE_INT));
LIVE_SCALE_SLOPE=((&_A_*&LIVE_SLOPE));

M_LIVE_SCALE_INT=(&_B_+&_A_*(&M_LIVE_INT));
M_LIVE_SCALE_SLOPE=((&_A_*&M_LIVE_SLOPE));

TSCORE_SCALE_INT=(&_B_+&_A_*(&TSCORE_INT));
TSCORE_SCALE_SLOPE=((&_A_*&TSCORE_SLOPE));

TUCK_SCALE_SCORE=(X1*TUCK_SCALE_SLOPE)+TUCK_SCALE_INT;
LIVE_SCALE_SCORE=(X1*LIVE_SCALE_SLOPE)+LIVE_SCALE_INT;
TSCORE_SCALE_SCORE=(X1*TSCORE_SCALE_SLOPE)+TSCORE_SCALE_INT;

M_TUCK_SCALE_SCORE=(X1*M_TUCK_SCALE_SLOPE)+M_TUCK_SCALE_INT;
M_LIVE_SCALE_SCORE=(X1*M_LIVE_SCALE_SLOPE)+M_LIVE_SCALE_INT;
```

```
RNDED_TUCKSS =ROUND(TUCK_SCALE_SCORE,1);
RNDED_LEVSS =ROUND(LIVE_SCALE_SCORE,1);
RNDED_TRUESS =ROUND(TSCORE_SCALE_SCORE,1);

M_RNDED_TUCKSS =ROUND(M_TUCK_SCALE_SCORE,1);
M_RNDED_LEVSS =ROUND(M_LIVE_SCALE_SCORE,1);
RUN;



proc export data=CONV_TABLE
outfile="&OUTPATH\&NEWFORM\CONVERSION_TABLE.TXT" dbms=dlm replace;
delimiter=",";
run;


/*CALCULATE THE PERCENT PASSING ACCORDING TO EACH EQUATING METHOD*/

%LET TUCKSS_CUT = 0;
%LET LEVSS_CUT = 0;
%LET TRUESS_CUT = 0;

DATA TUCK (KEEP=RNDED_TUCKSS TUCK_SCALE_INT TUCK_SCALE_SLOPE &NEWFORM)
LEV (KEEP=RNDED_LEVSS LIVE_SCALE_INT LIVE_SCALE_SLOPE &NEWFORM) TS
(KEEP=RNDED_TRUESS TSCORE_SCALE_INT TSCORE_SCALE_SLOPE &NEWFORM);
SET CONV_TABLE;

IF RNDED_TUCKSS = 75 THEN OUTPUT TUCK ;
IF RNDED_LEVSS  = 75 THEN OUTPUT LEV;
IF RNDED_TRUESS = 75 THEN OUTPUT TS;

IF RNDED_TUCKSS = 75 THEN CALL SYMPUTX ('TUCKSS_CUT ', &NEWFORM );
IF RNDED_LEVSS  = 75 THEN CALL SYMPUTX ('LEVSS_CUT', &NEWFORM );
IF RNDED_TRUESS = 75 THEN CALL SYMPUTX ('TRUESS_CUT ', &NEWFORM );
RUN;

/*FIGURE THE PERCENT PASSING*/
DATA PASSES;
SET NEWFORM;
TUCKSS_CUT = &TUCKSS_CUT ;
LEVSS_CUT=&LEVSS_CUT;
TRUESS_CUT=&TRUESS_CUT;

TUCKER_PASS = 0;
IF RAW_SCORE => TUCKSS_CUT THEN TUCKER_PASS = 1;

LEVINE_PASS = 0;
IF RAW_SCORE => LEVSS_CUT THEN LEVINE_PASS = 1;

TSCORE_PASS = 0;
IF RAW_SCORE => TRUESS_CUT THEN TSCORE_PASS = 1;

IDENTITY_PASS = 0;
IF RAW_SCORE => 55 THEN IDENTITY_PASS = 1;
```

```
KEEP CANDIDATEID RAWSCORE2 TSCORE_PASS LEVINE_PASS TUCKER_PASS
IDENTITY_PASS;
RUN;


proc export data=PASSES outfile="&OUTPATH\&NEWFORM\PASS_FAIL.TXT"
dbms=dlm replace;
delimiter=",";
run;

PROC FREQ DATA = PASSES ;TABLE IDENTITY_PASS/OUT= IDENTITY_PASS;RUN;
PROC FREQ DATA = PASSES ;TABLE LEVINE_PASS/OUT= LEVINE_PASS;RUN;
PROC FREQ DATA = PASSES ;TABLE TUCKER_PASS/OUT= TUCKER_PASS;RUN;
PROC FREQ DATA = PASSES ;TABLE TSCORE_PASS/OUT= TSCORE_PASS;RUN;

DATA _NULL_;SET IDENTITY_PASS;IF IDENTITY_PASS = 1 THEN CALL SYMPUTX
('IDENT_PASS ',PERCENT  );RUN; %PUT &IDENT_PASS;
DATA _NULL_;SET LEVINE_PASS;IF LEVINE_PASS = 1 THEN CALL SYMPUTX
('LEVINE_PASS ',PERCENT  );RUN; %PUT &IDENT_PASS;
DATA _NULL_;SET TUCKER_PASS;IF TUCKER_PASS = 1 THEN CALL SYMPUTX
('TUCKER_PASS ',PERCENT  );RUN; %PUT &IDENT_PASS;
DATA _NULL_;SET TSCORE_PASS;IF TSCORE_PASS = 1 THEN CALL SYMPUTX
('TSCORE_PASS ',PERCENT  );RUN; %PUT &IDENT_PASS;



DATA TUCK;
SET TUCK;
PASS = &TUCKER_pASS;
RENAME TUCK_SCALE_INT = INTERCEPT TUCK_SCALE_SLOPE = SLOPE RNDED_TUCKSS
= SCALE_SCORE;
METHOD = "TUCKER    ";
RUN;

DATA LEV;
SET LEV;
PASS = &LEVINE_PASS;
RENAME LIVE_SCALE_INT = INTERCEPT LIVE_SCALE_SLOPE = SLOPE RNDED_LEVSS
= SCALE_SCORE;
METHOD = "LEVINE     ";
RUN;

DATA TS;
SET TS;
PASS = &TSCORE_pASS;
RENAME TSCORE_SCALE_INT = INTERCEPT TSCORE_SCALE_SLOPE = SLOPE
RNDED_TRUESS = SCALE_SCORE;
METHOD = "TRUE_SCORE     ";
RUN;


DATA _NULL_;
SET ALLPVALUES2;
CALL SYMPUTX ('COMMON_REMAINING', _N_ );
RUN;

DATA SUMMARY;
```

```
RETAIN METHOD NEWFORM &NEWFORM INTERCEPT SLOPE SCALE_SCORE PASS
IDENTITY_PASS ;

SET TUCK LEV TS;

MEAN_BASE_COMMON = &M_BASE_P_COMMON ;
MEAN_NEW_COMMON = &M_NEW_P_COMMON   ;

MEAN_BASE_UNIQUE = &M_BASE_P_UNIQUE ;
MEAN_NEW_UNIQUE = &M_NEW_P_UNIQUE   ;

IDENTITY_PASS = &IDENT_pASS;
N_OBS = &N_OBS;
FORM = "&NEWFORM";
BASE = "XEAA";
MONTH = "&MONTH";
RENAME &NEWFORM = NEWFORM;
REMOVE_C = "&REMOVE_C";
A_DIF = &A_DIF;
B_DIF = &B_DIF;
C_DIF = &C_DIF;
MAX_TO_REMOVE = &MAX_DIF_REMOVE;
COMMON_REMAINING = &COMMON_REMAINING;
RUN;
proc export data=SUMMARY outfile="&OUTPATH\&NEWFORM\SUMMARY.TXT"
dbms=dlm replace;
delimiter=",";
run;

DATA RAW_SCORES;
SET NEWFORM;
RENAME RAW_SCORE2 = &NEWFORM;
KEEP CANDIDATE_ID RAW_SCORE2;
PROC SORT;
BY &NEWFORM;
RUN;
DATA SCORE_EQUIVALENTS;
MERGE RAW_SCORES (IN = U ) CONV_TABLE;
BY &NEWFORM; IF U;
IDENTITY = 20 + &NEWFORM;
KEEP CANDIDATE_ID &NEWFORM IDENTITY RNDED_TUCKSS RNDED_LEVSS
RNDED_TRUESS M_RNDED_TUCKSS M_RNDED_LEVSS;
RUN;

proc export data=SCORE_EQUIVALENTS outfile="&OUTPATH\&NEWFORM\SCORE
FILE.TXT" dbms=dlm replace;
delimiter=",";
run;


PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE RNDED_TUCKSS/ OUT=TUCKS ;
RUN;

proc export data=TUCKS outfile="&OUTPATH\&NEWFORM\TUCKER SCORE
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
```

```
run;


PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE RNDED_LEVSS/ OUT=LEVS ;
RUN;

proc export data=LEVS outfile="&OUTPATH\&NEWFORM\LEVINE SCORE
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
run;


PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE RNDED_TRUESS/ OUT=TSCORE ;
RUN;

proc export data=TSCORE outfile="&OUTPATH\&NEWFORM\TRUE SCORE
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
run;


PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE M_RNDED_TUCKSS/ OUT=M_TUCKS ;
RUN;

proc export data=M_TUCKS outfile="&OUTPATH\&NEWFORM\MEAN TUCKER
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
run;


PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE M_RNDED_LEVSS/ OUT=M_LEVSS ;
RUN;

proc export data=M_LEVSS outfile="&OUTPATH\&NEWFORM\MEAN LEVINE
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
run;

PROC FREQ DATA = SCORE_EQUIVALENTS;
TABLE IDENTITY/ OUT=IDENT ;
RUN;

proc export data=IDENT outfile="&OUTPATH\&NEWFORM\IDENTITY
DISTRIBUTION.TXT" dbms=dlm replace;
delimiter=",";
run;






PROC APPEND BASE = EQUATED2 DATA = SUMMARY   FORCE; RUN;
```

```
%END;

PROC SORT DATA =EQUATED2;
BY METHOD FORM;RUN;

PROC PRINT DATA= EQUATED2;
TITLE "EQUATED FORMS ";
RUN;

PROC PRINT DATA =NO_EQUATE;
TITLE "FORMS NOT EQUATED";
RUN;

PROC DATASETS;
SAVE t_b LIST EQUATED2 NO_EQUATE; QUIT; RUN;


%MEND;
```

```
%MACRO SCORE (PRINT=*, OUTPATH =C:\DISSERTATION\SIMULATION , CONDITION
=COND1 ,CAL_METHOD = STOCK_LORD );
/*GET THE OBSERVED RAW SCORES AND THE GENERATING TRUE SCORES*/
DATA CRITERION;
INFILE "&OUTPATH\&CONDITION\CRITERION_SCORES.TXT " DSD ;
INPUT FORM $ REPLICATION $ CANDID_ID $ THETA1 THETA2 COMPOSITE SUB1
SUB2 TRUE_SCORE PERCENT_TRUE_SCORE OBSERVED_SCORE ;
&PRINT PROC PRINT;
RUN;
PROC SORT DATA = CRITERION;
BY REPLICATION FORM OBSERVED_SCORE;
&PRINT PROC PRINT;
RUN;
/**/
DATA TS_CONV;
INFILE "&OUTPATH\&CONDITION\&CAL_METHOD._CONV_TABLE.TXT " ;
INPUT FORM $ REPLICATION $ TRUESCORE_2 PTS THETA PTS_BASE;
OBSERVED_SCORE = TRUESCORE_2;
METHOD = "&CAL_METHOD    ";
PROC SORT;
BY REPLICATION FORM TRUESCORE_2;
&PRINT PROC PRINT;
RUN;

DATA SCORE_FILE;
MERGE CRITERION (IN =H) TS_CONV;
BY REPLICATION FORM OBSERVED_SCORE;
IF H;
&PRINT PROC PRINT;RUN;

PROC APPEND BASE = &CONDITION._RESULTS DATA = SCORE_FILE;RUN;

