

Comparison of Two Logistic Multidimensional Item Response Theory Models

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Abstract

Test data generated according to two different multidimensional item response theory models were compared at both the item response level and the test score level to determine if measurable differences between the models could be detected when the data sets were constrained to be equivalent in terms of item p -values. Although differences could be detected at the item level, these differences decreased as the correlation between examinee abilities increased. Furthermore, these item differences were small in magnitude and could be considered unimportant or insignificant from a practical standpoint. No differences were found at the total test score level, and it was concluded that, at least for the data used in this study, the models were indistinguishable.

Comparison of Two Logistic Multidimensional Item Response Theory Models

Psychometricians who have some interest in multidimensional item response theory (MIRT) modeling may be familiar with the terms, *compensatory* and *noncompensatory* as they relate to two general model classification schemes. Ansley and Forsyth (1985) contrasted the two types of model classifications as follows. "Compensatory models, unlike noncompensatory models, permit high ability on one dimension to compensate for low ability on another dimension in terms of probability of correct response. In the noncompensatory models, the minimum factor (probability) in the denominator is the upper bound for the probability of a correct response. Thus, for a two-dimensional item, a person with a very low ability on one dimension and very high ability on the other has a very low probability of correctly answering the item" (p. 40).

Typically, MIRT models of the compensatory type, such as the logistic MIRT model (Doody-Bogan & Yen, 1983; Hattie, 1981; Reckase, 1985, 1986) or the normal ogive MIRT model (Samejima, 1974) imply linear combinations of the multidimensional abilities in the exponent of the expression for the probability of a correct response. In this linear fashion, a low ability on one or more of the k ability dimensions can be compensated by a higher ability on one or more of the remaining dimensions. Because the compensation is a characteristic of this linear combination, such models are probably more accurately labeled *linear* MIRT models. A typical linear logistic MIRT model of the compensatory type can be written as

$$P_j(\theta_i) = c_j + (1 - c_j) \frac{e^{[\sum_{m=1}^k f_{ijm}] + d_j}}{1 + e^{[\sum_{m=1}^k f_{ijm}] + d_j}} \quad (1)$$

where

$$f_{ijm} = a_{jm} \theta_{im}$$

c_j = the pseudo-guessing parameter of the j th item,
 a_{jm} = the discrimination parameter for the j th item on the m th dimension,
 d_j = the difficulty parameter for the j th item, and
 θ_{im} = the m th element in the i th person's ability vector, θ_i .

In this model the favorable response probability, $P_j(\theta_i)$, is bounded from below by c_j . However, because the upper bound of $P_j(\theta_i)$ is not a function of any one ability dimension, it increases monotonically as $\sum_{m=1}^k f_{ijm}$ increases.

On the other hand, noncompensatory MIRT models (Simpson, 1978; Embretson, 1984) describe the probability of a favorable response in terms of a product of k functions of ability on a single dimension and item characteristics. In its most common form, a logistic MIRT model of this noncompensatory or multiplicative type can be written as

$$P_j(\theta_i) = c_j + (1 - c_j) \prod_{m=1}^k \frac{e^{f_{ijm}}}{(1 + e^{f_{ijm}})}, \quad (2)$$

where now we let $f_{ijm} = [a_{jm} (\theta_{im} - b_{jm})]$ with b_{jm} = the difficulty parameter for the j th item on the m th dimension. $P_j(\theta_i)$ is bounded by an upper asymptote equal to the minimum of $\exp\{f_{ijm}\}/(1 + \exp\{f_{ijm}\})$, and the lower asymptote, c_j , for any given examinee with $\theta = \theta_i$. Thus, the noncompensatory nature of the model is due to the fact that $P_j(\theta_i)$ can never be greater than the minimum value of the terms in the product, $\exp\{f_{ijm}\}/(1 + \exp\{f_{ijm}\})$, a function of the smallest value of the k

ability dimensions for a given examinee. Because of its multiplicative form, the model is more generally labeled as a *multiplicative* MIRT model.

Researchers have used the multiplicative MIRT model to examine characteristics of unidimensional item response theory parameter estimates derived from MIRT response data (Ansley & Forsyth, 1985) and to model certain multicomponent latent traits in response processes (Embretson, 1984). Reckase (1985) has used a linear MIRT model on real response data to estimate two-dimensional item and person parameters on an ACT Assessment Mathematics Usage test. However, no one has actually shown that one model is more representative of the actual item-examinee response process than the other. It may even be possible that one model may be appropriate under one set of circumstances while the other type may be more appropriate in other situations.

In this paper we investigate the differences between item responses generated by these two logistic MIRT models. We have been interested in determining whether or not it is possible to distinguish one model or process from the other through some evaluation of response data. More specifically, our concern has been in establishing whether or not it is possible to detect differences between these two MIRT models, either at the item response or test score level, when the item parameters from each MIRT model have been matched or equated in some sense.

The first task was to establish the item parameters from one of the logistic MIRT models that would produce "reasonable" p -values or proportion-correct indices for a specified examinee population. Therefore, a target distribution of p -values for a 20-item test was conceived and item parameters for a linear or compensatory MIRT model were chosen, basically by trial-and-error, until the expected p -value with respect to this examinee population matched the target distribution. Table 1 gives the set of item parameters for the 20 items for the model given by equation (1). The table also gives the expected value of each p -value under the assumption that the ability vector, θ , for the examinee population,

was distributed as bivariate normal with mean vector, $\mathbf{0}$, and variance-covariance matrix of ones along the diagonal and with nondiagonal values equal to rho (.00, .25, .50, or .75). All c -parameters were set to zero.

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 Insert Table 1 Here

In order to produce a comparable or "matched" set of noncompensatory, or multiplicative model item parameters, estimates of these item parameters were obtained by minimizing

$$\sum_{i=1}^N \{ [P_C(\boldsymbol{\theta}_p, \mathbf{a}, d)] - [P_{NC}(\boldsymbol{\theta}_p, \hat{\mathbf{a}}, \hat{\mathbf{b}})] \}^2 \quad (3)$$

for $N = 2000$ randomly selected examinees with ability, $\boldsymbol{\theta}$, distributed as given previously, where P_C and P_{NC} represent logistic MIRT models given by equations (1) and (2), respectively. This process was repeated for 10 replications for each of $k = 1, 2, \dots, 20$ items to insure that the estimates obtained weren't unduly influenced by the samples selected or the starting values used. Mean values of the replication estimates yielded the noncompensatory item parameters listed in Tables 2-5, for rho values of .00, .25, .50, and .75. The expected value of each item's p -value is given in the last column of each table. Because the least squares minimization procedure produces unbiased estimates of P_{NC} , the expected value of each p -value under the noncompensatory model should be equal to that of the compensatory model, within some estimation error. Equivalence of p -values was the critical matching criterion between the two MIRT models.

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 Insert Tables 2-5
 Here

Model Differences at the Total Test Level

By treating the two sets of item parameters as known for each of the two MIRT models, we first investigated the differences between expected number-correct score frequencies of a 20-item test when $\boldsymbol{\theta}$ was distributed as a bivariate normal random vector with distributions given previously. These frequencies were estimated by evaluating either the number-correct distribution under the compensatory model, $h_C(y)$ or the noncompensatory model, $h_{NC}(y)$, for $y = 0, 1, 2, \dots, 20$, or

$$h_C(y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_C(y | \boldsymbol{\theta}) g(\boldsymbol{\theta}) d\theta_1 d\theta_2 \quad (4)$$

and

$$h_{NC}(y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{NC}(y | \boldsymbol{\theta}) g(\boldsymbol{\theta}) d\theta_1 d\theta_2 . \quad (5)$$

In each case, the conditional frequencies, $f_C(y | \boldsymbol{\theta})$ and $f_{NC}(y | \boldsymbol{\theta})$, were computed using either models (1) or (2), and a recursive procedure described by Lord and Wingersky (1984). Table 6 gives the signed differences between the frequencies, $h_C(y) - h_{NC}(y)$, for $y = 0, 1, 2, \dots, 20$, for rho values of .00, .25, .50, and .75. The greatest differences, as expected, occurred for the highest number-correct scores, but the differences in frequencies were small, never greater than .015. For most number-correct score values, these differences became smaller as rho increased.

Another way to assess the significance of these differences was to determine how much data would need to be observed before the differences were statistically detectable. This was done by calculating the minimum sample size required to reject the homogeneity of parallel populations with given levels of test significance and power. These calculations assumed a multivariate normal approximation for each model's multinomial distribution of observed-score frequencies which in turn produced the quadratic form of the noncentrality parameter of a noncentral chi square distribution. The minimum sample size followed as a direct function of this parameter, the specified test significance, and power. For example, with a significance level of .01 and power equal to .95, the minimum sample sizes were 1678, 3242, 7466, and 15311 for correlated ability distributions with rho equal to .00, .25, .50, and .75, respectively. These sample sizes state that even in the unlikely event of uncorrelated ability distributions, it would *still* require at least 1678 observed scores from both the compensatory *and* noncompensatory MIRT models before the null hypothesis of model equivalence could be rejected with a power of .95.

