RESEARCH MEMORANDUM NUMBER 23C

JUNE 1980

BICAL: CALIBRATING ITEMS WITH THE RASCH MODEL

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B I C A L

CALIBRATING ITEMS WITH THE RASCH MODEL

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This document illustrates and explains a FORTRAN computer program for calibrating test items and for evaluating the extent of their statistical fit to the log-odds measurement model of Georg Rasch.

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CALIBRATING ITEMS WITH THE RASCH MODEL

I. THE MEASUREMENT MODEL

Introduction

The quantity of a variable possessed by an object (e.g., mass, temperature, achievement in mathematics, attitude toward authority) cannot be observed directly but must be inferred from an observable reaction of the object to an appropriate agent designed to provoke useful manifestations of the variable.

We can infer something about the mass of an object from observing the distance it travels after being struck by an agent which applies a force to the object. The masses of two objects can be compared on the basis of their reactions to the same agent. If a class of agents can be established, any member of which leads to the same comparison of the two objects, then an objective comparison of the objects based on the variable specifically provoked by that class of agents will have been achieved.

When dichotomously scored test items are the agents and persons are the objects to be provoked and specific objectivity in the measurement of these persons is sought, then we are led to one, and only one, particular mathematical relation between the person, the item and the observed response, namely

$$p\{x_{vi}|\beta_v,\delta_i\} = \exp[x_{vi}(\beta_v-\delta_i)]/[1 + \exp(\beta_v-\delta)] \qquad [1]$$

This model specifies that the probability of observing a particular result (represented by $x_{vi} = 1$ for its occurrence and $x_{vi} = 0$ otherwise) upon exposing person v to item i depends only on the person's ability β_v and the item's difficulty δ_i and that their interaction can be captured by the difference of these two parameters $(\beta_v - \delta_i)$.

Expression (1) is the most familiar form of a family of measurement models due to Georg Rasch. It has unique properties which are fundamental for objectivity in measurement (Rasch, 1960, 1961; Wright, 1968, 1977a). Simple, natural sufficient statistics exist for estimating all its parameters. These are, for person ability, the count of the number of items answered correctly by that person and, for item difficulty, the number of persons answering that item correctly. Rasch models are the only latent trait models for which this kind of specific objectivity is possible (Rasch, 1968; Barndorff-Nielsen, 1973; Andersen, 1973a, 1977).

That Equation 1 leads to specific objectivity can be demonstrated by comparing the responses of two persons to any item. The probability that person v answers some item i correctly is given by

$$P\{x_{vi}=1|\beta_v,\delta_i\} = \exp(\beta_v-\delta_i)/[1 + \exp(\beta_v-\delta_i)] = P_{vi} \qquad [2]$$

Therefore his odds for success are

$$\exp(\beta_v-\delta_i) = P_{vi}/(1-P_{vi}) \qquad [3]$$

Taking logarithms gives

$$\beta_v - \delta_i = \ln[p_{vi}/(1 - p_{vi})]. \qquad [4]$$

Similarly for another person u,

$$\beta_u - \delta_i = \ln[p_{ui}/(1 - p_{ui})] \qquad [5]$$

and hence a comparison of person v and person u can be made by

$$\beta_v - \beta_u = \ln[p_{vi}/(1 - p_{vi})] - \ln[p_{ui}/(1 - p_{ui})] \qquad [6]$$

which does not involve the item parameter δ_i at all. As far as the model is concerned the same comparison between these two persons could have been obtained from any appropriate item. Thus, while the comparison depends on the use of some appropriate item, it does not depend on which particular item is used and so the comparison is "item-free."

An analogous argument leads to "person-free" comparisons of item difficulties. This does not mean that two persons can be compared on a variable without provoking a reaction from them with some item or that any old item at all will do. What it does mean is that any items from the appropriate class of items are supposed to lead to the same comparisons of persons and that the comparison of any two items in the class are supposed to be the same regardless of the particular abilities of the persons used. It is these comparisons that are "objective."

The log odds of success for a person on an item, i.e., $\ln[p_{vi}/(1 - p_{vi})]$, obviously depends on the difficulty of the item. Since this effect is present in the log odds of each person, however, it is subtracted out in the comparison. Thus what is known is not the absolute ability of person v but his distance from some other person u. This difference makes person u a kind of origin against which person v is measured. All measurements are comparisons with respect to some origin. The measurement model itself cannot define this origin. An origin must be provided by some external and, in that sense, arbitrary decision. The BICAL item analysis program defines the origin for both persons and items at the center of the set of estimated item difficulties. This temporary origin can be replaced later by a new one based on a substantive decision concerning a position on the latent variable which will serve well as a zero reference point.

The BICAL program estimates item parameters and tests the reasonableness of the hypothesis that all items are useful members of a single measurement class. If all items are from the same class, then they all measure on the same single variable and any items may be used to obtain equivalent measures of persons. If not, then comparisons of excluded items with items which are found to function properly will lead to an improved understanding of the variable originally sought and may even lead to the discovery of interesting new variables.

II. ESTIMATION OF ITEM PARAMETERS

Unconditional Maximum Likelihood Estimation: UCON

The following estimation equations may be derived either by unconditional maximum likelihood estimation or by the mean value method. For item difficulty, the equation to be solved is

$$s_i = \sum_{v=1}^{N} p_{vi} \qquad [7]$$

where s_i is the total number of successes by all persons on item i, and

$$p_{vi} = \exp(\beta_v - \delta)/[1+\exp(\beta_v - \delta)]$$

is the probability of success by person v on item i.

The corresponding equation for person ability is

$$r_v = \sum_{i=1}^{L} p_{vi} \qquad [8]$$

where r_v is the total number of successes on all items by person v.

That this expression can be used to estimate ability follows from that property of the model which says raw score is the sufficient statistic for ability. This in turn makes possible some simplification in Equations 7 and 8. Since raw score is sufficient, then for estimation we need only index the persons by their score and observe the number of persons at each score. Therefore Equation 7 may be replaced by

$$s_i = \sum_{r=1}^{L-1} n_r \, p_{ri} \qquad [9]$$

where L is the largest possible score, n_r is the number of persons who achieved the score of r, and p_{ri} is the estimated probability of success given the ability estimate b_r associated with a score of r and the difficulty estimate d_i associated with item i

$$p_{ri} = \exp(b_r - d_i)/[1+\exp(b_r - d_i)].$$

Equation 8 then becomes

$$r = \sum_{i=1}^{L} p_{ri} \qquad [10]$$

These equations are implicit with respect to ability and difficulty but may be solved easily by iteration. Solution equations for items are

$$d_i^{(t+1)} = d_i^t - \frac{s_i - \sum_r n_r \, p_{ri}^{(t)}}{\sum_r n_r \; p_{ri}^{(t)} \; 1-p_{ri}^{(t)}} \qquad [11]$$

and for scores

$$b_r^{(t+1)} = b_r^{(t)} + \frac{r - \sum_i p_{ri}^{(t)}}{\sum_i \; p_{ri}^{(t)} \; 1-p_{ri}^{(t)}} \qquad [12]$$

where $p_{ri}^{(t)}$ is the estimated probability of success on item i by a person with score r based on the estimates available at the t^{th} iteration.

These estimates are unconditional maximum likelihood estimates, so their asymptotic standard errors may be derived from the second derivative of the log likelihood function:

$$SEC = SE(d_i) = [\sum_r n_r\, p_{ri}\, (1-p_{ri})]^{-1/2} \qquad [13]$$

and

$$SEM = SE(b_r) = [\sum_i p_{ri}\, (1-p_{ri})]^{-1/2}. \qquad [14]$$

The estimates contain a slight bias due to their unconditional basis. This bias can be corrected by the scaling factors $(L-1)/L$ for the centered d_i and $(L-2)/(L-1)$ for the b_r.