%MEND;
```

```
%MACRO EQUIP (PRINT=*,OUTPATH = C:DISSERTATION\SIMULATION, CONDITION =
COND1, FORM = B , ADMIN = 2, OUTPATH =C:\DISSERTATION\SIMULATION);

DATA POPX;
INFILE "&OUTPATH\&CONDITION\POPULATION X.TXT" DSD;
INPUT CANDID $ X1 X2;
RUN;

DATA POPY;
INFILE "&OUTPATH\&CONDITION\POPULATION Y.TXT" DSD;
INPUT CANDID $ Y1 Y2;
RUN;

DATA DAT;
SET POPX POPY;
RUN;

DATA DAT;
SET DAT;
X1 = ROUND(X1,.1);
X2 = ROUND(X2,.1);
Y1 = ROUND(Y1,.1);
Y2 = ROUND(Y2,.1);
&PRINT PROC PRINT;
&PRINT VAR X1 X2 Y1 Y2;RUN;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE X1 / OUT =OUT1;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE X2 / OUT =OUT2;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE Y1 / OUT =OUT3;
RUN;

PROC FREQ DATA = DAT NOPRINT;
TABLE Y2 / OUT =OUT4;
RUN;

DATA OUT1;
SET OUT1;
RENAME X1 = VALUE;
THETA = 1;
RUN;
DATA OUT2;
SET OUT2;
RENAME X2 = VALUE;
THETA = 2;
RUN;

DATA OUT3;
SET OUT3;
RENAME Y1 = VALUE;
```

```
THETA = 3;
RUN;

DATA OUT4;
SET OUT4;
RENAME Y2 = VALUE;
THETA = 4;
RUN;

DATA ALLTHETAS;
SET OUT1 OUT2 OUT3 OUT4;
IF PERCENT = . THEN DELETE;
&PRINT PROC PRINT;RUN;




DATA FORMA;
INFILE "C:\DISSERTATION\SIMULATION\&CONDITION\FREQ_A.TXT" DSD ;
INPUT SCORE COUNT PERCENT NITEMS ;
FORM ="FORM_A";
&PRINT PROC PRINT;
RUN;

DATA FORM&FORM;
INFILE "C:\DISSERTATION\SIMULATION\&CONDITION\FREQ_&FORM..TXT" DSD ;
INPUT SCORE COUNT PERCENT NITEMS ;
FORM ="FORM_&FORM";
&PRINT PROC PRINT;
RUN;

DATA BOTH_TS;
SET FORMA FORM&FORM;
&PRINT PROC PRINT;
RUN;
&PRINT PROC PRINT DATA = BOTH;RUN;
DATA TEMP122;
SET BOTH_TS;
PROC SORT DATA = TEMP122;
BY DESCENDING COUNT;
RUN;

DATA _NULL_;
SET TEMP122;
COUNT = COUNT + 200;
IF _N_ = 1 THEN CALL SYMPUTX ('MAX_CNT',COUNT );
RUN;

%MEND;




%MACRO MAKE_TCC (PRINT=*, N_REPS=50,CAL_METHOD = FPC, OUTPATH
=C:\DISSERTATION\SIMULATION,REPLICATION = REP1, CONDITION = COND,
FORM2=B, FORM1=A );
```

```
%DO R = 1 %TO &N_REPS;

proc import
datafile="&OUTPATH\&CONDITION\REP&R\CONV_TABLES\FPC_CONV_TABLE_&FORM2..
TXT" out=FPC&FORM2 dbms=csv replace;
   getnames=YES;
run;

proc import
datafile="&OUTPATH\&CONDITION\REP&R\CONV_TABLES\STOCK_LORD_CONV_TABLE_&
FORM2..TXT" out=SL&FORM2 dbms=csv replace;
   getnames=YES;
run;

DATA FPC&FORM2;
SET FPC&FORM2;
METHOD = "FPC_";
RUN;
DATA SL&FORM2;
SET SL&FORM2;
METHOD = "SCSL";
RUN;



DATA &FORM2;
SET FPC&FORM2 SL&FORM2;
RUN;


DATA &FORM1;
SET &FORM2;
 RAWSCORE=TRUESCORE_1;
FORM = "&FORM1";
REP ="&REPLICATION";
KEEP RAWSCORE THETA FORM REP METHOD;
RUN;

DATA &FORM2;
SET &FORM2;
RAWSCORE= TRUESCORE_2 ;
FORM = "&FORM2";
REP ="&REPLICATION";
KEEP RAWSCORE THETA FORM REP METHOD;
RUN;

DATA BOTH&FORM2._&R;
SET &FORM1 &FORM2 ;
IF THETA > 4 THEN THETA = 4;
IF THETA <-4 THEN THETA = -4;
&PRINT PROC PRINT;RUN;

%IF &N_REPS = 1 %THEN %DO;
DATA NEW&FORM2;
SET BOTH&FORM2._&R;
RUN;
```

```
%END;
%ELSE %DO;
DATA NEW&FORM2;
SET NEW&FORM2 BOTH&FORM2._&R;
RUN;
%END;

%END;
&PRINT PROC PRINT DATA = NEWB;RUN;
DATA NEW&FORM2;
SET NEW&FORM2;
METHOD2 = COMPRESS(METHOD||"_"||FORM);
THETA = ROUND(THETA,.1);
RAWSCORE = ROUND(RAWSCORE,1);
RUN;


PROC MEANS DATA = NEW&FORM2 NOPRINT;
CLASS METHOD2 FORM RAWSCORE ;
VAR THETA;
OUTPUT OUT = ALLMEANS&FORM2
MEAN = ;
RUN;

DATA SCSLALLMEANS&FORM2 FPCALLMEANS&FORM2;
SET ALLMEANS&FORM2;
IF FORM NE " ";
IF METHOD2 NE " ";
METHOD_ = COMPRESS("FORM_"||SUBSTRN(METHOD2,6,1));
IF METHOD2 EQ "SCSL_A" THEN OUTPUT SCSLALLMEANS&FORM2;
IF METHOD2 EQ "SCSL_B" THEN OUTPUT SCSLALLMEANS&FORM2;
IF METHOD2 EQ "FPC__A" THEN OUTPUT FPCALLMEANS&FORM2;
IF METHOD2 EQ "FPC__B" THEN OUTPUT FPCALLMEANS&FORM2;

IF METHOD2 EQ "SCSL_C" THEN OUTPUT SCSLALLMEANS&FORM2;
IF METHOD2 EQ "SCSL_D" THEN OUTPUT SCSLALLMEANS&FORM2;
IF METHOD2 EQ "FPC__C" THEN OUTPUT FPCALLMEANS&FORM2;
IF METHOD2 EQ "FPC__D" THEN OUTPUT FPCALLMEANS&FORM2;

IF METHOD2 EQ "SCSL_E" THEN OUTPUT SCSLALLMEANS&FORM2;
IF METHOD2 EQ "FPC__E" THEN OUTPUT FPCALLMEANS&FORM2;


IF _TYPE_ EQ 7;
&PRINT PROC PRINT;
RUN;

%MEND;
```

```
%MACRO ITEM_RECOVERY (PRINT=*,OUTPATH = C:DISSERTATION\SIMULATION,
CONDITION = COND, FORM = B , ADMIN = 1);
DATA ITEM_ESTS;
INFILE "&OUTPATH\&CONDITION\FINAL_ITEMS.TXT" DSD ;
INPUT N CONDITION $ REPLICATION $ CAL_METHOD $ ADMINISTRATION  ITEMID $
SEQUENCE  A B C MEASURE_ A_E B_E C_E UNLINKED_ABS_DIF LINKED_ABS_DIF ;
&PRINT PROC PRINT;
RUN;
                  DATA  all_crit_est;
                  SET  ITEM_ESTS;
                  BIAS_A = (A_E- A);
                  BIAS_B = (B_E- B);
                  BIAS_C = (C_E- C);

                  SQ_ERROR_A = (A_E- A)**2;
                  SQ_ERROR_B = (B_E- B)**2;
                  SQ_ERROR_C = (C_E- C)**2;

                  ITEM_ORDER = COMPRESS(ITEMID,'ITEM') ;
                  &PRINT PROC PRINT;
                  RUN;

                  proc means data = all_crit_est mean var noprint;
                  CLASS CAL_METHOD itemID ADMINISTRATION;
                  var A MEASURE_ C BIAS_A BIAS_B  BIAS_C SQ_ERROR_A
SQ_ERROR_B SQ_ERROR_C ;
                  output out = sqbias
                  mean =
                  STD = STA STDMEASURE_ STB  STDBB STDBA STDBC STDEA
STDEB STDEC;
                  run;


data sqbias2;
set sqbias;
if _type_ = 7;
RMSE_A = SQRT(SQ_ERROR_A);
RMSE_B = SQRT(SQ_ERROR_B);
RMSE_C = SQRT(SQ_ERROR_C);
ST_ERROR_A = SQRT(RMSE_A**2 - BIAS_A**2 );
ST_ERROR_B = SQRT(RMSE_B**2 - BIAS_B**2 );
ST_ERROR_C = SQRT(RMSE_C**2 - BIAS_C**2 );
KEEP CAL_METHOD ITEMID _FREQ_ MEASURE_  BIAS_A BIAS_B BIAS_C STA
STDMEASURE_ STC
RMSE_A RMSE_B RMSE_C ST_ERROR_A ST_ERROR_B ST_ERROR_C ADMINISTRATION
_type_;
proc sort;
by ADMINISTRATION ;
&PRINT PROC PRINT;
run;


DATA ITEM_ERROR;
SET sqbias2;
IF ADMINISTRATION = &ADMIN;
RUN;
```

```
PROC SORT DATA = ITEM_ERROR;
BY CAL_METHOD;RUN;
DATA ITEM_ERROR;
SET ITEM_ERROR;
BY CAL_METHOD;
ITEM +1;
IF FIRST.CAL_METHOD THEN DO;
ITEM =1;
END;
IF CAL_METHOD = "STOCK_LO" THEN METHOD = "SCSL";
IF CAL_METHOD = "FPC" THEN METHOD = "FPC_";
RUN;



%MEND;
```

```
%MACRO COLLECT_COMMON (
PRINT =,
CAL_METHOD = STOCK_LORD,

OLD_ADMIN = 1,/*USED FOR SELECTION*/
OLD_FORM = A,/*LABELING ONLY*/

NEW_ADMIN = 2,/*USED FOR SELECTION*/
NEW_FORM = B,/*LABELING ONLY*/

OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION = CONDITION_7,
END = 50
);

%DO I = 1 %TO &END;
DATA ITEM_ESTS1_&I;
INFILE
"&OUTPATH\&CONDITION\REP&I\ADMIN&OLD_ADMIN\&CAL_METHOD\FINAL_ITEMS.TXT"
DSD ;
INPUT ITEMID $ ORDER A B C EST_B LINKED_A LINKED_B LINKED_C ERROR1
ERROR2;
ADMINISTRATION = "ADMIN1";
FORM = "&OLD_FORM";
RUN;

DATA ITEM_ESTS2_&I;
INFILE
"&OUTPATH\&CONDITION\REP&I\ADMIN&NEW_ADMIN\&CAL_METHOD\FINAL_ITEMS.TXT"
DSD ;
INPUT ITEMID $ ORDER A B C EST_B LINKED_A LINKED_B LINKED_C ERROR1
ERROR2;
ADMINISTRATION = "ADMIN&NEW_ADMIN";
FORM = "&NEW_FORM";
RUN;


%IF I = 1 %THEN %DO;
DATA ALL_COMMON;
SET ITEM_ESTS1_&I ITEM_ESTS2_&I;
RUN;
%END;

%IF I >1 %THEN %DO;
DATA ALL_COMMON;
SET ALL_COMMON ITEM_ESTS1_&I ITEM_ESTS2_&I;
RUN;
%END;
%END;

DATA ALL_COMMON;
SET ALL_COMMON;
COMMON = "COMMON &OLD_FORM &NEW_FORM";
RUN;