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Insert Table 6 Here
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The first four (central) moments of each number-correct distribution are given in Table 7 for each value of rho. Both distributions were negatively skewed with the compensatory distribution slightly more platykurtic and both were generally flatter than the normal distribution. The variances of the number-correct scores increased with an increase in rho, and in general, the distributions of number-correct scores became increasingly similar as rho increased.

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Insert Table 7 Here
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A contour plot of the (signed) difference between the number-correct true scores under the two models, or

$$\sum_{j=1}^{20} P_{jC}(\boldsymbol{\theta}) - \sum_{j=1}^{20} P_{jNC}(\boldsymbol{\theta})$$

was another way to observe model differences at the total test level for various (θ_1, θ_2) points in the ability space. The greatest differences occurred when either θ_1 or θ_2 was low. See Figures 1-4 for rho values of .00, .25, .50, and .75, respectively. It should be noted that, in these plots, the only influence of rho was through the values of the noncompensatory item parameters. Recall that the compensatory item parameters were fixed for all values of rho. Therefore, when interpreting these contour plots, one has to mentally superimpose the appropriate bivariate normal distribution over the contours in order to evaluate the importance of the true-score differences observed.

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 Insert Figures 1-4
 Here

Another way to compare the two MIRT models was to observe the amount of multidimensional information (MINF) for different points in the ability space between the two models. MINF has been defined (Reckase, 1986) as a direct generalization of the unidimensional IRT concept of item information (i.e, the ratio of the square of the slope of the item characteristic curve at an ability point, θ , to the variance of the error of the item score at that level of θ). For the definition of MINF, the slope of the item characteristic surface must be evaluated in a particular direction, α , a vector of angles with the coordinate axes of the ability space.

Plots of the absolute difference between the compensatory and noncompensatory test information vectors (i.e, the sum of item information across

the 20 items) for item parameters estimated with rho values of .00, .25, .50, and .75 (Figures 5-8, respectively) showed that model differences might be significant if abilities were negatively correlated. However, for all "likely" ability distributions, there were no meaningful differences in MINF between the two models, and these absolute differences appeared to decrease as rho increased.

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 Insert Figures 5-8 Here

Model Differences at the Item Level

It was also of interest to evaluate the differences between models at the single item response level. There were two ways in which this was done. The first involved the evaluation of the *ideal observer index* (Davey, Levine, & Williams, 1989; Levine, Drasgow, Williams, McCusker, & Thomasson, 1990). A more complete definition of this index is provided in the appendix of this paper. However, a simplified definition is as follows. The *ideal observer index* (IOI) is a measure of the proportional number of times that a correct decision is made concerning which of the two competing models produced a particular response to an item. The decision is one that is made hypothetically by an "ideal observer," or an individual who has access to all of the information necessary to yield the highest possible percent of model classification (i.e., compensatory vs. noncompensatory). As far as the ideal observer is concerned, if the item response data fail to distinguish between the two competing models, then the value of this index would be at or near the chance level of .5. Conversely, readily distinguishable models should yield an index near 1.0.

Table 8 shows that the IOI was greater than chance, implying that there was a difference between the models for all 20 items. However, the IOI was never greater than .60 and was greater than .55 for only three items, numbers 3, 6,

and 7, when rho was .00. The value of the IOI decreased for each item as rho increased, implying that it became more difficult to distinguish between the models as the correlation coefficient increased.

One way to think of the magnitude of the IOI was to imagine how many trials of the IO experiment would be necessary before the ideal observer could ascertain, with some given level of certainty, that the models were actually distinguishable. This would be comparable to a test of the difference between any obtained IOI from Table 8 and the null proportion of correct model classifications due to chance. For example, to be able to detect a true difference between the models for item number 6 with a zero value of rho would require at least 40 trials of the IO experiment. This would be comparable to a test of the null proportion of correct classifications due to chance or .50 versus the (true) alternative proportion (.555) with a significance of .01 and power of .95. Conversely, a true IOI of .52 would require more than 290 trials at similar levels of test significance and power.

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 Insert Table 8 Here

Another way to evaluate model differences at the item level was to use a generalized MIRT model, or a reparameterization of both the compensatory and noncompensatory models into a single MIRT model, or

$$P_j(\theta_i) = c_j + (1-c_j) \frac{e^{f_{ij1}+f_{ij2}}}{1 + e^{f_{ij1}+f_{ij2}} + \mu(e^{f_{ij1}} + e^{f_{ij2}})}, \quad (6)$$

where μ represented an indicator variable such that

$$\mu = \begin{cases} 0, & \text{for the linear or compensatory MIRT model,} \\ 1, & \text{for the multiplicative or noncompensatory MIRT model.} \end{cases}$$

Item response data, x_{ij} , were generated from samples of size $N = 2000$ of θ_i drawn from the bivariate normal distributions mentioned previously. The response data were known to have been produced by either the compensatory or noncompensatory MIRT model and were simulated by comparing the known values of $P_j(\theta_i)$ to a pseudorandomly drawn uniform deviate, ω , such that

$$x_{ij} = \begin{cases} 1, & 0 \leq \omega < P_j(\theta_i) \\ 0, & P_j(\theta_i) \leq \omega < 1. \end{cases}$$

The least squares estimation procedure was used to estimate the generalized MIRT model parameters. Each estimation was replicated 10 times with randomly selected starting values. Either four or five unique item parameters were estimated from the generalized MIRT model, as given by equation (6). The same item parameters that were given in tables 1-5 were used to generate the response data for the estimation procedure. When the response data were generated by the compensatory model, a_1 , a_2 , and d (i.e., $d = -a_1b_1 - a_2b_2$) as well as μ , were estimated. When the response data were generated by the noncompensatory model, a_1 , a_2 , b_1 , b_2 , and μ were estimated.

Table 9 shows the average bias in the item parameter estimates and the standard deviations of the estimates (in parentheses). For compensatory data, the model parameter, μ was estimated fairly accurately for the uncorrelated situation, but the amount of bias and the standard deviation of the estimates increased as rho increased. A similar situation occurred with noncompensatory data. However, although the amount of estimation error increased as the correlation between the abilities increased, the model still remained *identifiable*, in the sense that for compensatory data, the μ estimates were statistically "close" to zero.

Likewise, for noncompensatory data, the μ estimates were statistically "close" to one.

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Insert Table 9 Here
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The IOI analysis and the generalized MIRT model estimation gave similar results. That is, there were model differences at the item level, but these differences tended to decrease as the correlation in abilities increased. The generalized MIRT analysis also suggested that these differences might still be estimable, however, even when abilities are strongly correlated.

Summary and Conclusions

These analyses and results seem to indicate that even though it is difficult to observe model differences at the overall test score level, there still may be measurable differences between the responses at the item level. Because the matching criterion between the two models resulted in similar expected p -values, we anticipated small differences at the total test score response level, or at the true score level. The differences that were detected at this level were consistent with the differences implied in the two models. Fewer high, number-correct scores or estimated true scores were observed from the noncompensatory model, but these and other total test differences decreased as ρ increased. As for the item response level analysis, both the IOI and the generalized MIRT model estimation showed that it is possible to quantify these differences and to distinguish between the data generated by carefully matched item response models of these two types. However, these differences, although real, are very small and probably not significant from any practical standpoint.

Although it is difficult to generalize beyond the two-dimensional situation used in the present study, it would appear to be difficult to distinguish between the two models without the benefit of any prior knowledge of item parameters or abilities. Even *with* such prior knowledge, response data generated by the models are nearly indistinguishable, especially with correlated abilities, which is likely the case in many real testing situations.

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Appendix

Analytical Definition of the *Ideal Observer Index*

A hypothetical observer is presented with two abilities, t_1 and t_2 , each with their associated item responses, u_1 and u_2 . The observer is informed that one ability-response pair was generated by one of two competing item response models, while the other pair was generated under the second model. The task is to correctly match each ability-response pair with the proper generating model. To make this decision, the observer is given access to both competing item response functions, P_1 and P_2 , and the common ability distribution, $f(t)$.