The corrected unconditional estimation algorithm used by BICAL is

i) Obtain item scores (s_i) and counts of the number of persons at each score (n_r).

ii) Edit these data to remove perfect scores (i.e., $s_i = 0$ or N and $r = 0$ or L), recycling as many times as necessary as N and L change.

iii) Define an initial set of (b_r) as $b_r^o = \ell n \left[\frac{r}{L-r}\right]$, r=1, L-1

iv) Define an initial set of (d_i) as $d_i^o = \ell n \left[\frac{N-s_i}{s_i}\right]$, i=1, L

v) Center the item set at zero by subtracting $d = \sum_i d_i/L$ from each item.

vi) Obtain a revised set of (d_i) by iterating Equation 11 until convergence is achieved.

vii) Using the tentative set of (d_i), obtained from step vi, obtain a revised set of (b_r) by iterating Equation 12.

viii) Repeat steps v, vi, and vii until stable values for the (d_i) are observed.

ix) Correct for bias by multiplying each d_i by (L-1)/L.

x) Calculate the (b_r) for these unbiased (d_i).

xi) Correct for bias by multiplying each b_r by (L-2)/(L-1).

<u>Cohen's Approximation: PROX</u>

An economical alternative for estimating model parameters is to assume that person abilities can be approximated by an explicit function of total score and that this function is completely determined except for a single multiplying parameter which can be estimated by maximum likelihood (Cohen, 1976). The assumption implies that the distributions of person abilities and item difficulties can be adequately described by a normal distribution. To the extent this is so, the resulting estimates closely approximate those obtained by more expensive procedures.

To apply this approximation:

i) Define initial estimates of difficulties and abilities and their variances;

$$d_i^o = \ell n\left[\frac{N-s_i}{s_i}\right] - \sum_i^L \ell n\left[\frac{N-s_i}{s_i}\right] /L \quad , \qquad i=1,L$$

$$D = \sum_{i}^{L} (d_i^o)^2 / [(L-1)\ (2.89)]$$

$$b_r^o = \ln\left[\frac{r}{L-r}\right] \qquad , \qquad r=1,\ L-1$$

$$b_{.}^o = \sum_{r}^{L-1} n_r b_r^o / N$$

$$B = \sum_{r}^{L-1} b_r (b_r^o - b_{.}^o)^2 / [(N-1)\ (2.89)]$$

ii) Compute expansion coefficients:

$$X = [(1 + B)/(1 - BD)]^{1/2}$$

$$Y = [(1 + D)/(1 - BD)]^{1/2}$$

iii) Compute final estimates and their standard errors:

$$d_i = X d_i^o \qquad i = 1,L$$

$$SE(d_i) = X[N/s_i(N-s_i)]^{1/2}$$

$$b_r = Y b_r^o \qquad r = 1,\ L-1$$

$$SE(b_r) = Y[L/r(L-r)]^{1/2}$$

For moderately long tests and more or less symmetric score distributions, this PROX procedure yields estimates within a fraction of a standard error of the values obtained by the more expensive method UCON.

III. ITEM FIT

In the search for measurable variables, tentative estimation of item difficulties is only a first step. In order for these estimates to be useful as item calibrations, it must be established that it is reasonable to treat the items in question as members of the same measuring class. If that is found to be reasonable, then the measurement of persons based on the calibration of these items can proceed. If not, then the available data must be reconsidered to see if there are any subsets of items that may possibly belong to a single common measuring class. If that search fails, then no "measurements" will be possible with these items.

The most natural fit statistic in BICAL, labelled "Between Fit t" is derived directly from the "sample-free" requirements of the model. If estimates of difficulty are in fact free of the distribution of ability in the calibrating sample, then estimates based on different subgroups will be statistically equivalent to those based on the total sample. This can be tested most severely by dividing the sample into subgroups based on score level, that is by estimated ability, and then comparing the observed successes on each item in each ability subgroup with those predicted for that subgroup from the total sample item difficulty estimates.

If item i fits in ability group g, then successes in group g on item i should approximate their model expectation. Thus,

$$s_{gi} \approx \sum_{r \varepsilon g} n_r p_{ri}. \qquad [15]$$

This expression is identical to Equation 9 except that it is based on a subsample of persons. If the item difficulty estimate is indeed independent of the sample chosen, this expression should be satisfied for all subgroups. Equation 15 can be converted into the standardized residual

$$z_{gi} = \frac{s_{gi} - \sum_{r \varepsilon g} n_r p_{ri}}{\left[\sum_{r \varepsilon g} n_r p_{ri}(1-p_{ri})\right]^{1/2}} \qquad [16]$$

and hence into a mean square between the M groups

$$v_{Bi} = \sum_{g}^{m} \left[\frac{(s_{gi} - \sum_{r \varepsilon g} n_r p_{ri})^2}{\sum_{r \varepsilon g} n_r p_{ri}(1-p_{ri})} \right] \cdot \left[\frac{L}{(M-1)\ (L-1)} \right] \qquad [17]$$

Finally, this mean square between groups can be expressed in the standardized form

$$t_{Bi} = a v_{Bi}^{1/3} - a + 1.0/a \quad \text{where } a = [4.5(m-1)]^{1/2} \qquad [18]$$

This t-statistic tests whether the observed item characteristic curves have a common shape and slope. It has an expected value of about zero and a variance of about one.

A more general statistic can be constructed by comparing the result of each person-item interaction, x_{vi}, with its estimated expected value, p_{vi}. This standardized residual has the same form as the between group residual, i.e.

$$z_{vi} = \frac{x_{vi} - p_{vi}}{p_{vi}(1-p_{vi})^{1/2}} \qquad [19]$$

It too could be squared and summed, this time over all persons, to form a total mean square for the evaluation of item fit. The resulting mean square, however, is very sensitive to unexpected responses which are far off target. This is unfortunate because when a response is far off target, that is when the item and person are far apart so that the difference between person ability and item difficulty is many logits, then not only is there very little useful information about either person or item in that response, but we hardly expect, nor do we need to expect, the model to hold.

An alternative approach which has similar asymptotic properties, but is more robust against off-target data, is to weigh each squared residual by the information $p_{vi}(1-p_{vi})$ it contains and so calculate an information weighted mean square.

These weighted mean squares are formed by computing the difference between the observed response x and its estimated model expectation $p = \exp(b-d)/[1+\exp(b-d)]$ and summing the square of this difference $(x-p)^2$ over persons for item fit and over items for person fit.

The sum of squared differences $\Sigma(x-p)^2$ is then divided by its model expectation $\Sigma p(1-p)$ to form a mean square statistic.

$v = \Sigma(x-p)^2/\Sigma p(1-p)$ with an expectation of one and a variance of

$$s^2 = \{\Sigma p(1-p)-4\Sigma[p(1-p)]^2\}/[\Sigma_p(1-p)]^2.$$

A standardized value t for the mean square v is calculated from

$$t = (v^{1/3}-1)(3/s)+(s/3) \quad . \qquad [20]$$

In theory, the asymptotic distribution of this t-statistic should be normal with a mean of zero and a standard deviation of one. In practice we have not found this to be always so, especially for the "total t fit" item and person statistics. With data which fit the model the "total t fit" statistic can show a standard deviation as low as 0.7 when the data is off-target and/or the replications are less than 50. This implies that items and persons producing "total t fit" values larger than 1.5 ought to be examined for response irregularities. Certainly "total t fit" values greater than 2.0 are noteworthy.

The "total t fit" values summarize overall item fit from person to person.

The "between t fit" values focus on the variations in item response between the two to six score (i.e. ability) groups formed by BICAL. These between score group fit statistics have one less degree of freedom than there are score groups, i.e. from one to five degrees of freedom depending on the number of score groups formed. In contrast to the "total t fit" statistic, we have found the observed distribution of "between t fit" values to come close to the expected mean of zero and standard deviation of one for items which fit. The "between t fit" statistic is particularly sensitive to variations in item difficulty which are associated with variations in person ability.

The "error impact" of item misfit is calculated as $(v^{1/2} - 1)$. This statistic estimates the proportional inflation of standard errors of calibration or measurement which could be caused by misfit of the item.

In the case of the item's own calibration, the error impact is direct and the standard error of the item's difficulty is estimated to be $v^{1/2}$ times larger than reported.