PROC MEANS DATA = ALL_COMMON NOPRINT;
CLASS FORM ITEMID;
```

```
VAR A B LINKED_A lINKED_B EST_B;
OUTPUT OUT = ALL_COMM_MEANS
MEAN =;
RUN;
DATA ALL_COMM_MEANS;
SET ALL_COMM_MEANS;
IF _TYPE_ = 3;
RUN;

DATA &OLD_FORM &NEW_FORM;
SET ALL_COMM_MEANS;
IF FORM = "&OLD_FORM " THEN OUTPUT &OLD_FORM;
IF FORM = "&NEW_FORM " THEN OUTPUT &NEW_FORM;
KEEP ITEMID FORM LINKED_B LINKED_A;
RUN;


PROC SORT DATA = &OLD_FORM;
BY ITEMID;
PROC SORT DATA = &NEW_FORM;
BY ITEMID;
RUN;
DATA &OLD_FORM;
SET &OLD_FORM;
RENAME LINKED_B = BASE_B LINKED_A = BASE_A FORM = BASE_FORM;
RUN;

DATA COMMON_SIDE_BY_SIDE;
MERGE &OLD_FORM (IN=J) &NEW_FORM (IN=H);
BY ITEMID;
IF H; IF J;
RUN;

%MEND;
```

```
%MACRO GET_EIGEN_VAL(UNI= CONDITION_17, NEW= CONDITION_102, CORR=.90 );


proc import datafile="&OUTPATH\&NEW\REP1\ADMIN1\LINEAR\exam.dat"
out=BASE dbms=csv replace;
   getnames=YES;
run;

data base;
set base;
drop form candid_id_x;run;

data base2;
set base;
sub1 = sum(of x1 - x30);
sub2 = sum(of x31 - x60);
run;
proc corr data = base2;
var sub1 sub2;
run;

PROC FACTOR DATA=base METHOD=P priors=m SCREE CORR RES outstat = EIGEN
noprint;
RUN;
data eigen;
set eigen;
if _TYPE_ = "EIGENVAL";
RUN;


PROC TRANSPOSE DATA= EIGEN OUT=T_EIGEN;
ID _TYPE_;
VAR X1 -X60;
RUN;
data NEW;
set t_eigen;
n = _n_;
CONDITION = "&CORR";
run;



proc import datafile="&OUTPATH\&UNI\REP1\ADMIN1\LINEAR\exam.dat"
out=UNI dbms=csv replace;
   getnames=YES;
run;

data UNI;
set UNI;
drop form candid_id_x;run;

data UNI2;
set UNI;
sub1 = sum(of x1 - x30);
sub2 = sum(of x31 - x60);
run;
proc corr data = base2;
```

```
var sub1 sub2;
run;

PROC FACTOR DATA=UNI METHOD=P priors=m SCREE CORR RES outstat = EIGEN1
noprint;
RUN;
data UNI;
set EIGEN1;
if _TYPE_ = "EIGENVAL";
RUN;

PROC TRANSPOSE DATA= UNI OUT=T_EIGEN1;
ID _TYPE_;
VAR X1 -X60;
RUN;
data t_eigen1;
set t_eigen1;
n = _n_;
CONDITION = ".90";
run;

DATA T_EIGEN_BOTH;
SET NEW T_EIGEN1;
RUN;



%MEND;
```

```
%MACRO THETA_RECOVERY (PRINT=*, OUTPATH = C:DISSERTATION\SIMULATION,
CONDITION = COND1, FORM = B , ADMIN = 1);
DATA ESTS;
INFILE "&OUTPATH\&CONDITION\FINAL_THETAS.TXT" DSD ;
INPUT ADMINISTRATION CONDITION $ REPLICATION $ CAL_METHOD $ TRUE_THETA
UNLINKED ESTIMATE UNLINKED_ABS_DIF LINKED_ABS_DIF ;
RUN;

DATA ESTS2;
SET ESTS;
TRUE_THETA2 = ROUND(TRUE_THETA,.50);
ESTIMATE2 = ROUND(ESTIMATE,.50);
UNLINKED2 = ROUND(UNLINKED,.50);
PROC SORT;
BY CAL_METHOD;
RUN;
PROC FREQ DATA = ESTS2 NOPRINT;
TABLE THETA2/OUT= FREQS1;
BY CAL_METHOD;
RUN;

PROC FREQ DATA = ESTS2 NOPRINT;
TABLE ESTIMATE2/OUT= FREQS2;
BY CAL_METHOD;
RUN;

PROC FREQ DATA = ESTS2 NOPRINT;
TABLE UNLINKED2/OUT= FREQS3;
BY CAL_METHOD;
RUN;

DATA FREQS1;
SET FREQS1;
METHOD = COMPRESS(CAL_METHOD||"_GENERATED");
RENAME THETA2 = THETA;
RUN;

DATA FREQS2;
SET FREQS2;
METHOD = COMPRESS(CAL_METHOD||"_LINKED   ");
RENAME ESTIMATE2 = THETA;
RUN;

DATA FREQS3;
SET FREQS3;
METHOD = COMPRESS(CAL_METHOD||"_UNLINKED ");
RENAME UNLINKED2 = THETA;
RUN;

DATA FREQS;
SET FREQS1 FREQS2 ;
RUN;



                  DATA  ESTS;
                  SET  ESTS;
                  IF ADMINISTRATION = &ADMIN;
                  THETA2 = ROUND(ESTIMATE,.5);
                  BIAS = (ESTIMATE-TRUE_THETA);
                  SQ_ERROR = (ESTIMATE-TRUE_THETA)**2;
                  &PRINT PROC PRINT;
                  RUN;

                  proc print data = ests;run;
                  proc means data = ESTS mean var noprint;
                  CLASS CAL_METHOD THETA2;
                  var ESTIMATE BIAS SQ_ERROR ;
                  output out = sqbias
                  mean =
                  STD = STESTIMATE ;
                  run;



data THETA_RECOVERY;
set sqbias;
if _type_ = 3;
RMSE = SQRT(SQ_ERROR);
ST_ERROR= SQRT(RMSE**2 - BIAS**2 );
IF  CAL_METHOD NE "SEPARATE";
IF INDEX(CAL_METHOD,'STOCK')>0 THEN CAL_METHOD = "SCSL";
KEEP THETA2 CAL_METHOD  _FREQ_ MEASURE_ BIAS RMSE ST_ERROR _type_;
/*proc sort;
by ADMINISTRATION;*/
&PRINT PROC PRINT;
run;
%MEND;
```

```
/*Used to collect equating results*/
%MACRO EQUATING (PRINT =*,CONDITION = COND1, OUTPATH =
C:\DISSERTATION\SIMULATION );
DATA CRITERION;
INFILE "&OUTPATH\&CONDITION\CRITERION_SCORES.TXT " DSD ;
INPUT FORM $ REPLICATION $ CANDID_ID $ THETA1 THETA2 COMPOSITE SUB1
SUB2 TRUE_SCORE PERCENT_TRUE_SCORE OBSERVED_SCORE ;
&PRINT PROC PRINT;
RUN;
PROC SORT DATA = CRITERION;
BY REPLICATION FORM OBSERVED_SCORE;
&PRINT PROC PRINT;
RUN;

%LET STD_B = 0;
%LET STD_C = 0;
%LET STD_D = 0;
%LET STD_E = 0;
            proc means data = CRITERION mean var STD;
                  CLASS FORM ;
                  var OBSERVED_SCORE  ;
                  output out = DESCRIPTIVES
                  mean =
                  STD = STD;
                  run;
                  &PRINT PROC PRINT DATA = DESCRIPTIVES;RUN;
                  DATA _NULL_;
                  SET DESCRIPTIVES;
                  IF FORM = 'A' THEN CALL SYMPUTX ('STD_A', STD);
                  IF FORM = 'B' THEN CALL SYMPUTX ('STD_B', STD);
                  IF FORM = 'C' THEN CALL SYMPUTX ('STD_C', STD);
                  IF FORM = 'D' THEN CALL SYMPUTX ('STD_D', STD);
                  IF FORM = 'E' THEN CALL SYMPUTX ('STD_E', STD);
                  RUN;%PUT &STD_A;


DATA CONV_TABLES;
INFILE "&OUTPATH\&CONDITION\DIFFERENCE.TXT " DSD;
INPUT METHOD2 $ FORM $ REPLICATION $ OBSERVED CRITERION ESTIMATE;
IF INDEX(METHOD, "GENERATE") = 0;
&PRINT PROC PRINT;
RUN;

DATA CRIT_DIFFERENCE;
SET CONV_TABLES;
DIFFERENCE = OBSERVED - CRITERION;
METHOD11 = 'CRITERION';
KEEP OBSERVED DIFFERENCE METHOD11 form;
RUN;

DATA DIFFERENCES;
SET CONV_TABLES;
DIFFERENCE =  OBSERVED - ESTIMATE ;
IF METHOD2 = "IDENTITY" THEN DELETE;
METHOD11 = METHOD2;
KEEP OBSERVED DIFFERENCE METHOD11 form;
RUN;
```

```
DATA DIFFERENCES;
SET DIFFERENCES CRIT_DIFFERENCE;
IF INDEX(METHOD11,'STOCK')>0 THEN METHOD1 =           "4. SCSL      ";
IF INDEX(METHOD11,'LINEAR')>0 THEN METHOD1 =          "2. LLTS       ";
IF INDEX(METHOD11,'FPC')>0 THEN METHOD1 =             "3. FPC       ";
IF INDEX(METHOD11,'CRITERIO')>0 THEN METHOD1 =        "1. CRITERION ";
RUN;


PROC MEANS DATA = DIFFERENCES NOPRINT;
CLASS FORM METHOD1  OBSERVED;
VAR DIFFERENCE;
OUTPUT OUT = DIFF
MEAN=;
RUN;
DATA DIFF;
SET DIFF;
IF _TYPE_ = 7;
RUN;

DATA DB DC DD DE;
SET DIFF;
IF FORM = "B" THEN OUTPUT  DB;
IF FORM = "C" THEN OUTPUT  DC;
IF FORM = "D" THEN OUTPUT  DD;
IF FORM = "E" THEN OUTPUT  DE;
RUN;
&PRINT PROC PRINT DATA = DB;RUN;


PROC SORT DATA = DB;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = DB OUT = T_DB;
ID METHOD1;
VAR DIFFERENCE;
BY FORM OBSERVED;
RUN;

PROC SORT DATA = DC;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = DC OUT = T_DC;
ID METHOD1;
VAR DIFFERENCE;
BY FORM OBSERVED;
RUN;


PROC SORT DATA = DD;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = DD OUT = T_DD;
ID METHOD1;
VAR DIFFERENCE;
BY FORM OBSERVED;
```

```
RUN;


PROC SORT DATA = DE;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = DE OUT = T_DE;
ID METHOD1;
VAR DIFFERENCE;
BY FORM OBSERVED;
RUN;


/*ADD THE IDENTITY EQUATING*/
DATA IDENTITY;
SET CONV_TABLES;
IF METHOD2 = 'FPC';
IF REPLICATION = "REP1";
METHOD2 = "IDENTITY";
ESTIMATE = OBSERVED;
&PRINT PROC PRINT;RUN;
DATA CONV_TABLES;
SET CONV_TABLES IDENTITY;
RUN;
                  DATA COND1_RESULTS;
                  SET  CONV_TABLES;
                  BIAS = ESTIMATE- CRITERION;
                  SQ_ERROR = (ESTIMATE- CRITERION)**2;
                  &PRINT PROC PRINT;
                  RUN;

                  proc means data = COND1_RESULTS mean var ;
                  CLASS FORM METHOD2 OBSERVED;
                  var ESTIMATE BIAS  SQ_ERROR  ;
                  output out = sqbias
                  mean =
                  STD = STD_ESTIMATE  STD_BIAS STD_SQ_ERROR ;
                  run;

data sqbias2;
set sqbias;
LENGTH METHOD $12.;
METHOD = METHOD2;
if _type_ = 7;
RMSE = SQRT(SQ_ERROR);
ST_ERROR = SQRT(RMSE**2 - BIAS**2 );
DROP METHOD2;
*KEEP  _FREQ_ METHOD ESTIMATE BIAS  RMSE ST_ERROR FORM _type_
ST_ERR_CRIT;
proc sort;
by FORM OBSERVED ;
&PRINT PROC PRINT;
run;
&PRINT PROC PRINT DATA = SQBIAS2;RUN;