An ideal observer bases this decision on an optimal rule, δ , which is determined by the ratio of likelihood functions, $L_i(t_j, u_j) = P_i(t_j)^{u_j} Q_i(t_j)^{1-u_j}$, where $Q_i(t_j) = 1 - P_i(t_j)$, $i = 1, 2$; $j = 1, 2$. The decision rule, δ , is then defined as

$$\delta = \begin{cases} \text{if } L_1(t_1, u_1) \cdot L_2(t_2, u_2) > L_1(t_2, u_2) \cdot L_2(t_1, u_1), \text{ then decide model } \{P_1; f\} \\ \text{produced sample } \{t_1, u_1\} \text{ while model } \{P_2; f\} \text{ produced } \{t_2, u_2\}. \\ \\ \text{if } L_1(t_2, u_2) \cdot L_2(t_1, u_1) > L_1(t_1, u_1) \cdot L_2(t_2, u_2), \text{ then decide model } \{P_2; f\} \\ \text{produced sample } \{t_1, u_1\} \text{ while model } \{P_1; f\} \text{ produced } \{t_2, u_2\}. \end{cases}$$

The probability of this decision rule being correct, given the model, is

$$\begin{aligned} \text{Prob}[\delta \text{ correct} | \text{model}] = & \text{Prob}[L_1(t_1, u_1) \cdot L_2(t_2, u_2) > L_1(t_2, u_2) \cdot L_2(t_1, u_1) | \{P_1; f\} \& \{P_2; f\}] + \\ & \text{Prob}[L_1(t_2, u_2) \cdot L_2(t_1, u_1) > L_1(t_1, u_1) \cdot L_2(t_2, u_2) | \{P_2; f\} \& \{P_1; f\}]. \end{aligned}$$

The response pair, \mathbf{u} , where $\mathbf{u} = (u_1, u_2)$, can be defined in four possible patterns: (1,1), (1,0), (0,1), and (0,0). Therefore,

$$\begin{aligned} & \text{Prob}[L_1(t_1, u_1) \cdot L_2(t_2, u_2) > L_1(t_2, u_2) \cdot L_2(t_1, u_1) | \{P_1; f\} \& \{P_2; f\}] = \\ & \text{Prob}[P_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot P_2(t_1) | \mathbf{u}=(1,1)] \cdot \text{Prob}[\mathbf{u}=(1,1) | \{P_1; f\} \& \{P_2; f\}] \\ + & \text{Prob}[P_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot P_2(t_1) | \mathbf{u}=(1,0)] \cdot \text{Prob}[\mathbf{u}=(1,0) | \{P_1; f\} \& \{P_2; f\}] \\ + & \text{Prob}[Q_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot Q_2(t_1) | \mathbf{u}=(0,1)] \cdot \text{Prob}[\mathbf{u}=(0,1) | \{P_1; f\} \& \{P_2; f\}] \\ + & \text{Prob}[Q_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot Q_2(t_1) | \mathbf{u}=(0,0)] \cdot \text{Prob}[\mathbf{u}=(0,0) | \{P_1; f\} \& \{P_2; f\}]. \end{aligned}$$

$$\text{Define } \pi_{ij} = \iint P_1(t)^{u_i} Q_1(t)^{1-u_i} P_2(g)^{u_j} Q_2(g)^{1-u_j} f(t) f(g) dt dg.$$

$$\text{Then, } \text{Prob}[L_1(t_1, u_1) \cdot L_2(t_2, u_2) > L_1(t_2, u_2) \cdot L_2(t_1, u_1) | \{P_1; f\} \& \{P_2; f\}] =$$

$$\begin{aligned} & \pi_{11} \text{Prob}[P_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot P_2(t_1) | \mathbf{u}=(1,1)] + \\ & \pi_{10} \text{Prob}[P_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot P_2(t_1) | \mathbf{u}=(1,0)] + \\ & \pi_{01} \text{Prob}[Q_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot Q_2(t_1) | \mathbf{u}=(0,1)] + \\ & \pi_{00} \text{Prob}[Q_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot Q_2(t_1) | \mathbf{u}=(0,0)]. \end{aligned}$$

$$\text{Similarly, } \text{Prob}[L_1(t_2, u_2) \cdot L_2(t_1, u_1) > L_1(t_1, u_1) \cdot L_2(t_2, u_2) | \{P_2; f\} \& \{P_1; f\}] =$$

$$\begin{aligned} & \text{Prob}[P_1(t_2) \cdot P_2(t_1) > P_1(t_1) \cdot P_2(t_2) | \mathbf{u}=(1,1)] \cdot \text{Prob}[\mathbf{u}=(1,1) | \{P_2; f\} \& \{P_1; f\}] \\ + & \text{Prob}[P_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot P_2(t_2) | \mathbf{u}=(1,0)] \cdot \text{Prob}[\mathbf{u}=(1,0) | \{P_2; f\} \& \{P_1; f\}] \\ + & \text{Prob}[Q_1(t_2) \cdot P_2(t_1) > P_1(t_1) \cdot Q_2(t_2) | \mathbf{u}=(0,1)] \cdot \text{Prob}[\mathbf{u}=(0,1) | \{P_2; f\} \& \{P_1; f\}] \\ + & \text{Prob}[Q_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot Q_2(t_2) | \mathbf{u}=(0,0)] \cdot \text{Prob}[\mathbf{u}=(0,0) | \{P_2; f\} \& \{P_1; f\}]. \end{aligned}$$

Then, $\text{Prob}[L_1(t_2, u_2) \cdot L_2(t_1, u_1) > L_1(t_1, u_1) \cdot L_2(t_2, u_2) | \{P_2; f\} \& \{P_1; f\}] =$

$$\begin{aligned} & \pi_{11} \text{Prob}[P_1(t_2) \cdot P_2(t_1) > P_1(t_1) \cdot P_2(t_2) | \mathbf{u} = (1,1)] + \\ & \pi_{10} \text{Prob}[P_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot P_2(t_2) | \mathbf{u} = (1,0)] + \\ & \pi_{01} \text{Prob}[Q_1(t_2) \cdot P_2(t_1) > P_1(t_1) \cdot Q_2(t_2) | \mathbf{u} = (0,1)] + \\ & \pi_{00} \text{Prob}[Q_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot Q_2(t_2) | \mathbf{u} = (0,0)]. \end{aligned}$$

Let $\Omega_{u_1 u_2}$ be defined as that region of the ability space where

$$P_1(t_1)^{u_1} \cdot Q_1(t_1)^{u_1-1} \cdot P_2(t_2)^{u_2} \cdot Q_2(t_2)^{u_2-1} > P_1(t_2)^{u_2} \cdot Q_1(t_2)^{u_2-1} \cdot P_2(t_1)^{u_1} \cdot Q_2(t_1)^{u_1-1}$$

holds, and likewise let $\bar{\Omega}_{u_1 u_2}$ be defined as that region of the ability space where

$$P_1(t_2)^{u_2} \cdot Q_1(t_2)^{u_2-1} \cdot P_2(t_1)^{u_1} \cdot Q_2(t_1)^{u_1-1} > P_1(t_1)^{u_1} \cdot Q_1(t_1)^{u_1-1} \cdot P_2(t_2)^{u_2} \cdot Q_2(t_2)^{u_2-1}$$

is true. Then

$$\text{Prob}[P_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot P_2(t_1) | \mathbf{u} = (1,1)] = \int \int_{\Omega_{11}} f(t) f(g) dt dg,$$

$$\text{Prob}[P_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot P_2(t_1) | \mathbf{u} = (1,0)] = \int \int_{\Omega_{10}} f(t) f(g) dt dg,$$

$$\text{Prob}[Q_1(t_1) \cdot P_2(t_2) > P_1(t_2) \cdot Q_2(t_1) | \mathbf{u} = (0,1)] = \int \int_{\Omega_{01}} f(t) f(g) dt dg,$$

and

$$\text{Prob}[Q_1(t_1) \cdot Q_2(t_2) > Q_1(t_2) \cdot Q_2(t_1) | \mathbf{u} = (0,0)] = \int \int_{\Omega_{00}} f(t) f(g) dt dg.$$

Then

$$\text{Prob}[P_1(t_2) \cdot P_2(t_1) > P_1(t_1) \cdot P_2(t_2) | \mathbf{u} = (1,1)] = \int \int_{\Omega_{11}} f(t) f(g) dt dg,$$

$$\text{Prob}[P_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot P_2(t_2) | \mathbf{u} = (0,1)] = \int \int_{\Omega_{01}} f(t) f(g) dt dg,$$

$$\text{Prob}[Q_1(t_2) \cdot P_2(t_1) > Q_2(t_2) \cdot P_1(t_1) | \mathbf{u} = (1,0)] = \int \int_{\Omega_{10}} f(t) f(g) dt dg,$$

and

$$\text{Prob}[Q_1(t_2) \cdot Q_2(t_1) > Q_1(t_1) \cdot Q_2(t_2) | \mathbf{u} = (0,0)] = \int \int_{\Omega_{00}} f(t) f(g) dt dg.$$