In the case of the item's use for person measurement, however, the error impact of any single item's misfit is attenuated by the presence of other items. The number of items L in the measuring test diminishes the impact of unsystematic item misfit on measurement error by a factor of $1/L^{1/2}$ so that the measurement error inflation which could be caused by the misfit of any one item is only of order $(v/L)^{1/2}$.

If, however, an item's misfit is not idiosyncratic but is, instead, part of a trend shared with other items in the measuring test, then there can be a bias in measurement caused by this trend. Unfortunately, the magnitude of this bias cannot be estimated from individual item statistics. Its presence must be checked for during the analysis of person fit and its magnitude estimated separately for each person measured. Fortunately, the necessary person fit analysis is easy to perform. (To do this we use the supplementary Rasch programs PANAL and KID.)

BICAL also reviews the calibrating sample for person fit and deletes from calibration persons whose pattern of responses is excessively improbable. The criterion for this deletion can be chosen for each calibration. A good working value is a person "total t fit" statistic exceeding 2.0. This value will clean most of the implausible response patterns out of the calibrating sample and in this way focus the item fit analysis on item quality.

As an aid in diagnosing the nature of misfit for an item, BICAL calculates a residual discrimination index which describes the relative slope of each item characteristic curve. This descriptive statistic corresponds closely in meaning and magnitude with the item discrimination which other programs attempt to estimate simultaneously with item difficulty. The BICAL discrimination index, however, is based on residuals <u>after</u> the Rasch model has been fitted.

If the data came from a simulator that produced characteristic curves which varied in slope, then the person-item logit could be expressed as

$$p_{vi} = \alpha_1(\beta_v - \delta_i) + \varepsilon_{vi} \qquad [21]$$

or

$$\gamma_{vi} = (\alpha_i - 1)(\beta_v - \delta_i) + \varepsilon_{vi} \qquad [22]$$

where

$$\gamma_{vi} = p_{vi} - (\beta_v - \delta_i).$$

In this form, γ_{vi} is the difference between a "true" logit response and the Rasch model with which we have attempted to explain it. If the Rasch model adequately accounts for the data, the regression in Equation 22 should have a slope of zero.

In terms of estimates, this expression can be written as

$$y_{vi} = (\alpha_i - 1)\ (b_v - d_i) + e_{vi} \qquad [23]$$

$$y_{vi} = (x_{vi} - p_{vi})/[p_{vi}(1-p_{vi})].$$

Therefore an indication of α_i can be calculated as

$$a_i = [\sum_v (y_{vi} - y_{.i})(b_v - d_i)/\sum_v (b_v - d_i)^2] + 1. \qquad [24]$$

This is the residual discrimination index given in BICAL output.

IV. RECOVERY OF MODEL PARAMETERS

Andersen (1970) proves that a conditional maximum likelihood procedure for Rasch item analysis produces consistent estimates of item parameters. Since, however, conditional estimation is impractical for tests of more than thirty items (Wright and Douglas, 1977b), Wright and Panchapakesan (1969) developed an "unconditional" maximum likelihood procedure, UCON. Although this method is quite practical even for the largest tests, it produces slightly biased estimates. Wright and Douglas (1977a, 1977b) describe a corrected unconditional estimation which should make the bias in UCON negligible. The purpose of this chapter is to document the extent to which the unconditional maximum likelihood procedure used in BICAL produces accurate and consistent estimates, and so, incidentally, to see if there is any practical need to attempt conditional estimation of item difficulty parameters.

To explore this question, a study of data simulated to fit the model was performed. A comparison of estimates with their generating parameters was made for data generated from a variety of typical test and sample shapes.

Definition of Test and Sample

A test and a sample can be described adequately by four basic characteristics (Wright and Douglas, 1975). The units

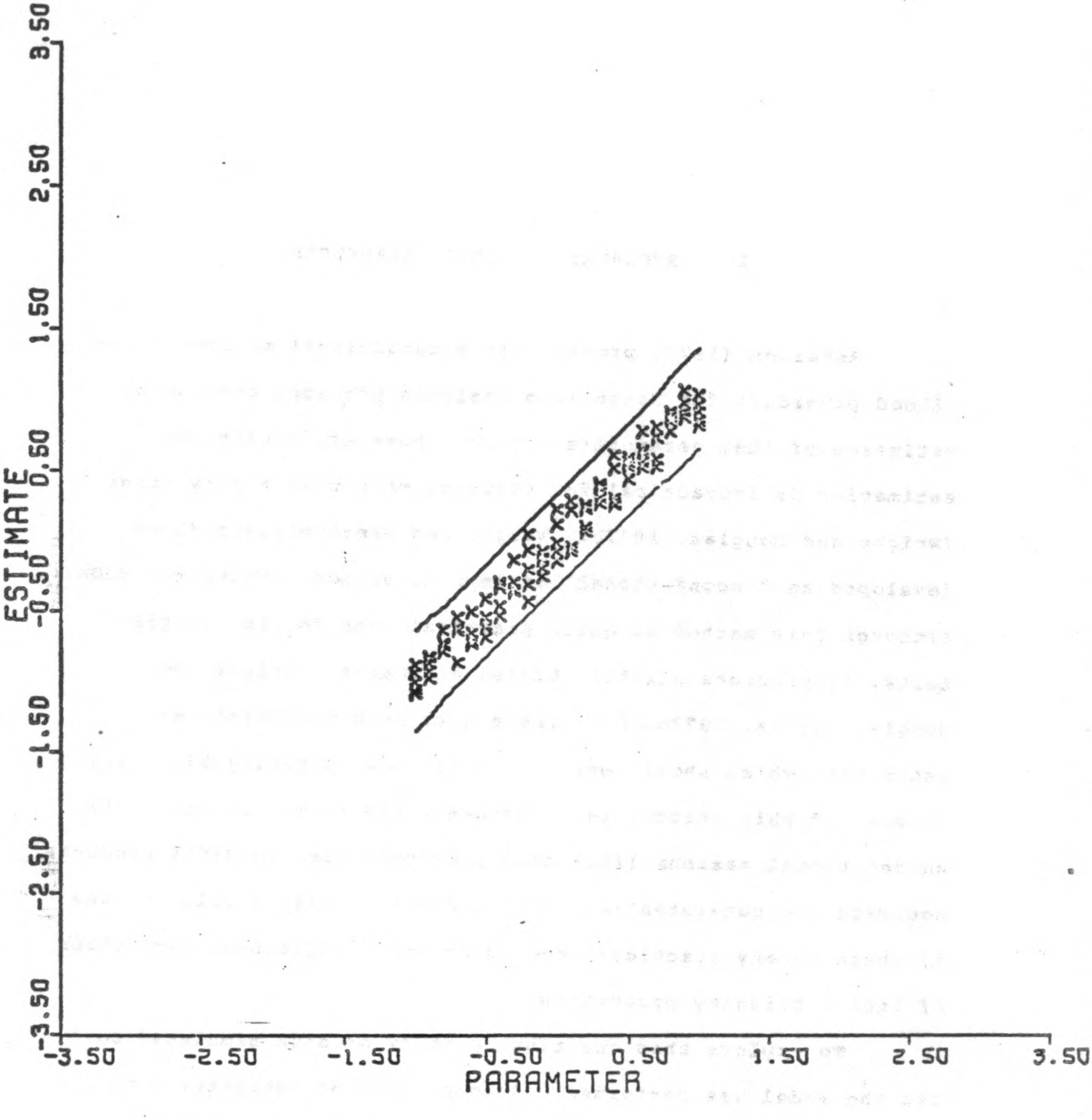

FIGURE 1

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=2 L=21 SAMPLE: M=0 S=0.5 N=400

REGRESSION: Y=1.00X X=0.97Y

in which those properties will be expressed are logits. Logits are natural log odds of frequency data such as test and item scores which transform these frequency data into a linear scale (for a discussion of logits, see Wright, 1977a).

Tests

The first characteristic of a test is its difficulty level or Height, H. This is the average difficulty of the test's items. A centered test is one with a height near the mean ability or center of the sample of persons.