DATA ST_ERR_CRIT;
DO OBSERVED =0 TO 60 BY 1;
```

```
FORM = "B";
OUTPUT; END;

DO OBSERVED =0 TO 60 BY 1;
FORM = "C";
OUTPUT; END;


DO OBSERVED =0 TO 60 BY 1;
FORM = "D";
OUTPUT; END;

DO OBSERVED =0 TO 60 BY 1;
FORM = "E";
OUTPUT; END;
RUN;


DATA ST_ERR_CRIT;
SET ST_ERR_CRIT;
METHOD = "CRITERION";
IF FORM = 'B' THEN ST_ERROR = (.10* &STD_B);
IF FORM = 'C' THEN ST_ERROR = (.10* &STD_C);
IF FORM = 'D' THEN ST_ERROR = (.10* &STD_D);
IF FORM = 'E' THEN ST_ERROR = (.10* &STD_E);
&PRINT PROC PRINT;RUN;

DATA SQBIAS2;
SET SQBIAS2 ST_ERR_CRIT;

&PRINT PROC PRINT;
RUN;

PROC SORT DATA = SQBIAS2;
BY FORM;
RUN;
DATA SQBIAS3;
SET SQBIAS2;
IF METHOD = "IDENTITY" THEN DELETE;
RUN;


DATA B C D E;
SET SQBIAS3;
IF INDEX(METHOD,'STOCK')>0 THEN METHOD =              "4. SCSL      ";
IF INDEX(METHOD,'LINEAR')>0 THEN METHOD =             "2. LLTS       ";
IF INDEX(METHOD,'FPC')>0 THEN METHOD =                "3. FPC       ";
IF INDEX(METHOD,'CRITERION')>0 THEN METHOD =    "1. CRITERION ";
IF FORM = "B" THEN OUTPUT  B;
IF FORM = "C" THEN OUTPUT  C;
IF FORM = "D" THEN OUTPUT  D;
IF FORM = "E" THEN OUTPUT  E;
RUN;
&PRINT PROC PRINT DATA = B;RUN;

/*NOW SYSTEMATIC ERROR*/
DATA SB SC SD SE;
```

```
SET SQBIAS2;
IF INDEX(METHOD,"CRITER") = 0;
IF INDEX(METHOD,'STOCK')>0 THEN METHOD =        "4. SCSL";
IF INDEX(METHOD,'LINEAR')>0 THEN METHOD =             "2. LLTS";
IF INDEX(METHOD,'FPC')>0 THEN METHOD =                "3. FPC ";
IF INDEX(METHOD,'IDENTITY')>0 THEN METHOD =     "1. IDENTITY";

IF FORM = "B" THEN OUTPUT  SB;
IF FORM = "C" THEN OUTPUT  SC;
IF FORM = "D" THEN OUTPUT  SD;
IF FORM = "E" THEN OUTPUT  SE;
RUN;
&PRINT PROC PRINT DATA = SB;RUN;


PROC SORT DATA = SB;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = SB OUT = T_SB;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_BIAS_B ;
SET T_SB;
IF _NAME_ = 'BIAS' THEN OUTPUT T_BIAS_B;
RUN;

PROC SORT DATA = B;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = B OUT = T_B;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_RAND_B;
SET T_B;
IF _NAME_ = 'ST_ERROR' THEN OUTPUT T_RAND_B;
RUN;


/*C*/


PROC SORT DATA = SC;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = SC OUT = T_SC;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_BIAS_C ;
```

```
SET T_SC;
IF _NAME_ = 'BIAS' THEN OUTPUT T_BIAS_C;
RUN;

PROC SORT DATA = C;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = C OUT = T_C;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_RAND_C;
SET T_C;
IF _NAME_ = 'ST_ERROR' THEN OUTPUT T_RAND_C;
RUN;
/*D*/


PROC SORT DATA = SD;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = SD OUT = T_SD;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;
DATA T_BIAS_D ;
SET T_SD;
IF _NAME_ = 'BIAS' THEN OUTPUT T_BIAS_D;
RUN;

PROC SORT DATA = D;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = D OUT = T_D;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_RAND_D;
SET T_D;
IF _NAME_ = 'ST_ERROR' THEN OUTPUT T_RAND_D;
RUN;
/*E*/


PROC SORT DATA = SE;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = SE OUT = T_SE;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;
```

```
DATA T_BIAS_E ;
SET T_SE;
IF _NAME_ = 'BIAS' THEN OUTPUT T_BIAS_E;
RUN;

PROC SORT DATA = E;
BY FORM OBSERVED;
RUN;
PROC TRANSPOSE DATA = E OUT = T_E;
ID METHOD;
VAR BIAS ST_ERROR;
BY FORM OBSERVED;
RUN;

DATA T_RAND_E;
SET T_E;
IF _NAME_ = 'ST_ERROR' THEN OUTPUT T_RAND_E;
RUN;
proc print data = t_bias_e;run;

%MEND;


%macro delcat(catname);
 %if %sysfunc(cexist(&catname)) %then %do;
  proc greplay nofs igout=&catname;
  delete _all_;
  run;
 %end;
 quit;
%mend delcat;
```

```
%MACRO PLOT (PRINT =*,FORM2 =B, FTEXT = SWISS, LIGHTTEXT = black,
NOTE=,  OUTPATH = C:\DISSERTATION\SIMULATION, CONDITION =COND1,DATASET
=BOTH, LINE_NAME=THETA, NAME = PLOT1, YAXIS = COUNT,
XAXIS=VALUE, MIN_X= -4, MAX_X = 4, BY =1, MIN_Y=0, MAX_Y = 1, BY_Y =
.25,
TITLE = THETAS, SUB_TITLE= , Y_LABEL=COUNT, X_LABEL =THETA,
START_LEGEND = 25, START_SYMBOL= 30,
START_Y = 75, COLOR1 = GREEN, COLOR2 =BLUE, COLOR3 = ORANGE, COLOR4 =
BLACK,
COLOR5 = PURPLE,  COLOR6 =RED, JOIN_POINTS=J, VREF=0, POSITION_=TOP
LEFT INSIDE, ACROSS = 1, DOWN =4, CAPTION=, SPECIAL=);

OPTIONS NOXWAIT ;
Data _null_;
call system ("mkdir &OUTPATH\&CONDITION\RESULTS\&FORM2");
RUN;



data data3;
set &dataset;
   length  html $400;
   html= 'title='||quote(trim(left(round(percent,.01 )))||'% of
examiness earned a score of  '|| trim(left(&XAXIS))||
      ' on THETA'||trim(left(&LINE_NAME))||'.' )
      ||' '|| 'href="'||"/files/HTML_FILES/SC.html"||'"';
&PRINT PROC PRINT;
run;

/*make LEGEND for plot*/
proc freq data = &dataset NOPRINT;
table &LINE_NAME/out= LINE_NAME;
run;

DATA LINE_NAME2;
SET LINE_NAME;
order =0; order2 = 0; b = 0;
drop count percent;
proc sort;
by &LINE_NAME ;
&PRINT PROC PRINT;
RUN;



DATA _NULL_;
SET LINE_NAME2;
BLANK = " ";
CALL SYMPUTX ('FIRST',BLANK );
CALL SYMPUTX ('SEC',BLANK);
CALL SYMPUTX ('THIRD',BLANK);
CALL SYMPUTX ('FOURTH',BLANK );
CALL SYMPUTX ('FIFTH',BLANK );
CALL SYMPUTX ('SIXTH',BLANK);
RUN;

DATA _NULL_;
```

```
SET LINE_NAME2;
IF _N_ = 1 THEN CALL SYMPUTX ('FIRST',&LINE_NAME);
IF _N_ = 2 THEN CALL SYMPUTX ('SEC',&LINE_NAME );
IF _N_ = 3 THEN CALL SYMPUTX ('THIRD',&LINE_NAME);
IF _N_ = 4 THEN CALL SYMPUTX ('FOURTH',&LINE_NAME);
IF _N_ = 5 THEN CALL SYMPUTX ('FIFTH',&LINE_NAME );
IF _N_ = 6 THEN CALL SYMPUTX ('SIXTH',&LINE_NAME );
RUN;%PUT &SEC;

proc transpose data = LINE_NAME2 out = t_LINE_NAME prefix = &LINE_NAME;
var &LINE_NAME;
run;


&print proc print data= t_LINE_NAME;run;

data ylegend;
yy1 = &start_y;/*vertical location of legend*/
yy2 = yy1 - 5;
yy3 = yy2 - 5;
yy4 = yy3 - 5;
yy5 = yy4 - 5;
yy6 = yy5 - 5;


SS1 = &start_y-1;/*vertical location of symbols*/
SS2 = SS1 - 5;
SS3 = SS2 - 5;
SS4 = SS3 - 5;
SS5 = SS4 - 5;
SS6 = SS5 - 5;
run;
data _null_;
set ylegend;
call symputx ('yy1', yy1 );
call symputx ('yy2', yy2 );
call symputx ('yy3', yy3 );
call symputx ('yy4', yy4 );
call symputx ('yy5', yy5 );
call symputx ('yy6', yy6 );


call symputx ('ss1', ss1 );
call symputx ('ss2', ss2 );
call symputx ('ss3', ss3 );
call symputx ('ss4', ss4 );
call symputx ('ss5', ss5 );
call symputx ('ss6', ss6 );
run;

data plot3_anno1;
length text $60. color $8. function $9.;
retain xsys '3' ysys '3' function 'label' when 'a' y_pct 82
       hsys '4' size 2;
set t_LINE_NAME;
if _n_ = 1 then do;
```

```
 x=&START_LEGEND; y=&yy1; text="&FIRST ";  color="&COLOR1"
;style="&ftext";  output;

 x=&START_LEGEND; y=&yy2; text="&SEC "; color="&COLOR2" ;  output;
 x=&START_LEGEND; y=&yy3; text="&THIRD "; color="&COLOR3" ;   output;

 x=&START_LEGEND; y=&yy4; text="&FOURTH ";  color="&COLOR4"
;style="&ftext";  output;
/* x=&START_LEGEND; y=&yy5; text="&FIFTH "; color="&COLOR5" ;  output;
 x=&START_LEGEND; y=&yy6; text="&SIXTH "; color="&COLOR6" ;   output;*/

 x=55; y=86; text="&SUB_TITLE "; color="&lighttext" ; size = 3.00;
output;

when='a'; style="&ftext"; color="&lighttext"; hsys='3'; size=6;
   function='label'; xsys='1'; x=50; ysys='3'; y=15; position='5';
text="&X_LABEL";
   output;

when='a'; style="&ftext"; color="&lighttext"; hsys='3'; size=6;
   function='label'; xsys='1'; x=50; ysys='3'; y=8; position='5';
text="&CAPTION";
   output;


FUNCTION = 'SYMBOL'; style = " ";  TEXT = "DOT "; color="&COLOR1" ;
x=&START_SYMBOL; y=&ss1;  size = 5.00; output;
FUNCTION = 'SYMBOL';TEXT = "TRIANGLE ";  color="&COLOR2" ;
x=&START_SYMBOL; y=&ss2; size = 5.00;  output;
FUNCTION = 'SYMBOL'; TEXT = "SQUARE"; color="&COLOR3" ;
x=&START_SYMBOL; y=&ss3; size = 5.00; output;
FUNCTION = 'SYMBOL'; TEXT = "CIRCLE "; color="&COLOR4" ;
x=&START_SYMBOL; y=&ss4; size = 5.00;  output;