Thus, $\text{Prob}[\delta \text{ correct} | \text{model}] =$

$$\begin{aligned} & \pi_{11} \int \int_{\Omega_{11}} f(t) f(g) dt dg + \pi_{10} \int \int_{\Omega_{10}} f(t) f(g) dt dg + \\ & \pi_{01} \int \int_{\Omega_{01}} f(t) f(g) dt dg + \pi_{00} \int \int_{\Omega_{00}} f(t) f(g) dt dg + \\ & \pi_{11} \int \int_{\Omega_{11}} f(t) f(g) dt dg + \pi_{10} \int \int_{\Omega_{10}} f(t) f(g) dt dg + \\ & \pi_{01} \int \int_{\Omega_{10}} f(t) f(g) dt dg + \pi_{00} \int \int_{\Omega_{00}} f(t) f(g) dt dg \end{aligned}$$

or

$$\begin{aligned} & \pi_{11} + \pi_{10} \left\{ \int \int_{\Omega_{10}} f(t) f(g) dt dg + \int \int_{\Omega_{01}} f(t) f(g) dt dg \right\} + \\ & \pi_{01} \left\{ \int \int_{\Omega_{01}} f(t) f(g) dt dg + \int \int_{\Omega_{10}} f(t) f(g) dt dg \right\} + \pi_{00} \end{aligned}$$

Finally, $\text{Prob}[\delta \text{ correct}] = \text{Prob}[\delta \text{ correct} | \text{model}] \cdot \text{Prob}[\text{selecting a model}]$. Because each model is equally likely, the probability of selecting a model is equal to .5. Thus, $\text{Prob}[\delta \text{ correct}] = .5(\text{Prob}[\delta \text{ correct} | \text{model}])$.

Table 1

Original Item Parameters for the Compensatory Model

Item #	a_1	a_2	d	E(p-value) rho			
				.00	.25	.50	.75
01	0.90	1.31	-0.67	.39	.39	.40	.40
02	2.10	0.50	-1.13	.34	.35	.36	.36
03	0.89	1.10	0.52	.59	.59	.58	.58
04	0.99	1.00	-0.44	.42	.42	.43	.43
05	0.58	1.65	0.78	.63	.62	.62	.61
06	0.91	1.27	0.42	.57	.57	.57	.56
07	1.03	0.95	1.08	.69	.68	.67	.67
08	0.32	2.27	0.38	.55	.55	.55	.55
09	0.61	0.72	1.63	.80	.79	.79	.78
10	0.67	1.12	0.60	.61	.61	.60	.60
11	0.91	0.91	-0.21	.46	.46	.46	.47
12	0.64	1.72	-0.05	.49	.49	.49	.49
13	1.65	0.38	0.40	.57	.56	.56	.56
14	0.18	1.61	1.84	.78	.78	.78	.77
15	0.82	1.02	0.09	.52	.52	.52	.51
16	1.45	0.81	-0.24	.46	.46	.46	.46
17	1.64	0.62	0.85	.64	.63	.63	.62
18	0.77	0.76	-0.91	.32	.33	.34	.34
19	1.46	0.62	0.10	.52	.52	.52	.52
20	0.39	1.37	0.32	.56	.56	.55	.55

Table 2

Item Parameters for the Noncompensatory Model with $Rho = .00$

Item #	a_1	a_2	b_1	b_2	E(p-value)
01	1.26	1.60	-0.92	-0.15	.38
02	2.30	1.04	0.38	-2.28	.34
03	1.22	1.39	-1.42	-0.99	.59
04	1.32	1.35	-0.62	-0.58	.42
05	1.02	1.82	-2.71	-0.62	.62
06	1.25	1.53	-1.45	-0.79	.56
07	1.30	1.26	-1.48	-1.63	.68
08	0.92	2.38	-3.95	-0.22	.55
09	0.93	1.00	-2.75	-2.35	.80
10	1.05	1.37	-1.96	-0.90	.61
11	1.24	1.25	-0.78	-0.75	.46
12	1.07	1.92	-2.17	-0.19	.49
13	1.81	0.88	-0.36	-3.25	.56
14	0.85	1.67	-5.26	-1.17	.78
15	1.17	1.32	-1.21	-0.75	.51
16	1.71	1.23	-0.27	-1.35	.45
17	1.83	1.06	-0.68	-2.55	.63
18	1.09	1.09	-0.31	-0.32	.32
19	1.69	1.07	-0.35	-1.98	.51
20	0.88	1.54	-2.98	-0.41	.55

Table 3

Item Parameters for the Noncompensatory Model with $Rho = .25$

Item #	a_1	a_2	b_1	b_2	E(p-value)
01	1.38	1.74	-0.79	-0.14	.39
02	2.40	1.14	0.35	-1.88	.34
03	1.36	1.50	-1.27	-0.91	.58
04	1.44	1.45	-0.56	-0.51	.42
05	1.17	1.94	-2.30	-0.60	.61
06	1.40	1.66	-1.28	-0.73	.56
07	1.45	1.40	-1.34	-1.47	.72
08	1.05	2.47	-3.30	-0.22	.55
09	1.02	1.09	-2.49	-2.17	.79
10	1.17	1.47	-1.72	-0.85	.60
11	1.34	1.34	-0.71	-0.68	.46
12	1.21	2.06	-1.82	-0.20	.49
13	1.90	0.98	-0.36	-2.80	.56
14	0.93	1.72	-4.65	-1.15	.78
15	1.29	1.42	-1.08	-0.69	.51
16	1.84	1.33	-0.27	-1.16	.45
17	1.97	1.20	-0.66	-2.19	.62
18	1.15	1.16	-0.28	-0.27	.33
19	1.80	1.18	-0.35	-1.71	.51
20	0.98	1.61	-2.57	-0.40	.55

Table 4

Item Parameters for the Noncompensatory Model with $Rho = .50$

Item #	a_1	a_2	b_1	b_2	E(p-value)
01	1.52	1.82	-0.66	-0.12	.39
02	2.48	1.27	0.32	-1.51	.35
03	1.49	1.63	-1.14	-0.85	.58
04	1.54	1.54	-0.50	-0.45	.42
05	1.32	2.04	-1.97	-0.59	.61
06	1.55	1.79	-1.13	-0.68	.56
07	1.58	1.55	-1.23	-1.33	.67
08	1.20	2.51	-2.78	-0.22	.55
09	1.10	1.17	-2.30	-2.03	.78
10	1.28	1.56	-1.53	-0.80	.60
11	1.44	1.43	-0.64	-0.61	.46
12	1.36	2.13	-1.54	-0.19	.49
13	1.96	1.09	-0.36	-2.39	.56
14	1.03	1.77	-4.07	-1.13	.77
15	1.39	1.51	-0.97	-0.64	.51
16	1.95	1.47	-0.26	-0.99	.46
17	2.08	1.35	-0.63	-1.89	.62
18	1.21	1.20	-0.23	-0.23	.33
19	1.89	1.30	-0.34	-1.46	.51
20	1.08	1.66	-2.23	-0.40	.55

Table 5

Item Parameters for the Noncompensatory Model with $Rho = .75$

Item #	a_1	a_2	b_1	b_2	E(p-value)
01	1.65	1.92	-0.51	-0.10	.40
02	2.53	1.43	0.31	-1.14	.35
03	1.60	1.73	-1.01	-0.77	.58
04	1.63	1.64	-0.42	-0.39	.43
05	1.48	2.14	-1.67	-0.57	.61
06	1.69	1.92	-0.98	-0.62	.56
07	1.69	1.66	-1.13	-1.21	.66
08	1.36	2.57	-2.25	-0.22	.55
09	1.15	1.21	-2.17	-1.93	.78
10	1.38	1.63	-1.36	-0.76	.60
11	1.50	1.51	-0.56	-0.54	.46
12	1.53	2.23	-1.22	-0.19	.49
13	1.98	1.26	-0.36	-1.99	.56
14	1.15	1.78	-3.60	-1.11	.77
15	1.47	1.59	-0.85	-0.59	.51
16	2.03	1.63	-0.23	-0.81	.46
17	2.15	1.53	-0.61	-1.60	.62
18	1.24	1.24	-0.18	-0.18	.34
19	1.94	1.44	-0.33	-1.23	.51
20	1.17	1.70	-1.92	-0.40	.55

Table 6

Compensatory Minus Noncompensatory Density Differences in Number-correct Score

Number-correct score (y)	rho			
	.00	.25	.50	.75
20	.013	.014	.014	.011
19	.015	.012	.009	.004
18	.012	.007	.003	.000
17	.007	.003	.000	-.002
16	.002	-.001	-.002	-.003
15	-.003	-.003	-.004	-.003
14	-.006	-.005	-.004	-.003
13	-.009	-.007	-.005	-.003
12	-.011	-.007	-.005	-.002
11	-.012	-.008	-.005	-.002
10	-.012	-.008	-.004	-.001
9	-.011	-.007	-.004	-.001
8	-.009	-.006	-.003	.000
7	-.006	-.004	-.002	.001
6	-.003	-.002	-.001	.001
5	.001	.000	.001	.002
4	.005	.002	.002	.002
3	.008	.005	.003	.002
2	.009	.006	.004	.001
1	.008	.006	.003	-.001
0	-.005	.003	.001	-.004