Width, W, is the second characteristic of a test. This is the range of item difficulties covered by a test, from the easiest item to the hardest.

Length, L, the number of items composing the test is the third characteristic of a test.

Finally, the distribution of the item difficulties must be specified. Typically, either a normal or uniform distribution is adequate to describe test shape. Wright and Douglas (1975) show that uniformly distributed items are the best overall test shape strategy and that in general, "best" tests should be constructed that way.

Samples

The mean ability level, M, of a sample corresponds in interpretation to the height of a test. In the construction of a scale, the origin, in general, is arbitrary. What is determined by the data is the difference (M - H) between sample and test.

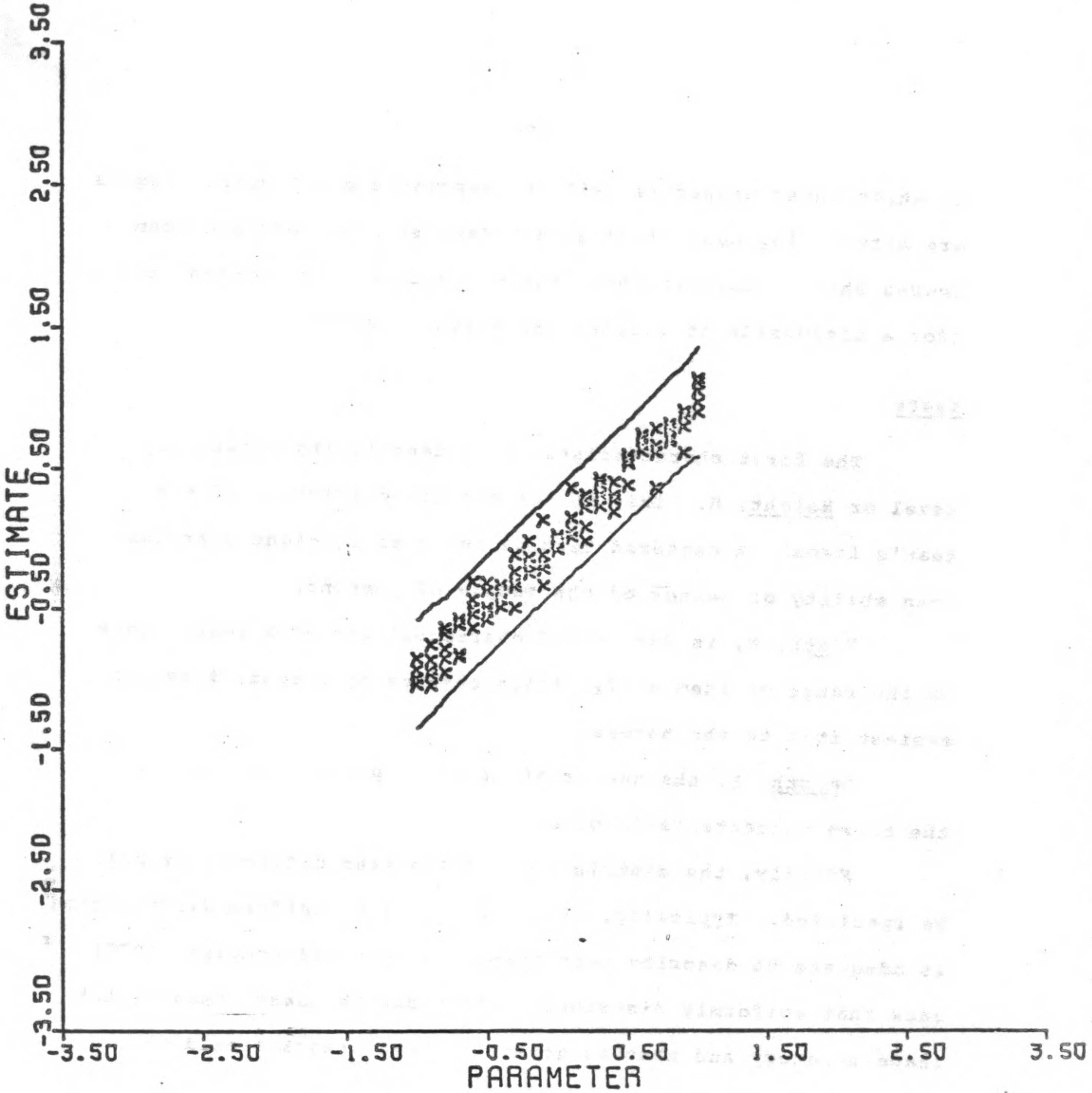

FIGURE 2

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=2 L=21 SAMPLE: M=0 S=1.0 N=400

REGRESSION: Y=0.97X X=1.00Y

For our simulations the height of the test was set at H=0 and the difference (M - H) was varied by varying M. Therefore, a sample less able than the test is difficult would have a mean ability less than zero, while a sample more able than the test is difficult would have a mean greater than zero. Since the response model functions symmetrically, we need only considered samples equal to or smarter than the test.

The second characteristic of a sample is its dispersion, or standard deviation, S. Just as the width of a test is the range of item difficulties composing the tests, so S indicates the spread of person abilities in the sample.

Sample size, N, is the third characteristic of a sample.

The last is sample characteristic shape. For most purposes a normal distribution of persons is an adequate representation of sample shape.

Scope of the Simulations

A wide variety of experience has shown that tests narrower than two logits or wider than six logits are rare. The most frequent test widths encountered have been in the region of three to five logits. Therefore, our simulations were performed for tests of width two, four, and six logits to cover this experience. A few simulations made at one and three logits in order to see the trend around two logits are shown in the summary tables, but are not included in the graphical analyses.

Test lengths of twenty-one and forty-one items were chosen for the simulations. Few serious tests are shorter than