FUNCTION = 'SYMBOL'; style = " ";  TEXT = "DOT "; color="&COLOR1" ;
x=&START_SYMBOL +4; y=&ss1;  size = 5.00; output;
FUNCTION = 'SYMBOL';TEXT = "TRIANGLE ";  color="&COLOR2" ;
x=&START_SYMBOL +4; y=&ss2; size = 5.00;  output;
FUNCTION = 'SYMBOL'; TEXT = "SQUARE"; color="&COLOR3" ; x=&START_SYMBOL
+4; y=&ss3; size = 5.00; output;
FUNCTION = 'SYMBOL'; TEXT = "CIRCLE "; color="&COLOR4" ;
x=&START_SYMBOL +4; y=&ss4; size = 5.00;  output;


FUNCTION = 'SYMBOL'; style = " ";  TEXT = "DOT "; color="&COLOR1" ;
x=&START_SYMBOL +8; y=&ss1;  size = 5.00; output;
FUNCTION = 'SYMBOL';TEXT = "TRIANGLE ";  color="&COLOR2" ;
x=&START_SYMBOL +8; y=&ss2; size = 5.00;  output;
FUNCTION = 'SYMBOL'; TEXT = "SQUARE"; color="&COLOR3" ; x=&START_SYMBOL
+8; y=&ss3; size = 5.00; output;
FUNCTION = 'SYMBOL'; TEXT = "CIRCLE "; color="&COLOR4" ;
x=&START_SYMBOL +8; y=&ss4; size = 5.00;  output;
```

```
      function='move'; x=&START_SYMBOL -3; y=&ss1 ; color="&COLOR1";
SIZE = 2;    output;   function='draw'; X=&START_SYMBOL+11;   output;
      function='move'; x=&START_SYMBOL -3; y=&ss2 ; color="&COLOR2";
SIZE = 2;    output;   function='draw'; X=&START_SYMBOL+11;   output;
      function='move'; x=&START_SYMBOL -3; y=&ss3; color="&COLOR3";
SIZE = 2;    output;   function='draw'; X=&START_SYMBOL+11;   output;
      function='move'; x=&START_SYMBOL -3; y=&ss4 ; color="&COLOR4";
SIZE = 2;    output;   function='draw'; X=&START_SYMBOL+11;   output;

end;
&print proc print;
run;

/*end of LEGEND*/
FILENAME GRAPHOUT "&OUTPATH\&CONDITION\RESULTS\&FORM2";
GOPTIONS RESET=ALL
DEVICE = GIF
GSFNAME=GRAPHOUT
;
options mlogic symbolgen;
goptions xpixels=300 ypixels=200;
goptions gunit=pct htitle=8 htext=5 ftitle=&ftext ftext=&ftext
ctext=&lighttext;


%LET MAJORCOLOR =BLUE ;*cx50A6C2;
%LET FTEXT = 'SWISS';


axis1 color=&lighttext  minor=none label=(a = 90 font = 'swiss'
"&y_label" )  order = (&min_Y to &max_Y by &by_Y )offset=(0,0);
axis2 color=&lighttext  minor=none label = none major=none order =
(&min_X to &max_X by &by )  offset=(2,2) style=0;/**/

%IF &TITLE = _ %THEN %DO;
title1 j=l c=WHITE "&TITLE";
%END;

footnote1 h=10 " ";

proc sort data = data3;
by &LINE_NAME;
&PRINT PROC PRINT;
run;

data line_name;
set line_name;
drop count percent;
run;
proc sort data = LINE_NAME;
by &LINE_NAME;run;


data data34;
merge data3 (in=u) LINE_NAME;
by &LINE_NAME;
if u;
```

```
run;


legend1 LABEL = NONE
value = ("&FIRST " "&SEC" "&THIRD" "&FOURTH " "&FIFTH ")
ACROSS = &ACROSS DOWN = &DOWN
POSITION = (&position_)
MODE =PROTECT
CFRAME = WHITE
OFFSET = (1 PCT);

symbol1 i=&JOIN_POINTS v=dot c=&COLOR1 w=2 h=4          ;
symbol2 i=&JOIN_POINTS  v=TRIANGLE c=&COLOR2  w=2 h=4   ;
symbol3 i=&JOIN_POINTS  v=SQUARE c=&COLOR3 w=2 h=4      ;
symbol4 i=&JOIN_POINTS  v=CIRCLE c=&COLOR4 w=2 h=4      ;

TITLE2 ' ';
%IF &SPECIAL = %THEN %DO;

proc gplot data=data34 anno=plot3_anno1;/* */
   plot &YAXIS*&XAXIS=&LINE_NAME / haxis = axis2 vaxis=axis1
     vref=&VREF
      noframe
        name="&NAME"
         NOLEGEND
        HTML = HTML;
      run;  quit;
%END;
%IF &SPECIAL = Y %THEN %DO;


symbol1 i=&JOIN_POINTS v=NONE c=&COLOR1 w=4 h=4       ;
symbol2 i=&JOIN_POINTS v=NONE c=&COLOR2  w=4 h=4      ;
symbol3 i=&JOIN_POINTS  v=NONE c=&COLOR3 w=4 h=4      ;
symbol4 i=&JOIN_POINTS  v=NONE c=&COLOR4 w=4 h=4      ;
symbol5 i=NONE v=DOT c=&COLOR1 w=4 h=5                ;
symbol6 i=NONE v=TRIANGLE c=&COLOR2  w=4 h=5          ;
symbol7 i=NONE  v=SQUARE c=&COLOR3 w=4 h=5           ;
symbol8 i=NONE v=CIRCLE c=&COLOR4  w=4 h=5            ;


%IF %UPCASE(&Y_LABEL) = BIAS %THEN %DO;
      %LET D_SET = T_BIAS_&FORM2;
      %LET CRIT=IDENTITY;
%END;

%IF %UPCASE(&Y_LABEL) NE BIAS %THEN %DO;
      %LET D_SET = T_RAND_&FORM2;
      %LET CRIT=CRITERION;
%END;

%IF %UPCASE(&Y_LABEL) EQ DIFFERENCE %THEN %DO;
      %LET D_SET = T_D&FORM2;
      %LET CRIT=CRITERION;
%END;

DATA &D_SET;
```

```
SET &D_SET;
IF OBSERVED = 2 OR OBSERVED = 12 OR OBSERVED = 22 OR OBSERVED = 32 OR
OBSERVED = 42 OR OBSERVED = 52 THEN DO;
ONE = _1__&CRIT;
END;

IF OBSERVED = 5 OR OBSERVED = 15 OR OBSERVED = 25 OR OBSERVED = 35 OR
OBSERVED = 45 OR OBSERVED = 55 THEN DO;
 TWO = _2__llts;
END;

IF OBSERVED = 7 OR OBSERVED = 17 OR OBSERVED = 27 OR OBSERVED = 37 OR
OBSERVED = 47 OR OBSERVED = 57 THEN DO;
 THREE = _3__fpc;
END;

IF OBSERVED = 10 OR OBSERVED = 20 OR OBSERVED = 30 OR OBSERVED = 40 OR
OBSERVED = 50 OR OBSERVED = 60 THEN DO;
FOUR = _4__sCSL;
END;
RUN;
proc gplot data=&D_SET anno=plot3_anno1;
   plot _1__&CRIT.*observed
            _2__llts*OBSERVED
            _3__fpc*observed
            _4__sCSL*observed
            ONE*OBSERVED
            TWO*OBSERVED
            THREE*OBSERVED
            FOUR*OBSERVED
/ overlay haxis = axis2 vaxis=axis1
     vref=0
      noframe
        name="&NAME"
         NOLEGEND;
      run;  quit;
%END;
%MEND;
```

```
%GLOBAL MAX_CNT COR SHIFT A1 C1;

%MACRO SIMULATE (FILE = FORMS, OUTPATH = C:\DISSERTATION\SIMULATION,
CONDITION = COND2, COR = .90, SHIFT_P = 0, YA = 0, YB = 1, YC = 0, YD =
0, A1 = .05, A2 = 1,  C1 = .25, EQUATE_B = Y, EQUATE_C =Y, EQUATE_D =Y,
EQUATE_E =Y, BOOT_STRAP = N, START_BOOT =2, END_BOOT = 50, CALIBRATE =
, EQUATE =);
%IF &EQUATE_B = Y %THEN %DO;
            %MAKE_POPULATIONS (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION = &CONDITION,SHIFT_P = &SHIFT_P, COR = &COR, Y1A=&YA, Y1B =
&YB, Y1C = &YC, Y1D =&YD, Y2A=&YA, Y2B = &YB, Y2C = &YC, Y2D =&YD);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";

/*NOTE: MAKE_ITEMS_PARAMS WAS USED INITIALLY. ONCE ALL FORMS WERE MADE,
THESE MACROS WERE TURNED OFF AND THE SAME FORMS WERE JUST COPIED INTO
THE FOLDERS FOR SUBSEQUENT SIMULATIONS*/

%COPY_FORMS(CONDITION = &CONDITION,OUTPATH =C:\DISSERTATION\SIMULATION,
FILE = &FILE);

                  *%MAKE_ITEM_PARAMS(PRINT =* ,THETA2 = 1,CONDITION
=&CONDITION, N_OPER_ITEMS = 60, A1 =&A1/*STD*/ , A2 =&A2/*LOCATION*/,
B1=0, B2=1.1 , C1= &C1);
/*ASSEMBLE FORM A*/     *%ASSEMBLE_FORM (PRINT =* ,THETA2 = 0, OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
N_PILOT_ITEMS= 20, FORM=A, SHIFT = +1.5, START_ITEM_ID = 61, REPLACE  =
N );
/*ASSEMBLE FORM B*/           *%ASSEMBLE_FORM (PRINT = *,THETA2= 0,
OUTPATH= C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION,
N_PILOT_ITEMS= 20, FORM=B, SHIFT = +1.2, START_ITEM_ID = 81, REPLACE  =
Y );

/*EQUATE GENERATED VALUES*/   *%EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =B, CAL_METHOD = GENERATED);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";

                                    %SPIRAL(OUTPATH =
C:\DISSERTATION\SIMULATION, CONDITION= &CONDITION, SAMPLE_SIZE =
50000);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                                    %GET_POP_TRUE_SCORES(PRINT
=*,CONDITION =&CONDITION, CAL_METHOD = GENERATED, FORM = A,
EXCLUDE_FORM = B, POOL =YES , GROUP = 1, OUTPATH=
C:\DISSERTATION\SIMULATION,
                                    ADMIN_EVENT = 1, START_THETA1 = 1,
NITEMS= 80, N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
REPLICATION = REP1,
                                    END_THETA2 = 60, LIMIT_POOL=80
,START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 =
71,END_PILOT_THETA2 = 80);
```

```
                                    %MAKE_RESPONSES (PRINT =*,OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
GROUP = X, FORM = A, ADMIN_EVENT =1, SAMPLE_SIZE=500);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*CALIBRATE SUBTEST 1 TO GENERATED*/&CALIBRATE %CALIBRATE (PRINT = *,
LINK_METH = MEAN_MEAN, ESTIMATE = Y, LINK_START = 1, LINK_STOP = 30,
N_LINK_ITEMS = 30, ADMIN_EVENT = 1, CONDITION = &CONDITION, REPLICATION
= REP1,FORM=A, BASE_FORM = A, BASE_CAL_METHOD = GENERATED,  CAL_METHOD
= SEPARATE,   SEPARATE = Y, FIRST_OPER_ITEMID = 1,
FIRST_PILOT_ITEMID=61, N_SELECTED = 80, N_REPLACED = 0,
CALIBRATE_PILOTS =N , FPC =N );
/*CALIBRATE SUBTEST 2 TO GENERATED*/&CALIBRATE %CALIBRATE (PRINT = *,
LINK_METH = MEAN_MEAN, ESTIMATE = N, LINK_START = 31, LINK_STOP = 60,
N_LINK_ITEMS = 30, ADMIN_EVENT = 1, CONDITION = &CONDITION, REPLICATION
= REP1,FORM=A, BASE_FORM = A, BASE_CAL_METHOD = GENERATED,  CAL_METHOD
= SEPARATE,   SEPARATE = Y, FIRST_OPER_ITEMID = 1,
FIRST_PILOT_ITEMID=61, N_SELECTED = 80, N_REPLACED = 0,
CALIBRATE_PILOTS =N , FPC =N );