Table 7

Central Moments of Number-correct Scores

MIRT Models	rho	Mean	Second Central Moment	Third Central Moment	Fourth Central Moment
	.00	10.90	25.79	-16.56	1362.83
Compensatory	.25	10.88	29.40	-20.44	1680.36
	.50	10.86	32.64	-24.01	1980.03
	.75	10.84	35.57	-27.27	2262.98
	.00	10.79	20.67	-9.42	946.49
Noncompensatory	.25	10.78	25.43	-15.86	1336.75
	.50	10.78	30.12	-24.30	1760.64
	.75	10.78	34.70	-32.74	2200.57

Table 8

Ideal Observer Index

Item #	rho			
	.00	.25	.50	.75
01	.5479	.5397	.5295	.5179
02	.5311	.5265	.5205	.5128
03	.5513	.5418	.5307	.5183
04	.5461	.5377	.5279	.5171
05	.5421	.5353	.5265	.5157
06	.5550	.5451	.5332	.5194
07	.5511	.5419	.5304	.5175
08	.5243	.5212	.5165	.5102
09	.5276	.5227	.5162	.5092
10	.5430	.5351	.5254	.5149
11	.5435	.5355	.5260	.5156
12	.5448	.5375	.5281	.5166
13	.5291	.5246	.5185	.5112
14	.5124	.5109	.5082	.5048
15	.5456	.5370	.5271	.5161
16	.5497	.5411	.5307	.5182
17	.5442	.5371	.5276	.5162
18	.5281	.5232	.5175	.5114
19	.5425	.5352	.5260	.5156
20	.5292	.5241	.5179	.5108

Table 9

Average Bias (parameter estimate - true parameter) and Standard Deviation of Bias in Estimates of the Generalized MIRT Model Parameters

Response Data Model	rho	a ₁	a ₂	d	b ₁	b ₂	μ
Compensatory	.00	.044 (.042)	.024 (.073)	.069 (.158)			.013 (.009)
	.25	.044 (.047)	.040 (.042)	.125 (.275)			.026 (.052)
	.50	.078 (.055)	.069 (.081)	.255 (.238)			.064 (.060)
	.75	.098 (.128)	.113 (.080)	.787 (1.930)			.107 (.094)
Noncompensatory	.00	-.008 (.099)	.009 (.115)		.130 (.448)	.230 (.354)	-.199 (.163)
	.25	-.006 (.090)	-.004 (.083)		.250 (.622)	.254 (.464)	-.197 (.144)
	.50	.039 (.145)	-.076 (.104)		.191 (.888)	.183 (.265)	-.200 (.125)
	.75	-.155 (.220)	-.059 (.105)		.071 (.439)	.250 (.421)	-.288 (.175)

Note: standard deviations are in parentheses

Figure Captions

Figure 1. Difference Between Compensatory and Noncompensatory True Scores:
Rho = .00

Figure 2. Difference Between Compensatory and Noncompensatory True Scores:
Rho = .25

Figure 3. Difference Between Compensatory and Noncompensatory True Scores:
Rho = .50

Figure 4. Difference Between Compensatory and Noncompensatory True Scores:
Rho = .75

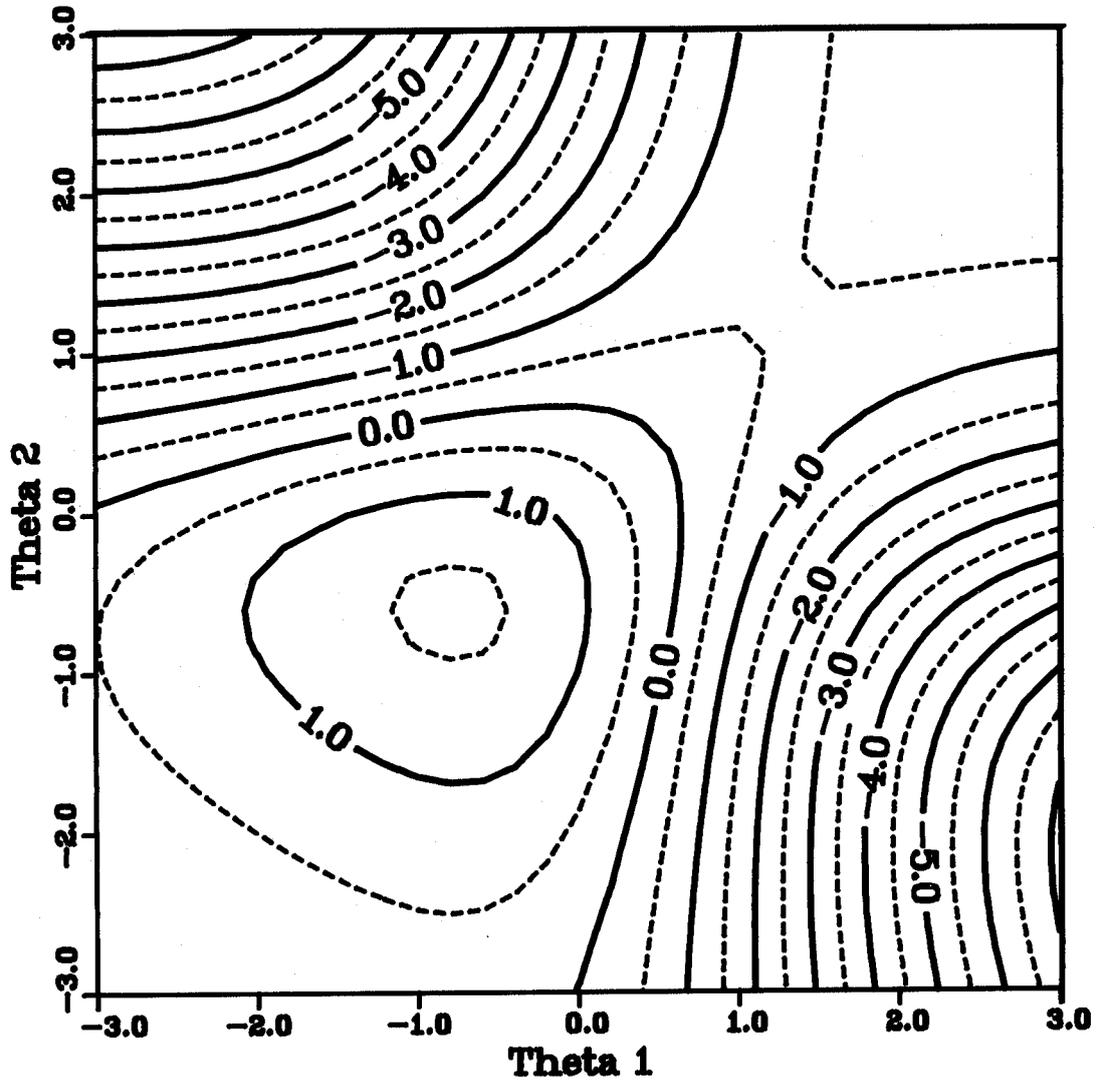
Figure 5. Absolute Difference Between Compensatory and Noncompensatory Test
Information Vectors: Rho = .00

Figure 6. Absolute Difference Between Compensatory and Noncompensatory Test
Information Vectors: Rho = .25