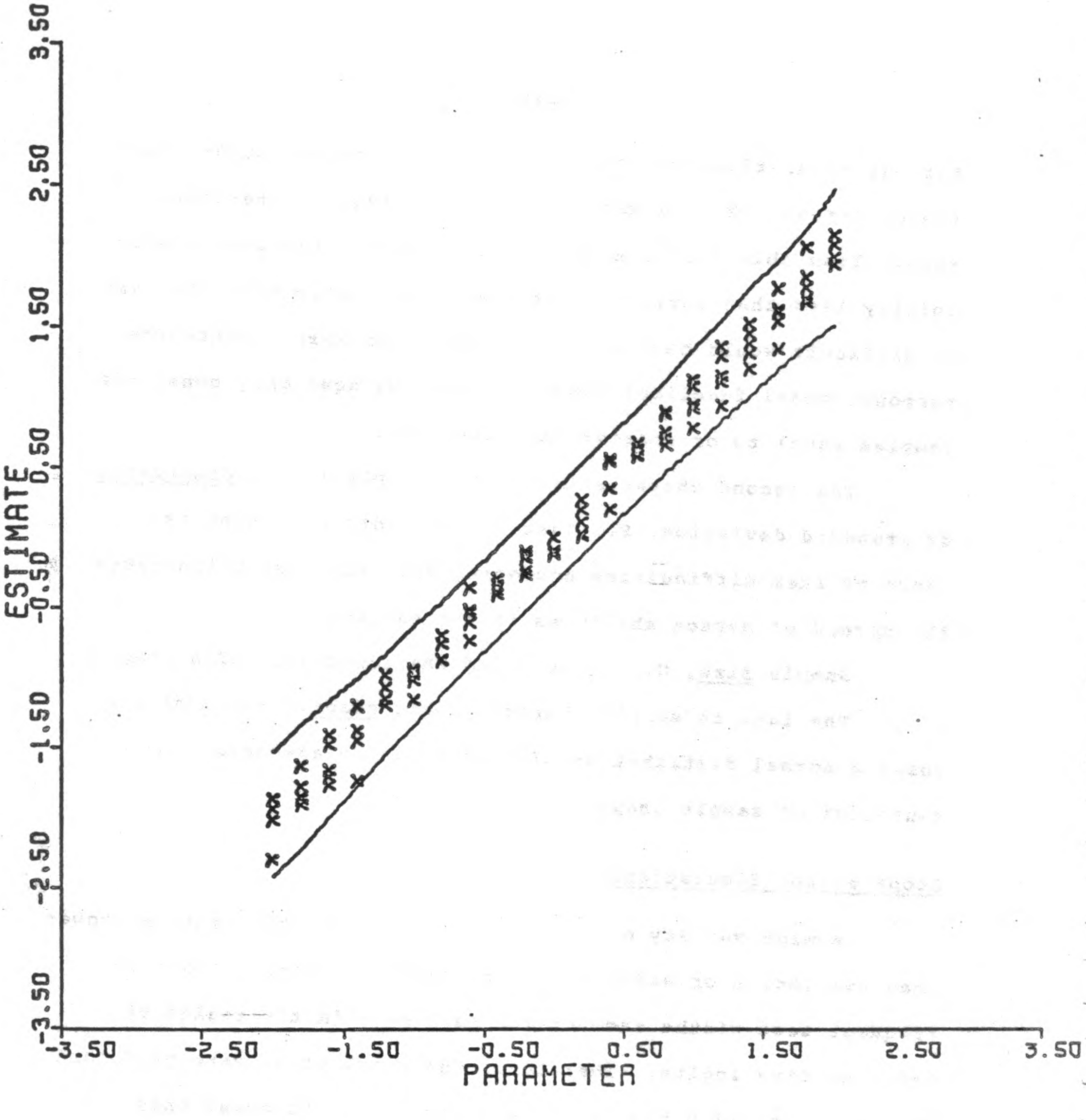

FIGURE 3

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=21 SAMPLE: M=0 S=0.5 N=400

REGRESSION: Y=0.99X X=1.00Y

twenty items and, as tests exceed forty or fifty items, the impact of the amount of data available becomes sufficient to wipe out the problem of bias in the unconditional estimates. Twenty-one was chosen because it occasionally happens that an in-class test or one subtest of a lengthy battery is as short as twenty items. Forty-one was chosen to show how increasing test length eases estimation problems and improves the estimates. A second reason was that subtests in many widely used batteries run about forty to fifty items in length.

Two levels of sample ability were chosen for the simulations. The first level was centered on the tests (M = 0), as that is the most desirable relation between test and sample. The second level was set at one logit above test center (M = 1), because calibration samples are often selected to be somewhat more able than the test is difficult in order to avoid the provocation of guessing.

Practical experience with typical school tests has shown that within-grade ability standard deviations tend to run around one logit. When attempts are made to calibrate a test over several grade levels in a single analysis ability standard deviations can reach 1.5 logits. In the development of a calibrated bank of items, however, it is usually more efficient and more informative to calibrate items within grade levels first and then to verify the stability of these calibrations across grades with common item links. In order to cover this situation sample abilities were simulated at standard deviations of 0.5,

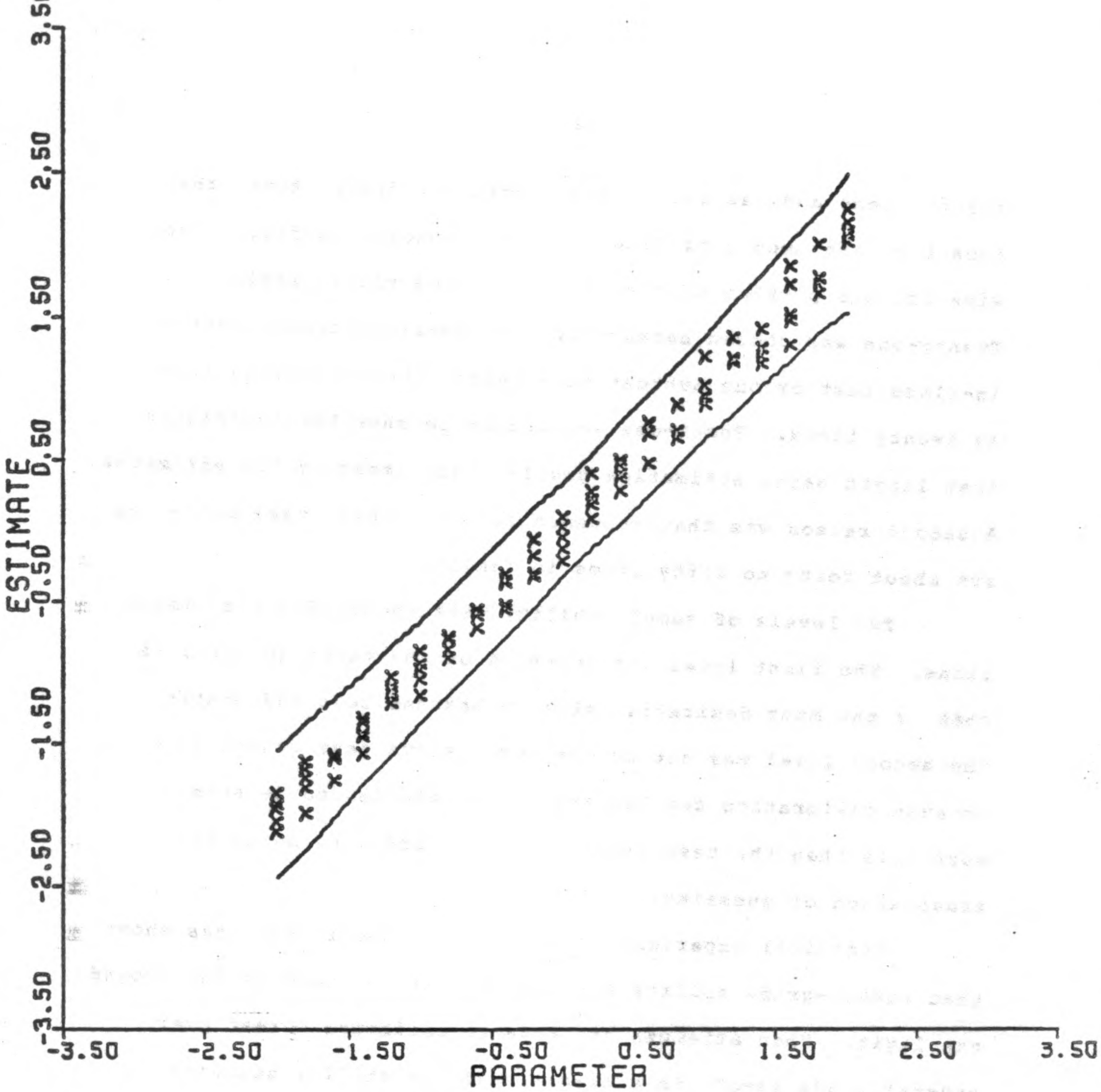

FIGURE 4

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=21 SAMPLE: M=0 S=1.0 N=400

REGRESSION: Y=1.00X X=0.99Y

1.0, and 1.5 logits.

Sample sizes of four and eight hundred persons were used, because in principle, given the model, four hundred suitably chosen persons should be enough to determine item characteristics effectively, and eight hundred persons should be more than enough.

All of the simulations made in this study had an average item difficulty of zero, items that were uniformly distributed in difficulty and samples that were normally distributed. Test length and sample size were combined into two typical setups, a test of twenty-one items taken by four hundred persons and a test of forty-one items taken by eight hundred persons. Plausible combinations of test width, sample mean, and sample dispersion were formed for each of these set-ups. Table 1 specifies the various combinations which resulted. Five or more random replications of each of these combinations were simulated. These similations provide the data used here to investigate the extent to which BICAL satisfactorily recovers item difficulty parameters and evaluates fit.

Not all possible combinations of the variables in Table 1 were simulated because some combinations generate unrealistic situations. For instance, it would be unreasonable to give a narrow test (W = 2) to a sample that was more able than average (M = 1), because too many of the people would be above the useful range of the test.