/*CALIBRATE PILOT ITEMS*/&CALIBRATE %CALIBRATE (PRINT = *,ADMIN_EVENT =
1,  LINK_METH = MEAN_MEAN, CONDITION = &CONDITION, REPLICATION =
REP1,FORM=A, BASE_FORM = A, BASE_CAL_METHOD = SEPARATE,   CAL_METHOD =
STOCK_LORD, SEPARATE = Y, FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61,
N_SELECTED = 80, N_REPLACED = 0, CALIBRATE_PILOTS =Y , FPC =N );
/*CALIBRATE PILOT ITEMS*/&CALIBRATE %CALIBRATE (PRINT = *,ADMIN_EVENT =
1, LINK_METH = MEAN_MEAN, CONDITION = &CONDITION, REPLICATION =
REP1,FORM=A, BASE_FORM = A, BASE_CAL_METHOD = NA, CAL_METHOD = FPC,
SEPARATE = N, FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_SELECTED
= 80, N_REPLACED = 0, CALIBRATE_PILOTS =Y , FPC =Y );

DM "CLEAR OUTPUT";
DM "CLEAR LOG";

                                    %GET_POP_TRUE_SCORES(PRINT
=*,CONDITION =&CONDITION, CAL_METHOD = GENERATED, FORM = B,
EXCLUDE_FORM = B, POOL =NO , GROUP = 1, OUTPATH=
C:\DISSERTATION\SIMULATION,
                                    ADMIN_EVENT = 1, START_THETA1 = 1,
NITEMS= 80, N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
REPLICATION = REP1,
                                    END_THETA2 = 60, LIMIT_POOL=80
,START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 =
71,END_PILOT_THETA2 = 80);

                              &EQUATE     %EQUIPERCENTILE_EQUATE
(OUTPATH = C:\DISSERTATION\SIMULATION, BASE = A, NEWFORM =B , CONDITION
= &CONDITION );
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*PREEQUATE*/          &EQUATE        %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =B, CAL_METHOD = STOCK_LORD);
/*PREEQUATE*/          &EQUATE            %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =B, CAL_METHOD = FPC);
```

```
                                    %MAKE_RESPONSES (PRINT =*,OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
GROUP = Y, FORM = B, ADMIN_EVENT =2,SAMPLE_SIZE=500);

DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*POSTEQUATE LINEAR*/&EQUATE        %LINEAR_EQUATE(CONDITION =
&CONDITION, REPLICATION = REP1, ADMIN_EVENT = 1, NITEMS =60, CUT = 55,
REMOVE_C = N, PASSFAIL =N, ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION,
                                                             base=A,
BASE_ADMIN = 1, newform =B ,NEW_ADMIN =2 , _A_ = 1, _B_ = 1, CIPE = N,
PRINT = *,ROUND_SCALE=N)


/*CALIBRATE OPER. ITEMS*/&CALIBRATE %CALIBRATE (PRINT = *,ADMIN_EVENT =
2, LINK_METH = MEAN_MEAN, CONDITION = &CONDITION, REPLICATION =
REP1,FORM=B, GROUP = Y, BASE_FORM = A, BASE_CAL_METHOD = STOCK_LORD,
CAL_METHOD = STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID = 21,
FIRST_PILOT_ITEMID=81, N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =N );
/*CALIBRATE PILOT ITEMS*/&CALIBRATE   %CALIBRATE (PRINT = *,ADMIN_EVENT
= 2, LINK_METH = MEAN_MEAN, CONDITION = &CONDITION, REPLICATION =
REP1,FORM=B,GROUP = Y, BASE_FORM = A, BASE_CAL_METHOD = NA,
CAL_METHOD = FPC,         SEPARATE = N,FIRST_OPER_ITEMID = 21,
FIRST_PILOT_ITEMID=81, N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =Y );
DM "CLEAR OUTPUT";
DM "CLEAR LOG";

%END;
%IF &EQUATE_C = Y %THEN %DO;
                                    *%ASSEMBLE_FORM (PRINT = *,
OUTPATH= C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION,
N_PILOT_ITEMS= 20, FORM=C, SHIFT = -.50, START_ITEM_ID = 101, REPLACE
= Y );
                                    %GET_POP_TRUE_SCORES(PRINT
=*,CONDITION =&CONDITION, CAL_METHOD = GENERATED, FORM = C, POOL
=GENERATED , GROUP = 1, OUTPATH= C:\DISSERTATION\SIMULATION,
                                    ADMIN_EVENT = 1, START_THETA1 = 1,
NITEMS= 80, N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
REPLICATION = REP1,
                                    END_THETA2 = 60, LIMIT_POOL=80
,START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 =
71,END_PILOT_THETA2 = 80);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                        &EQUATE           %EQUIPERCENTILE_EQUATE
(OUTPATH = C:\DISSERTATION\SIMULATION, BASE = A, NEWFORM =C , CONDITION
= &CONDITION );
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*PREEQUATE*/ &EQUATE            %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =C, CAL_METHOD = STOCK_LORD);
```

```
/*PREEQUATE*/&EQUATE                      %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =C, CAL_METHOD = FPC);

DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                                    %MAKE_RESPONSES (PRINT =*,OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
GROUP = Y, FORM = C, ADMIN_EVENT =3,SAMPLE_SIZE=500);
                              &EQUATE
      %LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP1,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION,
                                                            base=B,
BASE_ADMIN = 2, newform =C ,NEW_ADMIN =3 , _A_ = 1, _B_ = 1, CIPE = N,
PRINT = *,ROUND_SCALE=N)
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*CALIBRATE OPER. ITEMS*/&CALIBRATE    %CALIBRATE (PRINT =
*,ADMIN_EVENT = 3, CONDITION = &CONDITION, REPLICATION = REP1,FORM=C,
GROUP = Y, BASE_FORM = B, BASE_CAL_METHOD = STOCK_LORD,   CAL_METHOD =
STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID = 41, FIRST_PILOT_ITEMID=101
N_SELECTED = 80, N_REPLACED = 20, CALIBRATE_PILOTS =Y , FPC =N );
/*CALIBRATE PILOT ITEMS*/&CALIBRATE  %CALIBRATE (PRINT = *,ADMIN_EVENT
= 3, CONDITION = &CONDITION, REPLICATION = REP1,FORM=C, GROUP = Y,
BASE_FORM = B, BASE_CAL_METHOD = NA,           CAL_METHOD = FPC,
SEPARATE = N,FIRST_OPER_ITEMID = 41, FIRST_PILOT_ITEMID=101 N_SELECTED
= 80, N_REPLACED = 20, CALIBRATE_PILOTS =Y , FPC =Y );
%END;
%IF &EQUATE_D = Y %THEN %DO;
DM "CLEAR OUTPUT";
DM "CLEAR LOG";

                              *%ASSEMBLE_FORM (PRINT = *, OUTPATH=
C:\DISSERTATION\SIMULATION,CONDITION =&CONDITION,  N_PILOT_ITEMS= 20,
FORM=D, SHIFT = -1.50, START_ITEM_ID = 121, REPLACE  = Y );
                                    %GET_POP_TRUE_SCORES(PRINT
=*,CONDITION =&CONDITION, CAL_METHOD = GENERATED, FORM = D, POOL
=GENERATED , GROUP = 1, OUTPATH= C:\DISSERTATION\SIMULATION,
                                    ADMIN_EVENT = 1, START_THETA1 = 1,
NITEMS= 80, N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
REPLICATION = REP1,
                                    END_THETA2 = 60, LIMIT_POOL=80
,START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 =
71,END_PILOT_THETA2 = 80);

                        &EQUATE           %EQUIPERCENTILE_EQUATE
(OUTPATH = C:\DISSERTATION\SIMULATION, BASE = A, NEWFORM =D , CONDITION
= &CONDITION );
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*PREEQUATE*/     &EQUATE             %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =D, CAL_METHOD = STOCK_LORD);
```

```
/*PREEQUATE*/     &EQUATE                 %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =D, CAL_METHOD = FPC);


                                    %MAKE_RESPONSES (PRINT =*,OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
GROUP = Y, FORM = D, ADMIN_EVENT =4, SAMPLE_SIZE=500);
                        &EQUATE
      %LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP1,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION,
                                                            base=C,
BASE_ADMIN = 3, newform =D ,NEW_ADMIN =4 , _A_ = 1, _B_ = 1, CIPE = N,
PRINT = *,ROUND_SCALE=N)
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
/*CALIBRATE OPER. ITEMS*/&CALIBRATE    %CALIBRATE (PRINT =
*,ADMIN_EVENT = 4, CONDITION = &CONDITION, REPLICATION = REP1,FORM=D,
GROUP = Y, BASE_FORM = C, BASE_CAL_METHOD = STOCK_LORD,   CAL_METHOD =
STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID = 61, FIRST_PILOT_ITEMID=121
N_SELECTED = 80, N_REPLACED = 20, CALIBRATE_PILOTS =Y , FPC =N );
/*CALIBRATE PILOT ITEMS*/&CALIBRATE    %CALIBRATE (PRINT =
*,ADMIN_EVENT = 4, CONDITION = &CONDITION, REPLICATION = REP1,FORM=D,
GROUP = Y, BASE_FORM = C, BASE_CAL_METHOD = NA,           CAL_METHOD =
FPC,         SEPARATE = N,FIRST_OPER_ITEMID = 61,
FIRST_PILOT_ITEMID=121 N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =Y );
%END;
%IF &EQUATE_E = Y %THEN %DO;
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                              *%ASSEMBLE_FORM (PRINT = *, OUTPATH=
C:\DISSERTATION\SIMULATION,CONDITION =&CONDITION,  N_PILOT_ITEMS= 20,
FORM=E, SHIFT = -1.5, START_ITEM_ID = 141, REPLACE  = Y );
                                    %GET_POP_TRUE_SCORES(PRINT
=*,CONDITION =&CONDITION, CAL_METHOD = GENERATED, FORM = E, POOL
=GENERATED , GROUP = 1, OUTPATH= C:\DISSERTATION\SIMULATION,
                                    ADMIN_EVENT = 1, START_THETA1 = 1,
NITEMS= 80, N_OPER_ITEMS=60, END_THETA1 = 30, START_THETA2 = 31,
REPLICATION = REP1,
                                    END_THETA2 = 60, LIMIT_POOL=80
,START_PILOT_THETA1 = 61,END_PILOT_THETA1 = 70, START_PILOT_THETA2 =
71,END_PILOT_THETA2 = 80);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                        &EQUATE           %EQUIPERCENTILE_EQUATE
(OUTPATH = C:\DISSERTATION\SIMULATION, BASE = A, NEWFORM =E , CONDITION
= &CONDITION );