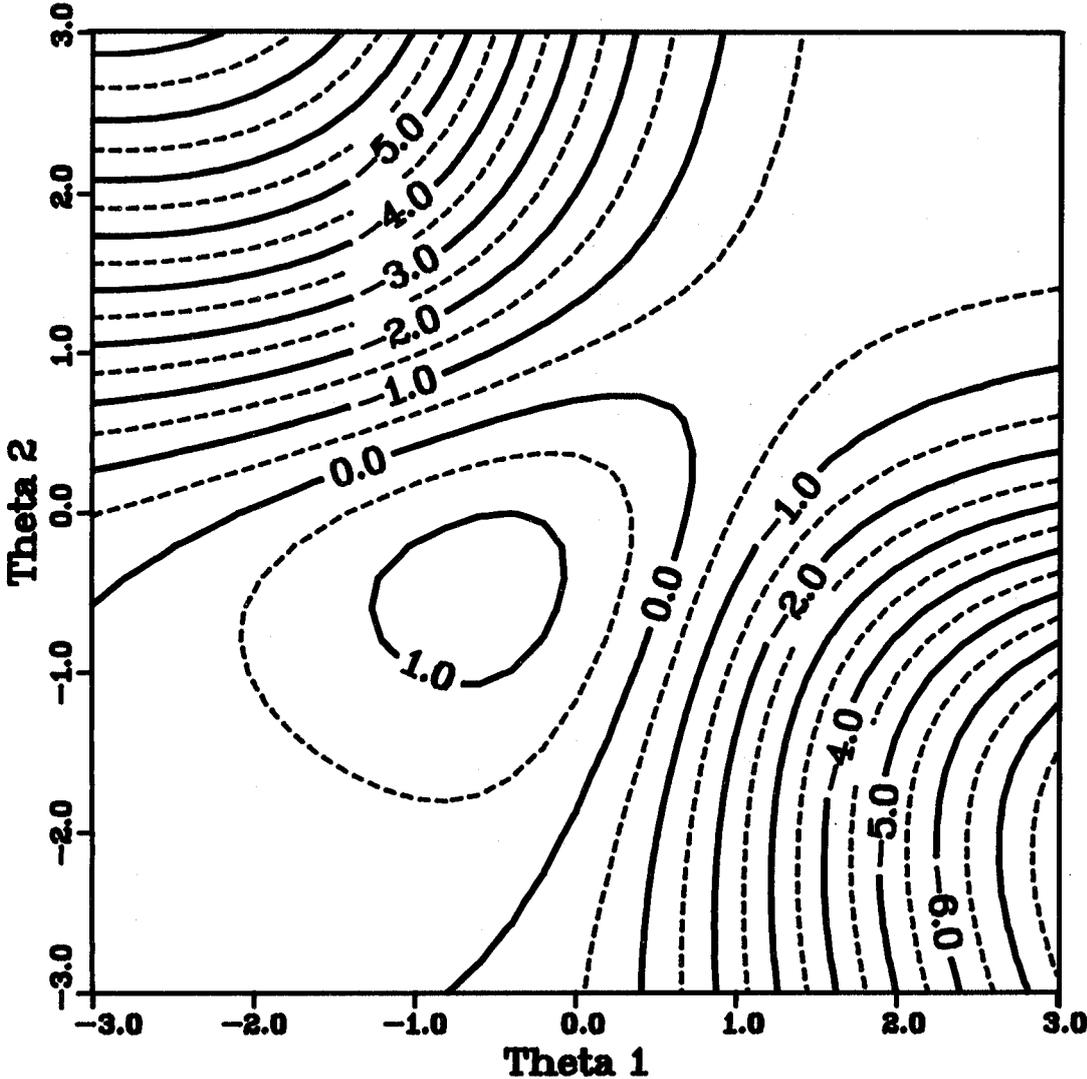
Figure 7. Absolute Difference Between Compensatory and Noncompensatory Test
Information Vectors: Rho = .50

Figure 8. Absolute Difference Between Compensatory and Noncompensatory Test
Information Vectors: Rho = .75

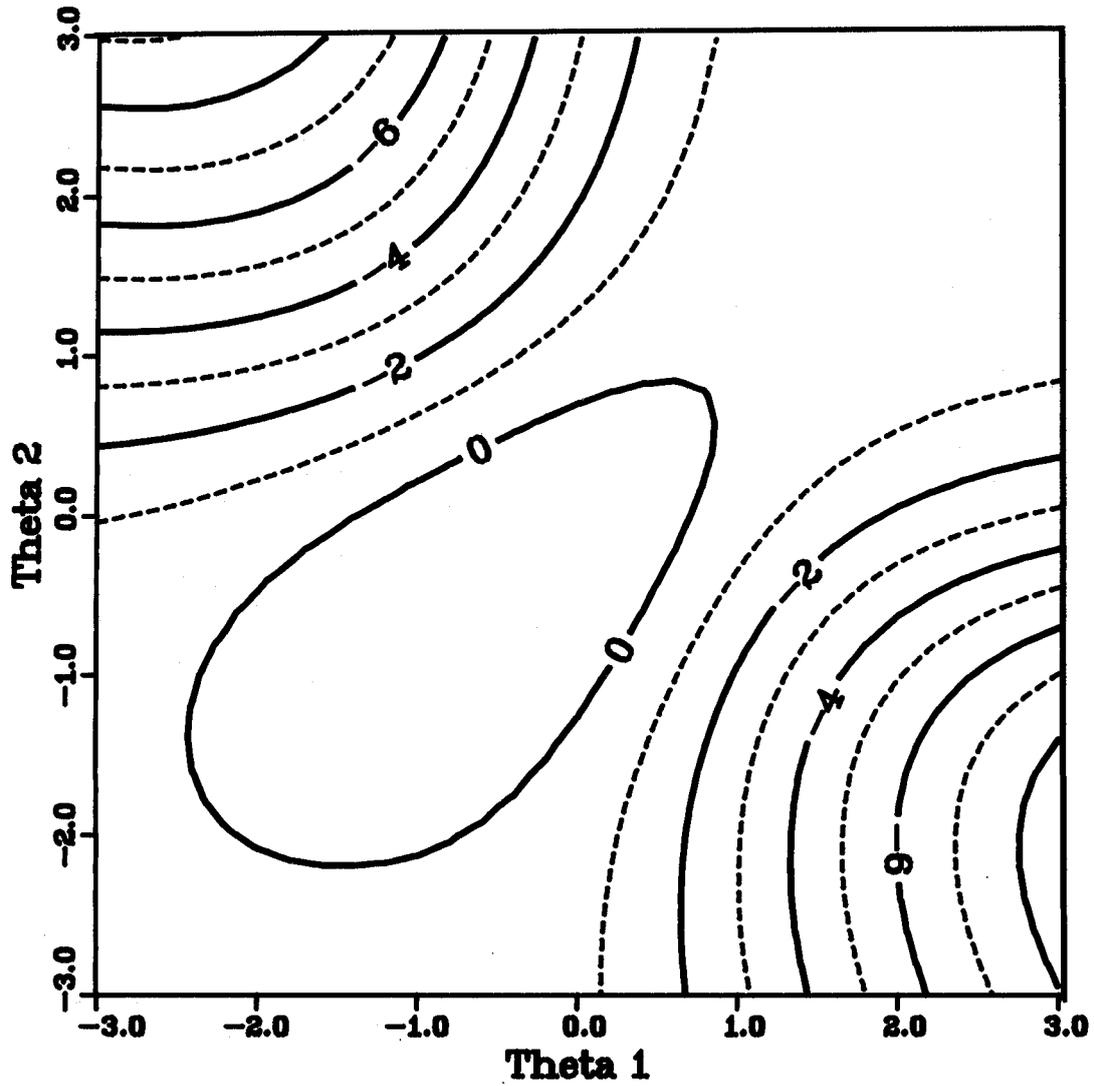
**Difference Between Compensatory
and Noncompensatory True Scores:
Rho = .00**



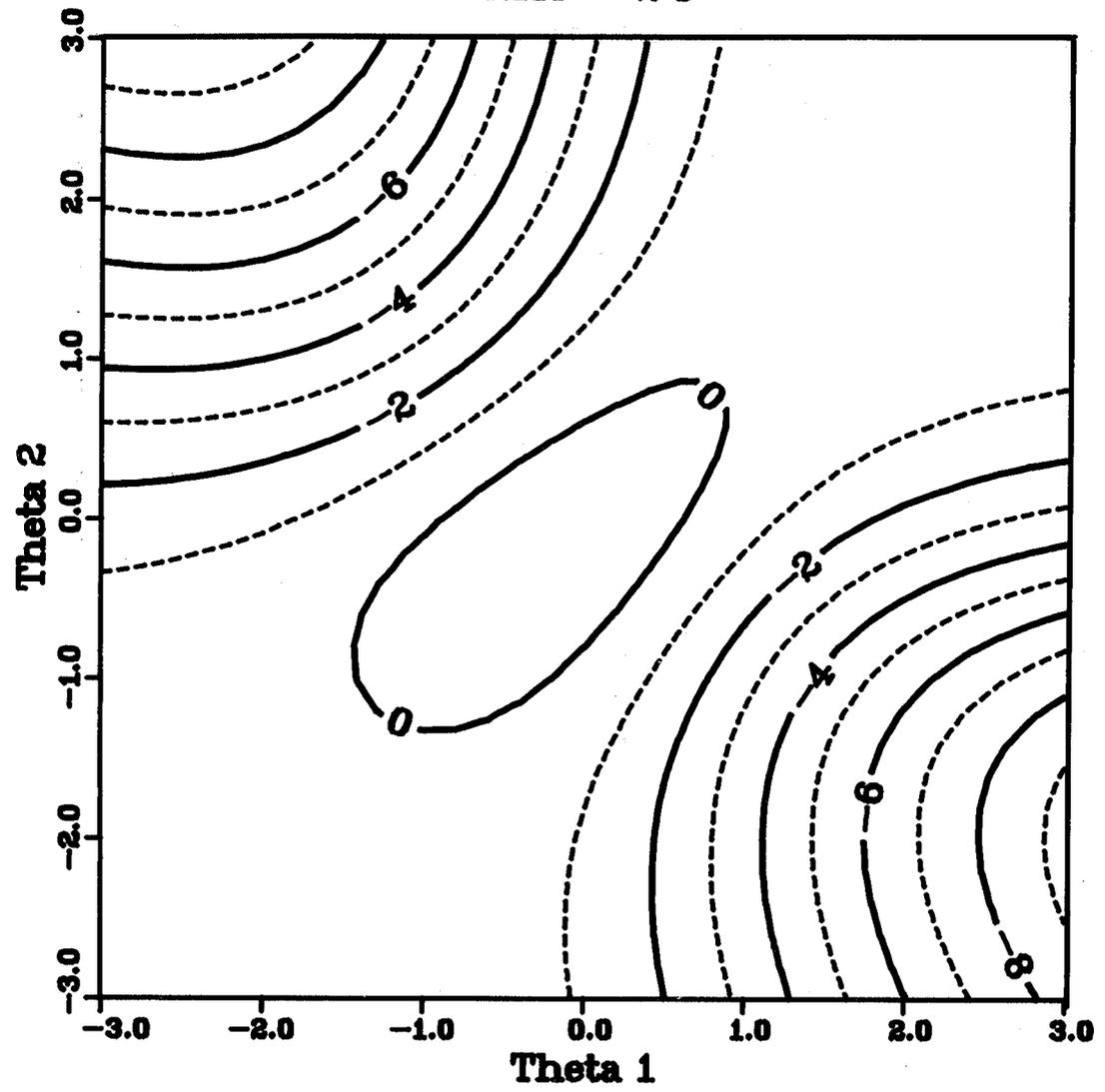
**Difference Between Compensatory
and Noncompensatory True Scores:
Rho = .25**