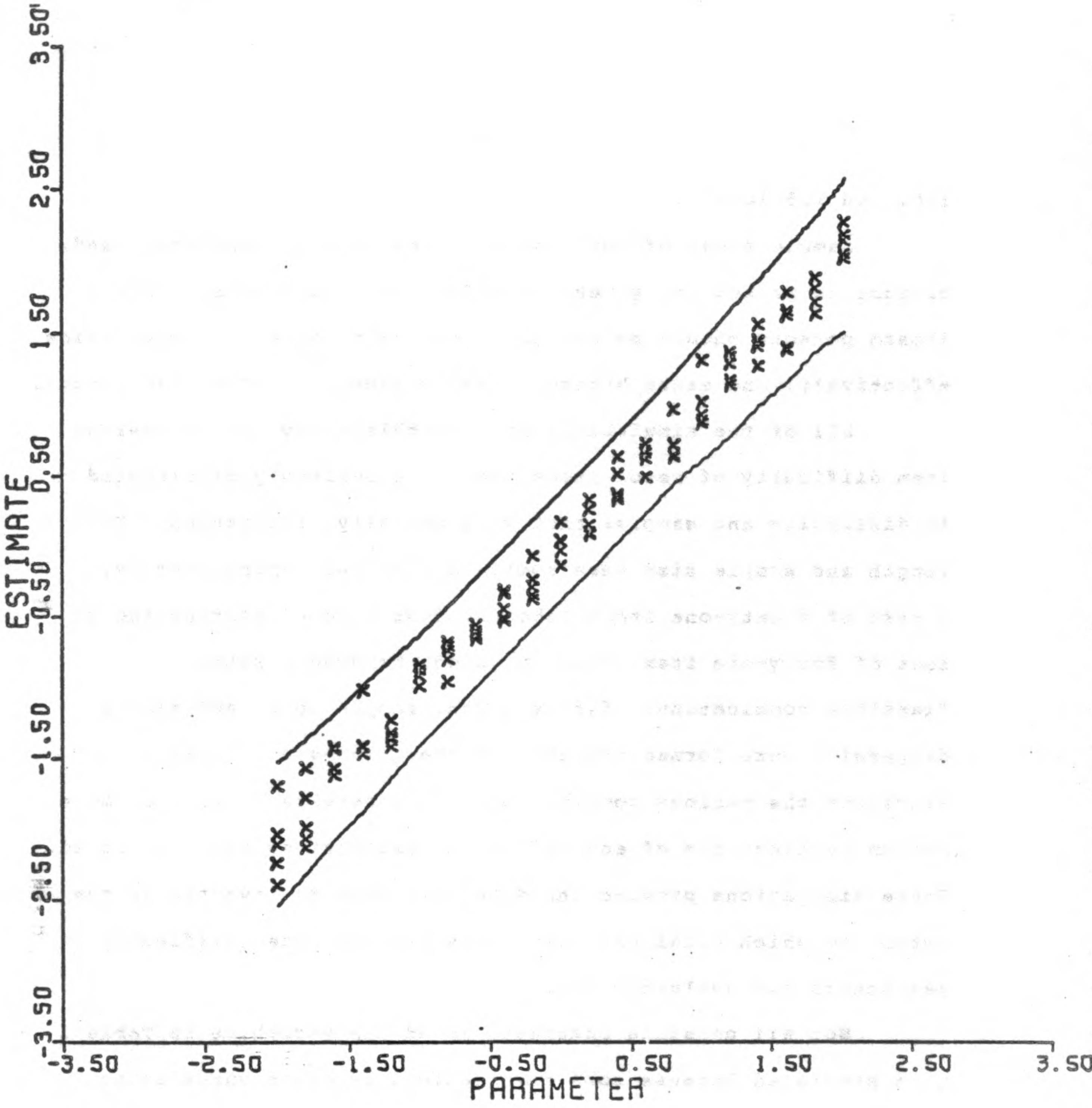

FIGURE 5

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=21 SAMPLE: M=0 S=1.5 N=400

REGRESSION: Y=1.02X X=0.97Y

Recovery of Item Difficulties

The first analysis of the simulation results concerns possible bias in the recovery of item difficulties. Bias can be analyzed by comparing the estimated dispersion of item difficulties with the generating dispersion. If the estimated disperson is statistically equivalent to the generating, then bias could only be present in the relative positions of items with respect to one another. Table 2 shows that BICAL recovery of item difficulty dispersion is excellent at all but the most extreme combinations of tests and samples. The worst recovery is for the short, wide tests ($L = 21$, $W = 6$) given to off-center samples ($M = 1$) where estimated item difficulty dispersion runs five percent too large. This minor bias is reduced to two percent for the long, wide tests ($L = 41$) even when $W = 6$ and $M = 1$. Regardless of test width, the average excess in estimated dispersion over all simulations is about two percent for the shorter test and one percent for the longer test. This suggests the possibility that a slight additional correction for bias based on test length might be useful for shorter tests ($L < 30$).

More detailed analysis of calibration bias on an item-by-item basis appears in Tables 3 and 4. These tables show the regression of individual item difficulty estimates on their generating parameters, for the tests of twenty-one items by four hundred persons and forty-one items by eight hundred persons, respectively. It is hard to see how the BICAL recovery could be much better. Overall, the best estimates are recovered