/*PREEQUATE*/     &EQUATE             %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =E, CAL_METHOD = STOCK_LORD);
```

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/*PREEQUATE*/     &EQUATE                 %EQUATE_TRUE_SCORES (OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION=&CONDITION, REPLICATION =REP1,
NEW_FORM =E, CAL_METHOD = FPC);
DM "CLEAR OUTPUT";
DM "CLEAR LOG";
                                    %MAKE_RESPONSES (PRINT =*,OUTPATH=
C:\DISSERTATION\SIMULATION, CONDITION =&CONDITION, REPLICATION = REP1,
GROUP = Y, FORM = E, ADMIN_EVENT =5, SAMPLE_SIZE=500);
                              &EQUATE
      %LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP1,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION,
                                                            base=D,
BASE_ADMIN = 4, newform =E ,NEW_ADMIN =5 , _A_ = 1, _B_ = 1, CIPE = N,
PRINT = *,ROUND_SCALE=N);
%END;
                         *   %SAVE_LIN_CONV(FORMS = E D C B A, OUTPATH
=C:\DISSERTATION\SIMULATION, CONDITION = &CONDITION, REPLICATION
=REP1);


%IF &BOOT_STRAP = Y %THEN %DO;
%RESAMPLE(START_BOOT =&START_BOOT , END_BOOT =&END_BOOT, OUTPATH =
&OUTPATH , CONDITION = &CONDITION, EQUATE_B = Y, EQUATE_C =Y, EQUATE_D
=Y, EQUATE_E =Y);
%END;

%MEND SIMULATE;


%MACRO RESAMPLE(START_BOOT =2 , END_BOOT =50, OUTPATH =
C:\DISSERTATION\SIMULATION , CONDITION = CONDITION1, EQUATE_B = Y,
EQUATE_C =Y, EQUATE_D =Y, EQUATE_E =Y););
%DO RS = &START_BOOT %TO &END_BOOT;

%MAKE_RESPONSES (PRINT =*,OUTPATH= C:\DISSERTATION\SIMULATION,
CONDITION =&CONDITION, REPLICATION = REP&RS, GROUP = X, FORM = A,
ADMIN_EVENT =1, SAMPLE_SIZE=500);

%IF &EQUATE_B = Y %THEN %DO;
/*CALIBRATE SUBTEST 1 TO GENERATED*/%CALIBRATE (PRINT = *,ESTIMATE = Y,
LINK_START = 1, LINK_STOP = 30, N_LINK_ITEMS = 30, ADMIN_EVENT = 1,
CONDITION = &CONDITION, REPLICATION = REP&RS,FORM=A, BASE_FORM = A,
BASE_CAL_METHOD = GENERATED,  CAL_METHOD = SEPARATE,   SEPARATE = Y,
FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_SELECTED = 80,
N_REPLACED = 0, CALIBRATE_PILOTS =N , FPC =N );
/*CALIBRATE SUBTEST 2 TO GENERATED*/%CALIBRATE (PRINT = *, ESTIMATE =
N, LINK_START = 31, LINK_STOP = 60, N_LINK_ITEMS = 30, ADMIN_EVENT = 1,
CONDITION = &CONDITION, REPLICATION = REP&RS,FORM=A, BASE_FORM = A,
BASE_CAL_METHOD = GENERATED,  CAL_METHOD = SEPARATE,   SEPARATE = Y,
FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_SELECTED = 80,
N_REPLACED = 0, CALIBRATE_PILOTS =N , FPC =N );

%CALIBRATE (PRINT = *,  LINK_METH = MEAN_MEAN,ADMIN_EVENT = 1,
CONDITION = &CONDITION, REPLICATION = REP&RS,FORM=A, BASE_FORM = A,
BASE_CAL_METHOD = SEPARATE,   CAL_METHOD = STOCK_LORD, SEPARATE = Y,
FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_SELECTED = 80,
N_REPLACED = 0, CALIBRATE_PILOTS =Y , FPC =N );

%CALIBRATE (PRINT = *, LINK_METH = MEAN_MEAN,ADMIN_EVENT = 1, CONDITION
= &CONDITION, REPLICATION = REP&RS,FORM=A, BASE_FORM = A,
BASE_CAL_METHOD = NA, CAL_METHOD = FPC,                 SEPARATE = N,
FIRST_OPER_ITEMID = 1, FIRST_PILOT_ITEMID=61, N_SELECTED = 80,
N_REPLACED = 0, CALIBRATE_PILOTS =Y , FPC =Y );

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =B, CAL_METHOD =
STOCK_LORD);

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =B, CAL_METHOD =
FPC);

%MAKE_RESPONSES (PRINT =*,OUTPATH= C:\DISSERTATION\SIMULATION,
CONDITION =&CONDITION, REPLICATION = REP&RS, GROUP = Y, FORM = B,
ADMIN_EVENT =2, SAMPLE_SIZE=500);

/*POSTEQUATE LINEAR*/
%LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP&RS,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION,  base=A, BASE_ADMIN = 1, newform =B
,NEW_ADMIN =2 , _A_ = 1, _B_ = 1, CIPE = N, PRINT = *,ROUND_SCALE=N);
%END;

%IF &EQUATE_C = Y %THEN %DO;
%CALIBRATE (PRINT = *,ADMIN_EVENT = 2, CONDITION = &CONDITION,
REPLICATION =REP&RS,FORM=B, GROUP = Y, BASE_FORM = A, BASE_CAL_METHOD =
STOCK_LORD,   CAL_METHOD = STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID =
21, FIRST_PILOT_ITEMID=81, N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =N );

/*CALIBRATE PILOT ITEMS*/
%CALIBRATE (PRINT = *,ADMIN_EVENT = 2, CONDITION = &CONDITION,
REPLICATION = REP&RS,FORM=B,GROUP = Y, BASE_FORM = A, BASE_CAL_METHOD =
NA,           CAL_METHOD = FPC,          SEPARATE = N,FIRST_OPER_ITEMID
= 21, FIRST_PILOT_ITEMID=81, N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =Y );

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =C, CAL_METHOD =
STOCK_LORD);

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =C, CAL_METHOD =
FPC);
```

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%MAKE_RESPONSES (PRINT =*,OUTPATH= C:\DISSERTATION\SIMULATION,
CONDITION =&CONDITION, REPLICATION = REP&RS, GROUP = Y, FORM = C,
ADMIN_EVENT =3, SAMPLE_SIZE=500);

/*POSTEQUATE LINEAR*/
%LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP&RS,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION, base=B, BASE_ADMIN = 2, newform =C
,NEW_ADMIN =3 , _A_ = 1, _B_ = 1, CIPE = N, PRINT = *,ROUND_SCALE=N);
%END;
%IF &EQUATE_D = Y %THEN %DO;


%CALIBRATE (PRINT = *,ADMIN_EVENT = 3, CONDITION = &CONDITION,
REPLICATION = REP&RS,FORM=C, GROUP = Y, BASE_FORM = B, BASE_CAL_METHOD
= STOCK_LORD,   CAL_METHOD = STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID
= 41, FIRST_PILOT_ITEMID=101 N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =N );

%CALIBRATE (PRINT = *,ADMIN_EVENT = 3, CONDITION = &CONDITION,
REPLICATION = REP&RS,FORM=C, GROUP = Y, BASE_FORM = B, BASE_CAL_METHOD
= NA,           CAL_METHOD = FPC,         SEPARATE =
N,FIRST_OPER_ITEMID = 41, FIRST_PILOT_ITEMID=101 N_SELECTED = 80,
N_REPLACED = 20, CALIBRATE_PILOTS =Y , FPC =Y );

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =D, CAL_METHOD =
STOCK_LORD);
/*PREEQUATE*/

%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =D, CAL_METHOD =
FPC);


%MAKE_RESPONSES (PRINT =*,OUTPATH= C:\DISSERTATION\SIMULATION,
CONDITION =&CONDITION, REPLICATION = REP&RS, GROUP = Y, FORM = D,
ADMIN_EVENT =4,SAMPLE_SIZE=500);
/*POSTEQUATE LINEAR*/

%LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP&RS,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION, base=C, BASE_ADMIN = 3, newform =D
,NEW_ADMIN =4 , _A_ = 1, _B_ = 1, CIPE = N, PRINT = *,ROUND_SCALE=N);

%END;

%IF &EQUATE_E = Y %THEN %DO;

%CALIBRATE (PRINT = *,ADMIN_EVENT = 4, CONDITION = &CONDITION,
REPLICATION = REP&RS,FORM=D, GROUP = Y, BASE_FORM = C, BASE_CAL_METHOD
= STOCK_LORD,   CAL_METHOD = STOCK_LORD, SEPARATE = Y,FIRST_OPER_ITEMID
= 61, FIRST_PILOT_ITEMID=121 N_SELECTED = 80, N_REPLACED = 20,
CALIBRATE_PILOTS =Y , FPC =N );

%CALIBRATE (PRINT = *,ADMIN_EVENT = 4, CONDITION = &CONDITION,
REPLICATION = REP&RS,FORM=D, GROUP = Y, BASE_FORM = C, BASE_CAL_METHOD
= NA,           CAL_METHOD = FPC,         SEPARATE =
N,FIRST_OPER_ITEMID = 61, FIRST_PILOT_ITEMID=121 N_SELECTED = 80,
N_REPLACED = 20, CALIBRATE_PILOTS =Y , FPC =Y );

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =E, CAL_METHOD =
STOCK_LORD);

/*PREEQUATE*/
%EQUATE_TRUE_SCORES (OUTPATH =C:\DISSERTATION\SIMULATION,
CONDITION=&CONDITION, REPLICATION =REP&RS, NEW_FORM =E, CAL_METHOD =
FPC);

%MAKE_RESPONSES (PRINT =*,OUTPATH= C:\DISSERTATION\SIMULATION,
CONDITION =&CONDITION, REPLICATION = REP&RS, GROUP = Y, FORM = E,
ADMIN_EVENT =5, SAMPLE_SIZE=500);

/*POSTEQUATE LINEAR*/
%LINEAR_EQUATE(CONDITION = &CONDITION, REPLICATION = REP&RS,
ADMIN_EVENT = 1, NITEMS =60, CUT = 55, REMOVE_C = N, PASSFAIL =N,
ROUND_BUF = ,ODSOUT
=C:\DISSERTATION\SIMULATION\&CONDITION\REP1\ADMIN2\LINEAR, outpath
=C:\DISSERTATION\SIMULATION, base=D, BASE_ADMIN = 4, newform =E
,NEW_ADMIN =5 , _A_ = 1, _B_ = 1, CIPE = N, PRINT = *,ROUND_SCALE=N);
   %END;
%END;