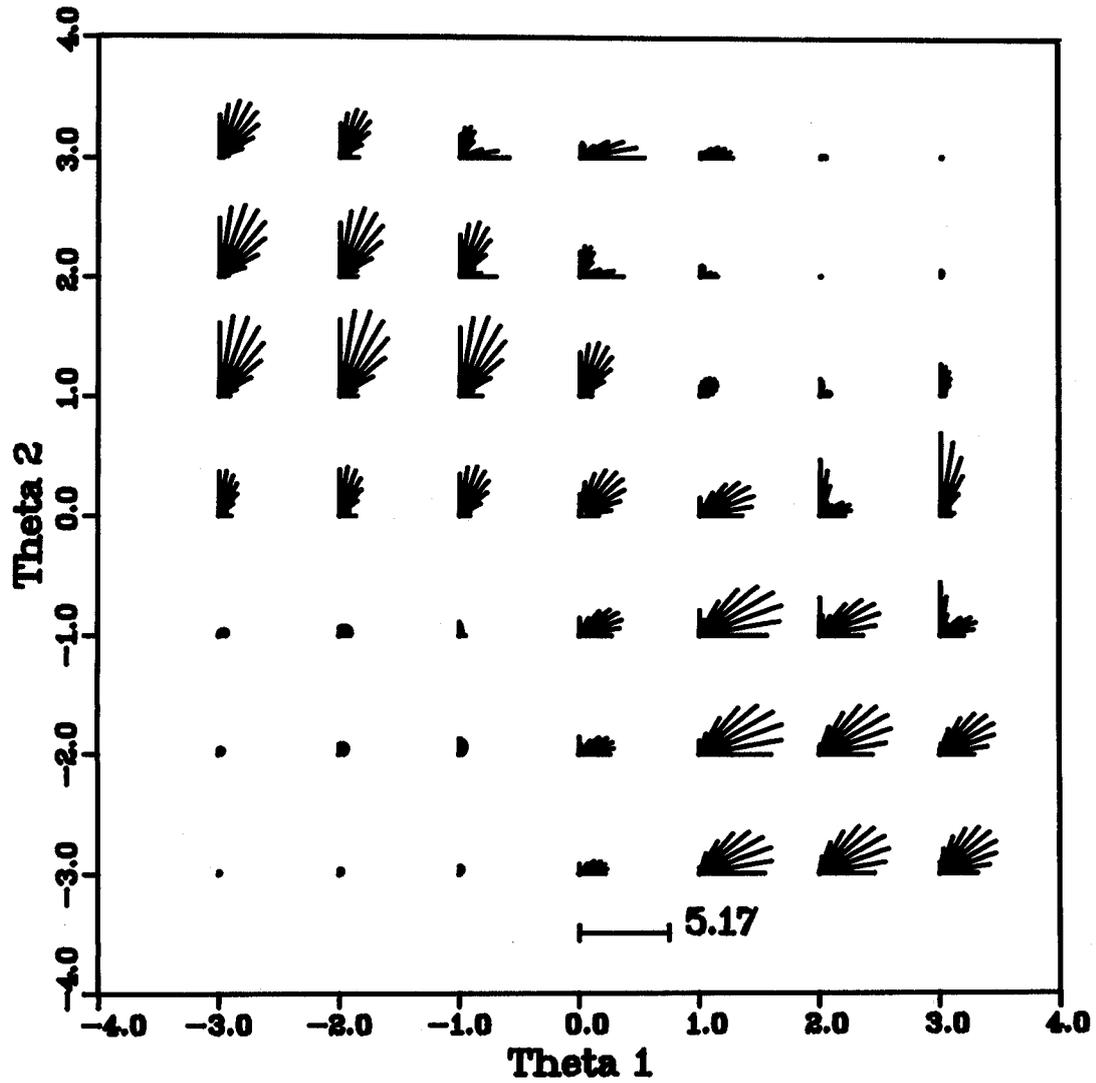
**Difference Between Compensatory
and Noncompensatory True Scores:
Rho = .50**



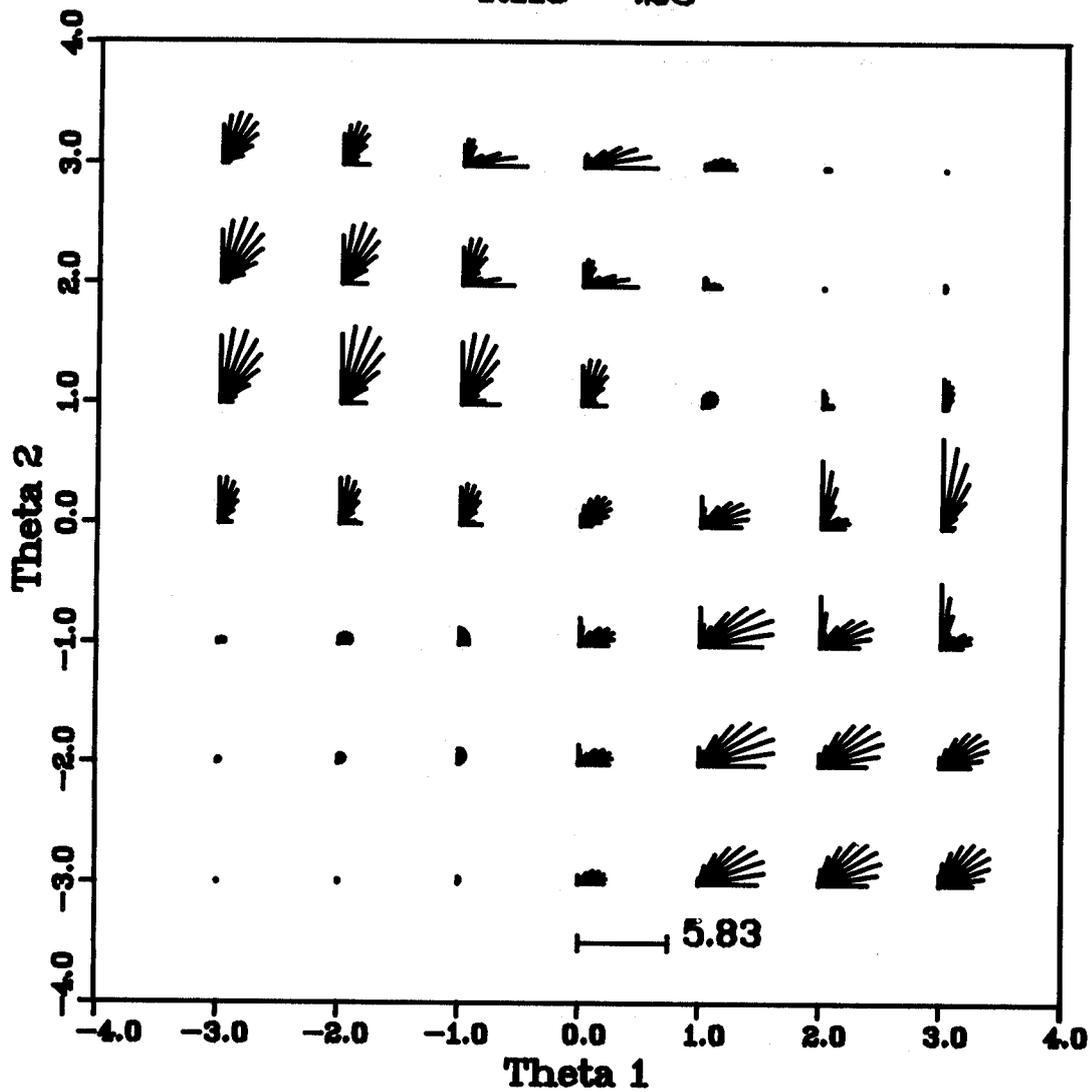
**Difference Between Compensatory
and Noncompensatory True Scores:
 $\rho = .75$**