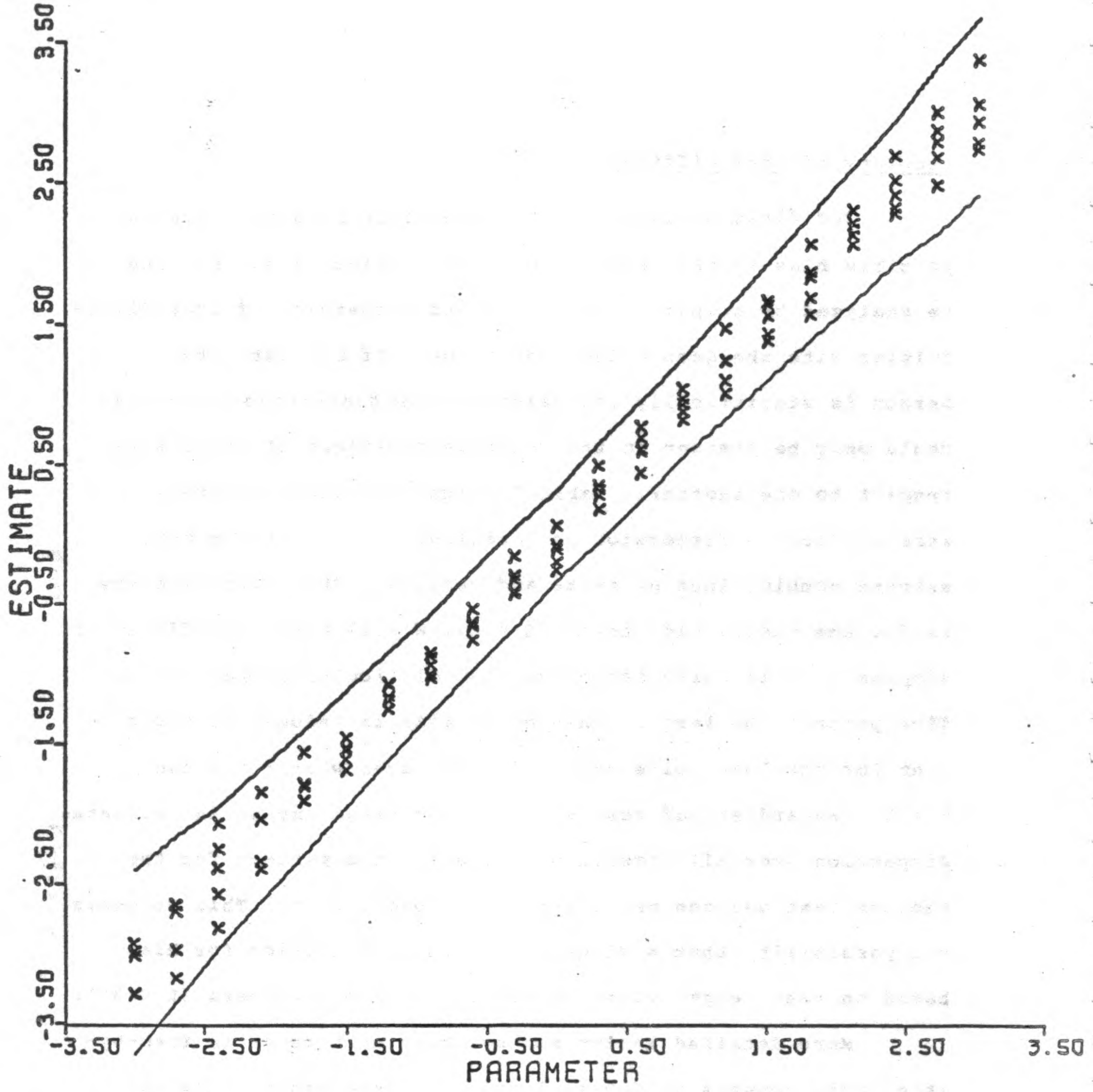

FIGURE 6

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=21 SAMPLE: M=0 S=1.0 N=400

REGRESSION: Y=1.02X X=0.97Y

TABLE 1

COMBINATIONS OF TESTS AND SAMPLES SIMULATED

Test: H=0, W, L=21 Sample: M, S, N=400

Test Width W	M=0 Sample Dispersion S 0.5	1.0	1.5	M=1 Sample Dispersion S 0.5	1.0	1.5
1	*	*				
2	x	x	*	*	*	
3		*	*	*	*	*
4	x	x	x	x	x	
6		x	x	x	x	x

Test: H=0, W, L=41 Sample: M, S, N=800

Test Width W	M=0 Sample Dispersion S 0.5	1.0	1.5	M=1 Sample Dispersion S 0.5	1.0	1.5
2	x	x				
4	x	x	x	x	x	
6		x	x	x	x	*

x data based on five replications and reported fully.

* additional data of five or more replications generated in the pilot phases of this report.

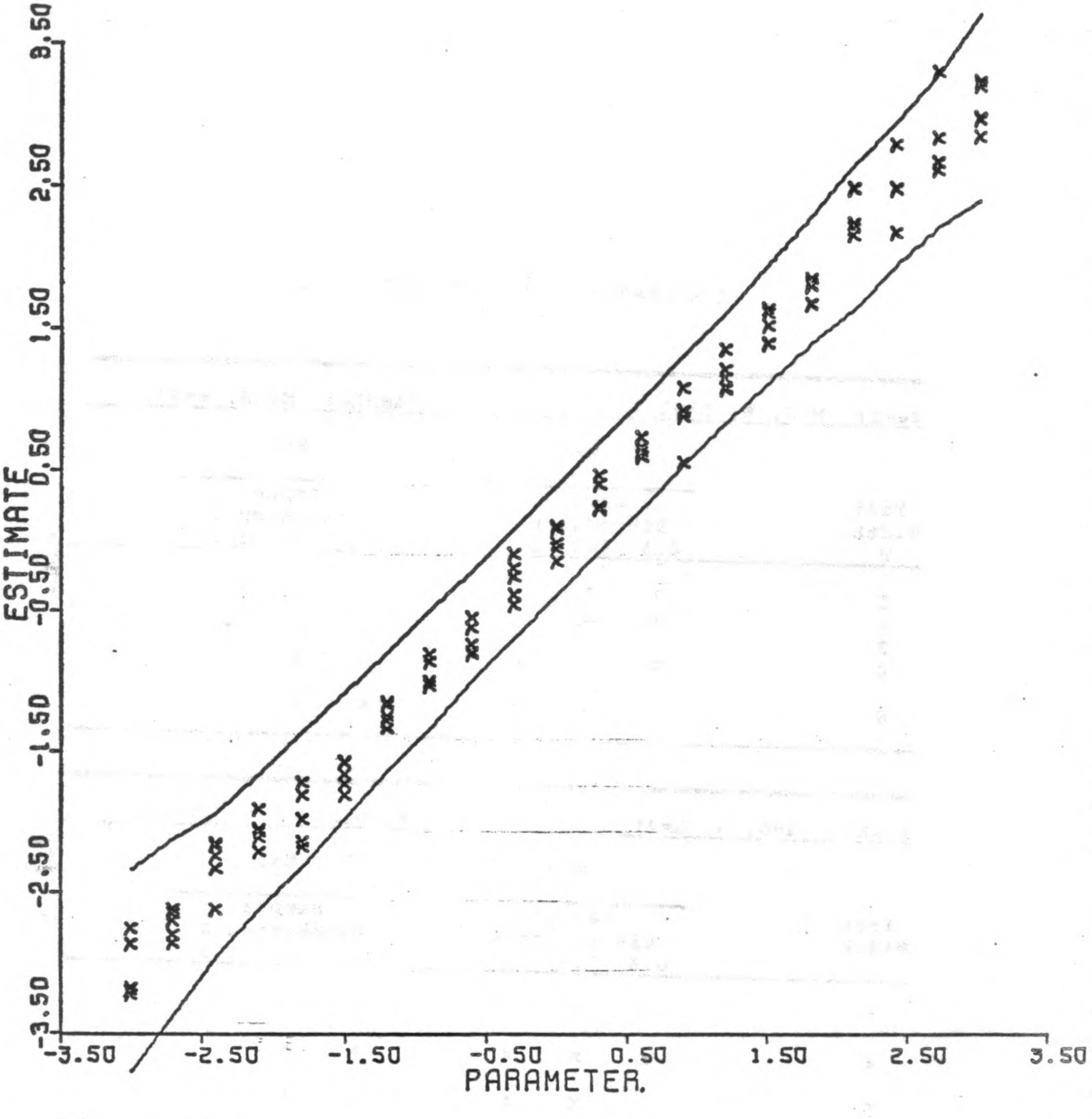

FIGURE 7

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=21 SAMPLE: M=0 S=1.5 N=400

REGRESSION: Y=1.02X X=0.97Y

TABLE 2

BICAL RECOVERY OF ITEM DIFFICULTY DISPERSION
(Means of five replications)

Test: H=0, W, L=21 Sample: M, S, N=400

		Estimated Dispersion s_d					
		M = 0			M = 1		
Generating Dispersion σ_d	Test Width W	Sample Dispersion S 0.5	1.0	1.5	Sample Dispersion S 0.5	1.0	1.5
0.31	1	0.31	0.31				
0.62	2	0.63	0.61	0.63	0.62	0.62	
0.93	3		0.94	0.95	0.94	0.93	0.93
1.24	4	1.24	1.24	1.27	1.26	1.30	
1.86	6		1.91	1.92	1.96	1.88	1.95

	Ratio s_d/σ_d					
	M = 0			M = 1		
Test Width W	Sample Dispersion S 0.5	1.0	1.5	Sample Dispersion S 0.5	1.0	1.5
1	1.00	1.00				
2	1.02	0.98	1.02	1.00	1.00	
3		1.01	1.02	1.01	1.00	1.00
4	1.00	1.00	1.02	1.02	1.05	
6		1.03	1.03	1.05	1.01	1.05