%MEND;
```

APPENDIX B: DESCRIPTIVE STATISTICS OF GENERATED TEST FORMS

Table B1

Descriptive Statistics of 60 Operational *a*, *b*, and *c* Item Parameters for Phase 1 Forms

	Mean			Standard Deviation			Minimum			Maximum		
FORM	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	c	*a*	*b*	*c*
FORM 1 (Ideal form)												
A	1.03	0.07	0.02	0.01	0.87	0.01	1.00	-1.77	0.00	1.05	2.02	0.05
B	1.02	-0.43	0.02	0.01	1.15	0.01	1.00	-3.06	0.00	1.05	2.02	0.05
FORM 2 (*a* = ideal, *c* = mild)												
A	1.03	0.07	0.05	0.01	0.87	0.03	1.00	-1.77	0.00	1.05	2.02	0.10
B	1.02	-0.43	0.05	0.01	1.15	0.03	1.00	-3.06	0.00	1.05	2.02	0.10
FORM 3 (*a* = ideal, *c* = moderate)												
A	1.03	0.07	0.08	0.01	0.87	0.05	1.00	-1.77	0.00	1.05	2.02	0.15
B	1.02	-0.43	0.07	0.01	1.15	0.04	1.00	-3.06	0.00	1.05	2.02	0.15
FORM 4 (*a* = ideal, *c* = severe)												
A	1.03	0.07	0.10	0.01	0.87	0.06	1.00	-1.77	0.00	1.05	2.02	0.20
B	1.02	-0.43	0.10	0.01	1.15	0.06	1.00	-3.06	0.00	1.05	2.02	0.20
FORM 5 (*a* = ideal, *c* = very severe)												
A	1.03	0.07	0.12	0.01	0.87	0.08	1.00	-1.77	0.00	1.05	2.02	0.25
B	1.02	-0.43	0.13	0.01	1.15	0.07	1.00	-3.06	0.01	1.05	2.02	0.25

Table B2

Descriptive Statistics of 60 Operational *a*, *b*, and *c* Item Parameters for Phase 1Forms

	Mean			Standard Deviation			Minimum			Maximum		
FORM	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*
FORM 6 (*a* =ideal, *c* = ideal)												
A	1.03	0.07	0.02	0.01	0.87	0.00	1	-1.77	0.00	1.05	2.02	0
B	1.02	-0.43	0.02	0.01	1.15	0.00	1	-3.06	0.00	1.05	2.02	0
FORM 7 (*a* = mild, *c* = ideal)												
A	0.85	0.07	0.00	0.09	0.87	0.00	0.70	-1.77	0.00	1.00	2.02	0.00
B	0.85	-0.43	0.00	0.09	1.15	0.00	0.71	-3.06	0.00	0.99	2.02	0.00
FORM 8 (*a* = moderate, *c* = ideal)												
A	0.85	0.07	0.00	0.18	0.87	0.00	0.52	-1.77	0.00	1.12	2.02	0.00
B	0.81	-0.43	0.00	0.19	1.15	0.00	0.53	-3.06	0.00	1.14	2.02	0.00
FORM 9 (*a* =severe, *c* = ideal)												
A	0.80	0.07	0.00	0.21	0.87	0.00	0.40	-1.77	0.00	1.17	2.02	0.00
B	0.76	-0.43	0.00	0.23	1.15	0.00	0.41	-3.06	0.00	1.18	2.02	0.00
FORM 10 (*a* = very severe, *c* = ideal)												
A	0.78	0.07	0.00	0.24	0.87	0.00	0.34	-1.77	0.00	1.28	2.02	0.00
B	0.78	-0.43	0.00	0.29	1.15	0.00	0.33	-3.06	0.00	1.29	2.02	0.00

Table B3

Descriptive Statistics of 60 Operational *a*, *b*, and *c* Item Parameters used in Phase 2

	Mean			Standard Deviation			Minimum			Maximum		
FORM	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*
FORM 11 (*a* = ideal, *c* = ideal)												
A	1.03	0.07	0.00	0.01	0.87	0.00	1.00	-1.77	0.00	1.05	2.02	0.00
B	1.02	-0.43	0.00	0.01	1.15	0.00	1.00	-3.06	0.00	1.05	2.02	0.00
C	1.02	-0.43	0.00	0.01	1.14	0.00	1.00	-3.06	0.00	1.05	2.02	0.00
D	1.02	-0.38	0.00	0.01	1.16	0.00	1.00	-3.06	0.00	1.05	2.02	0.00
E	1.02	-0.34	0.00	0.01	1.13	0.00	1.00	-2.96	0.00	1.05	2.02	0.00
FORM 12 (*a* = moderate, *c* = moderate)												
A	0.76	0.07	0.09	0.17	0.87	0.04	0.51	-1.77	0.01	1.10	2.02	0.14
B	0.82	-0.43	0.07	0.17	1.15	0.05	0.54	-3.06	0.00	1.09	2.02	0.15
C	0.80	-0.43	0.08	0.16	1.14	0.05	0.53	-3.06	0.00	1.08	2.02	0.15
D	0.74	-0.38	0.09	0.18	1.16	0.04	0.50	-3.06	0.00	1.08	2.02	0.15
E	0.79	-0.34	0.09	0.17	1.13	0.04	0.53	-2.96	0.00	1.10	2.02	0.15
FORM 13 (*a* = moderate, *c* = severe)												
A	0.84	0.07	0.11	0.17	0.87	0.06	0.50	-1.77	0.00	1.09	2.02	0.20
B	0.79	-0.43	0.09	0.17	1.15	0.06	0.51	-3.06	0.00	1.10	2.02	0.19
C	0.82	-0.43	0.10	0.17	1.14	0.06	0.52	-3.06	0.00	1.08	2.02	0.20
D	0.80	-0.38	0.09	0.16	1.16	0.06	0.51	-3.06	0.00	1.10	2.02	0.20
E	0.78	-0.34	0.10	0.18	1.13	0.05	0.50	-2.96	0.00	1.09	2.02	0.20
FORM 14 (*a* =moderate, *c* =very severe)												
A	0.80	0.07	0.12	0.18	0.87	0.07	0.51	-1.77	0.00	1.09	2.02	0.25
B	0.78	-0.43	0.13	0.16	1.15	0.08	0.51	-3.06	0.00	1.08	2.02	0.25
C	0.78	-0.43	0.13	0.17	1.14	0.07	0.51	-3.06	0.00	1.09	2.02	0.24
D	0.80	-0.38	0.12	0.18	1.16	0.06	0.51	-3.06	0.01	1.10	2.02	0.23
E	0.78	-0.34	0.13	0.17	1.13	0.07	0.50	-2.96	0.01	1.07	2.02	0.25

Table B4

Descriptive Statistics of 60 Operational a, b, and c Item Parameters used in Phase 2

	Mean			Standard Deviation			Minimum			Maximum		
FORM	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*
FORM 15 (*a* = severe, *c* =moderate)												
A	0.84	0.07	0.08	0.22	0.87	0.04	0.41	-1.77	0.00	1.15	2.02	0.15
B	0.80	-0.43	0.08	0.23	1.15	0.04	0.40	-3.06	0.00	1.16	2.02	0.15
C	0.79	-0.43	0.07	0.25	1.14	0.05	0.43	-3.06	0.00	1.20	2.02	0.15
D	0.80	-0.38	0.07	0.25	1.16	0.04	0.43	-3.06	0.00	1.19	2.02	0.15
E	0.84	-0.34	0.08	0.22	1.13	0.05	0.42	-2.96	0.00	1.17	2.02	0.15
FORM 16 (*a* = severe, *c* =severe)												
A	0.81	0.07	0.11	0.23	0.87	0.05	0.41	-1.77	0.00	1.18	2.02	0.20
B	0.81	-0.43	0.09	0.24	1.15	0.05	0.41	-3.06	0.00	1.19	2.02	0.19
C	0.79	-0.43	0.10	0.25	1.14	0.05	0.42	-3.06	0.00	1.20	2.02	0.20
D	0.81	-0.38	0.09	0.23	1.16	0.06	0.41	-3.06	0.00	1.19	2.02	0.20
E	0.80	-0.34	0.09	0.22	1.13	0.06	0.45	-2.96	0.00	1.18	2.02	0.19
FORM 17 (*a* = severe, *c* = very severe)												
A	0.77	0.07	0.12	0.24	0.87	0.07	0.41	-1.77	0.01	1.18	2.02	0.24
B	0.80	-0.43	0.12	0.22	1.15	0.07	0.40	-3.06	0.01	1.18	2.02	0.25
C	0.76	-0.43	0.12	0.23	1.14	0.06	0.41	-3.06	0.00	1.19	2.02	0.24
D	0.82	-0.38	0.12	0.26	1.16	0.07	0.43	-3.06	0.00	1.18	2.02	0.25
E	0.78	-0.34	0.13	0.21	1.13	0.07	0.43	-2.96	0.01	1.19	2.02	0.25
FORM 18 (*a* = very severe, *c* = moderate)												
A	0.79	0.07	0.07	0.30	0.87	0.04	0.30	-1.77	0.00	1.27	2.02	0.14
B	0.83	-0.43	0.08	0.30	1.15	0.04	0.32	-3.06	0.00	1.29	2.02	0.15
C	0.76	-0.43	0.07	0.30	1.14	0.04	0.30	-3.06	0.00	1.25	2.02	0.15
D	0.83	-0.38	0.07	0.29	1.16	0.04	0.30	-3.06	0.00	1.26	2.02	0.15
E	0.78	-0.34	0.08	0.31	1.13	0.04	0.30	-2.96	0.00	1.29	2.02	0.15

Table B5

Descriptive Statistics of 60 Operational *a*, *b*, and *c* Item Parameters used in Phase 2

	Mean			Standard Deviation			Minimum			Maximum		
FORM	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*
				FORM 19 (*a* = very severe, *c* =severe)								
A	0.78	0.07	0.11	0.31	0.87	0.06	0.31	-1.77	0.00	1.28	2.02	0.20
B	0.84	-0.43	0.10	0.28	1.15	0.06	0.31	-3.06	0.00	1.29	2.02	0.20
C	0.77	-0.43	0.10	0.27	1.14	0.05	0.31	-3.06	0.01	1.29	2.02	0.20
D	0.82	-0.38	0.10	0.28	1.16	0.06	0.34	-3.06	0.00	1.29	2.02	0.20
E	0.84	-0.34	0.10	0.30	1.13	0.05	0.31	-2.96	0.01	1.28	2.02	0.20
				FORM 20 (*a* = very severe, *c* =very severe)								
A	0.79	0.07	0.13	0.28	0.87	0.08	0.31	-1.77	0.00	1.29	2.02	0.25
B	0.80	-0.43	0.10	0.31	1.15	0.08	0.31	-3.06	0.00	1.30	2.02	0.25
C	0.76	-0.43	0.12	0.32	1.14	0.07	0.30	-3.06	0.00	1.29	2.02	0.25
D	0.80	-0.38	0.13	0.29	1.16	0.07	0.30	-3.06	0.00	1.30	2.02	0.25
E	0.78	-0.34	0.14	0.31	1.13	0.07	0.30	-2.96	0.01	1.26	2.02	0.25

APPENDIX C: DESCRIPTIVE STATISTICS FOR GENERATED THETA DISTRIBUTIONS

Table C1

Generated One Dimensional and Two Dimensional Thetas

Descriptive Statistics for Modeled Theta Distributions

Group	Means		Standard Deviations		Skewness		Kurtosis		Correlation
	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1 and Theta 2
Base form	-0.003	0.000	1.000	1.001	0.000	0.005	0.006	0.002	0.302
New form	-0.004	-0.001	1.000	1.001	-0.001	0.013	0.008	-0.001	0.299
Base form	0.000	0.002	0.997	0.996	-0.006	0.005	0.015	0.000	0.599
New form	-0.001	0.003	0.999	0.998	-0.004	0.004	0.012	-0.001	0.599
Base form	0.005	0.004	1.001	1.000	0.002	0.001	0.000	-0.014	0.901
New form	0.005	0.007	1.000	1.001	0.000	0.003	-0.016	-0.002	0.901

Note:100,000 Thetas per form were modeled to be equivalent between groups and correlated at .90, .60, and .30 within groups.

Table C2

Generated One Dimensional and Two Dimensional Thetas Shifted -.60 STD

Descriptive Statistics for Modeled Theta Distributions

Group	Means		Standard Deviations		Skewness		Kurtosis		Correlation
	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1 and Theta 2
Base form	-0.001	-0.001	1.004	1.000	0.002	0.002	0.004	-0.009	0.299
New form	-0.603	-0.600	1.052	1.051	0.275	0.275	0.023	0.017	0.294
Base form	-0.001	-0.003	1.002	0.999	-0.007	0.005	0.009	-0.003	0.602
New form	-0.602	-0.604	1.052	1.050	0.280	0.273	0.022	0.019	0.599
Base form	0.001	0.002	0.998	0.999	0.013	0.012	0.015	-0.004	0.899
New form	-0.601	-0.600	1.051	1.049	0.284	0.286	0.039	0.054	0.899

Note:100,000 Thetas were shifted -0.60 STD between groups and correlated at .90, .60, and .30 within groups.

Table C3

Generated One Dimensional and Two Dimensional Thetas

Descriptive Statistics for Modeled Theta Distributions

Group	Means		Standard Deviations		Skewness		Kurtosis		Correlation
	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1	Theta 2	Theta 1 and Theta 2
Base form	-0.001	-0.003	0.999	0.996	0.017	-0.004	0.009	-0.028	0.304
New form	-1.199	-1.206	1.108	1.102	0.534	0.499	0.280	0.140	0.302
Base form	0.002	0.000	0.997	0.999	0.013	0.014	0.020	-0.013	0.601
New form	-1.198	-1.201	1.106	1.106	0.516	0.513	0.210	0.190	0.596
Base form	-0.002	-0.001	1.002	1.003	-0.005	-0.003	-0.012	-0.023	0.901
New form	-1.200	-1.202	1.108	1.110	0.497	0.506	0.143	0.160	0.899

Note:100,000 Thetas were shifted -1.20 STD between groups and correlated at .90, .60, and .30 within groups.

ABOUT THE AUTHOR

Garron has worked as a psychometrician in the certification and licensing field since 2005. He is currently employed as a psychometrician at Professional Testing, Inc. in Orlando, Fl., where he is responsible for exam scoring, equating, and reporting. Previous to that, he was employed as a psychometrician at the Institute for Instructional Research and Practice at the University of South Florida. At the Institute, he was responsible for the scoring, equating, and reporting of tests for the Florida Educational Leadership Exam. In addition, he prepared technical reports for the Florida Teacher Certification Exams. Garron has proficiency in Base SAS, SAS graph, and the SAS macro language. His research interests include traditional and IRT equating, IRT item calibration, and score reporting. Garron is married to Kristie and has a four year old daughter, Eliana. He currently resides with his family in Raleigh, North Carolina.