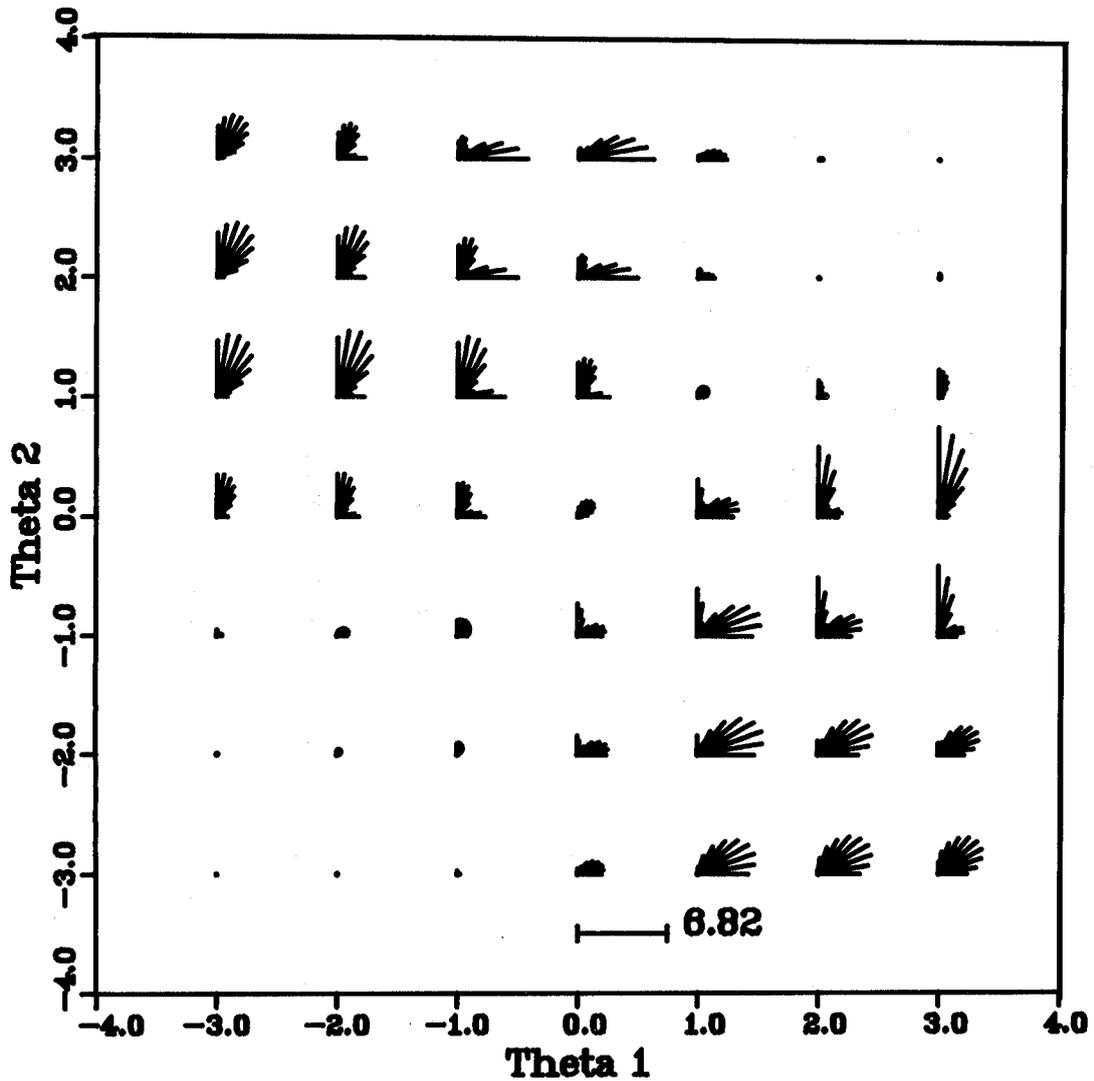
**Absolute Difference Between Compensatory
and Noncompensatory Test Information Vectors:
 $\rho = .00$**



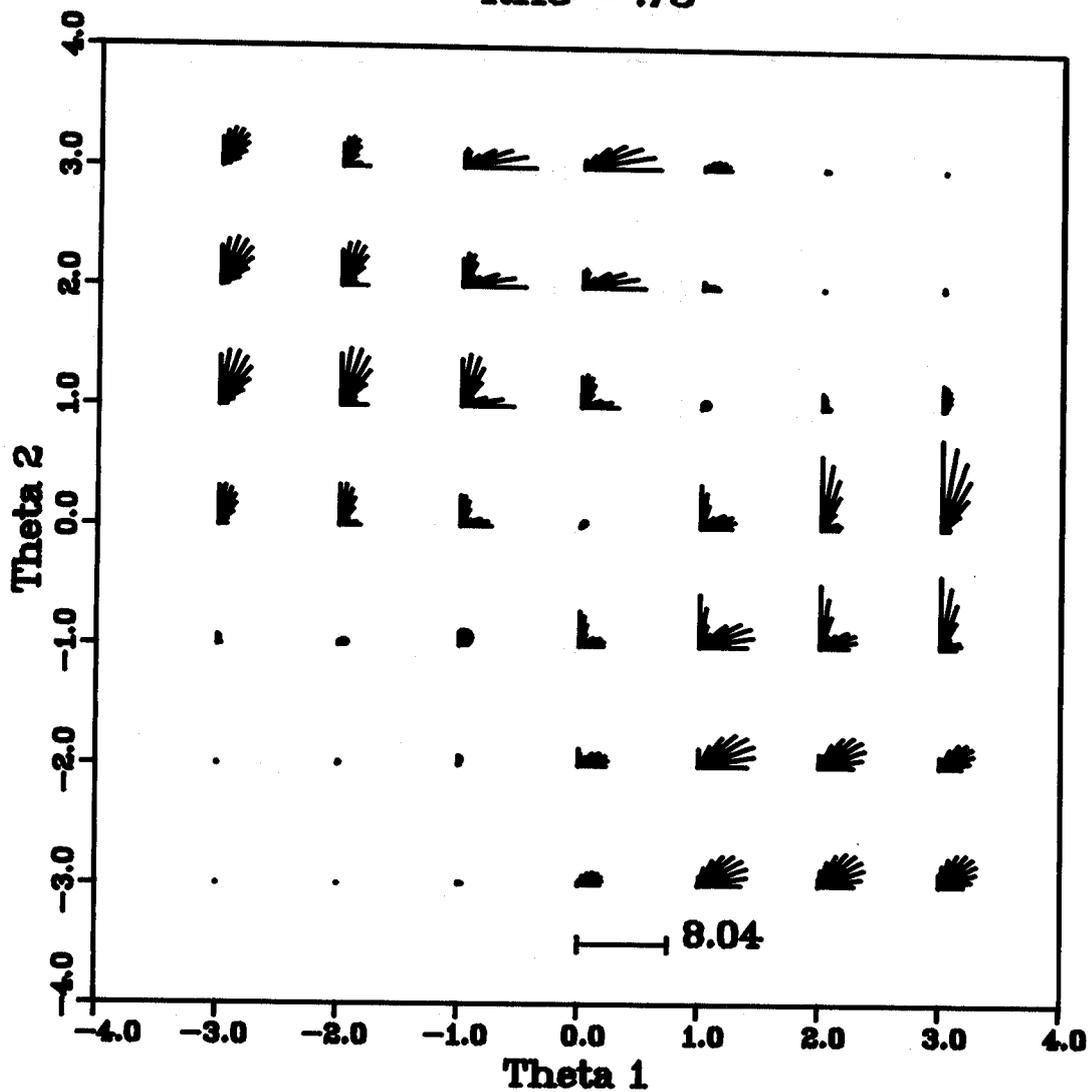
Absolute Difference Between Compensatory and Noncompensatory Test Information Vectors: $\rho = .25$



**Absolute Difference Between Compensatory
and Noncompensatory Test Information Vectors:
 $\rho = .50$**



**Absolute Difference Between Compensatory
and Noncompensatory Test Information Vectors:
 $\rho = .75$**



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