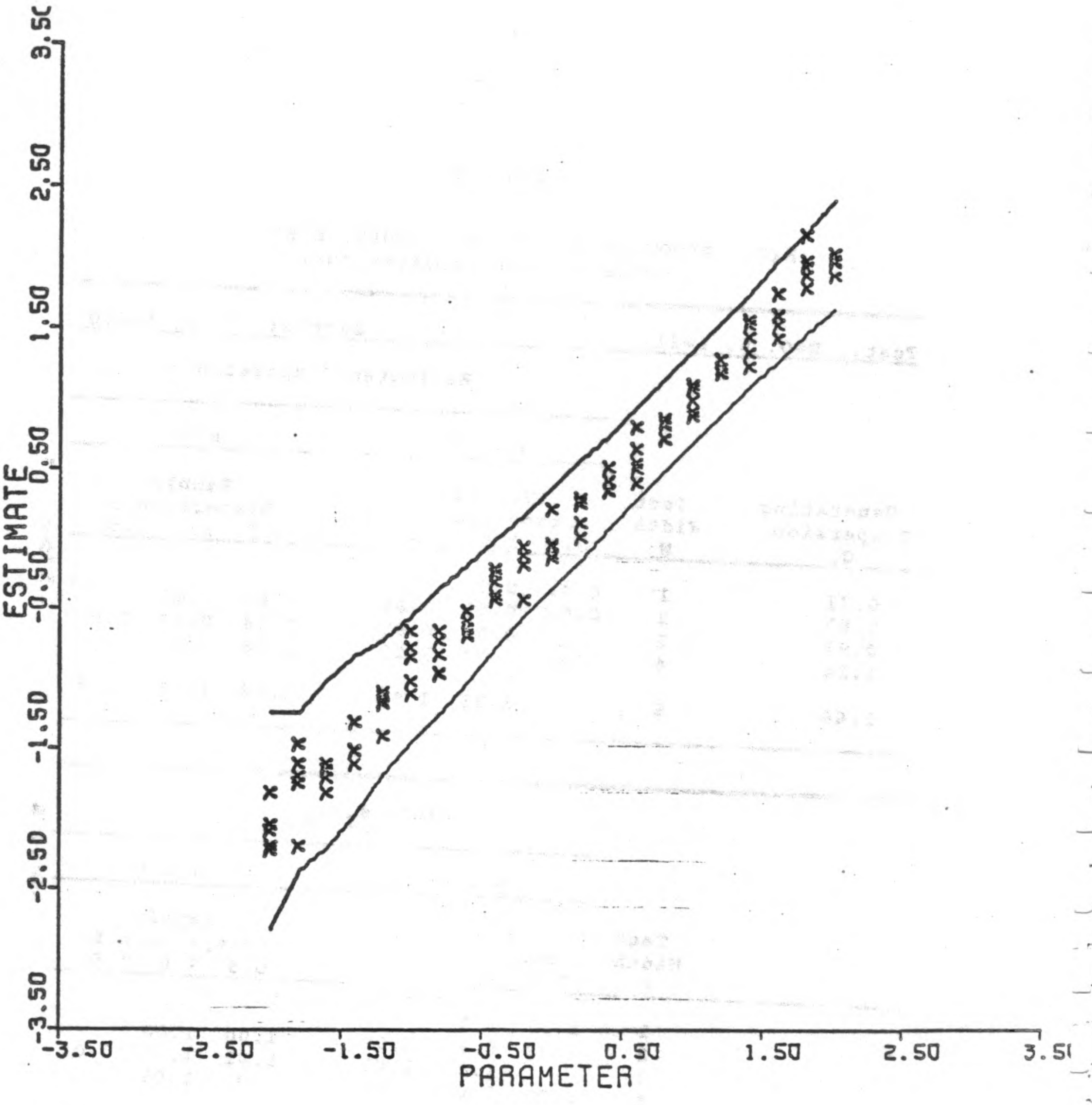

FIGURE 8

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=21 SAMPLE: M=1 S=0.5 N=400

REGRESSION: Y=1.01X X=0.98Y

TABLE 2

BICAL RECOVERY OF ITEM DIFFICULTY DISPERSION
(Means of five replications)

Continued

Test: H=0, W, L=41 — Sample: M, S, N=800

Estimated Dispersion s_d

Generating Dispersion σ_d	Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
0.60	2	0.61	0.60				
1.20	4	1.21	1.21	1.20	1.21	1.19	
1.80	6		1.82	1.82	1.84	1.80	1.82

Ratio s_d/σ_d

Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
2	1.02	1.00				
4	1.01	1.01	1.00	1.01	0.99	
6		1.01	1.01	1.02	1.00	1.01

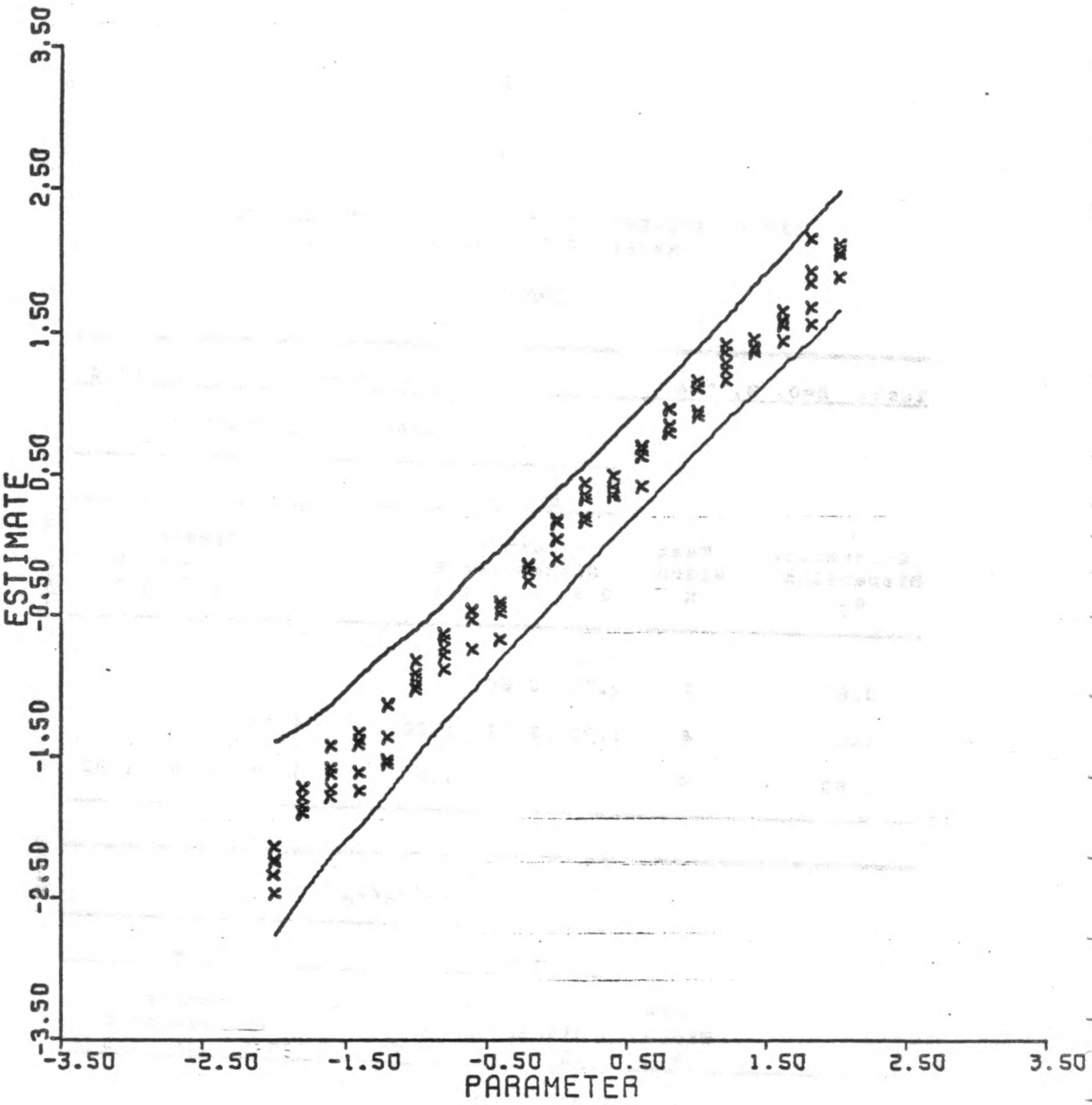

FIGURE 9

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=21 SAMPLE: M=1 S=1.0 N=400

REGRESSION: Y=1.04X X=0.95Y

by the longer test. Tables 3 and 4 show again that the largest estimation bias (5 percent) occurs for the shorter, wider tests (L = 21, W = 6) (M = 1) with off-center samples which are either narrowly or widely dispersed (S = 0.5 or 1.5) and for average tests which are off-center, but moderately dispersed (L = 21, W = 4, M = 1, S = 1.0). For the longer tests, the largest bias (2 percent) occurs on the narrow test with centered, narrowly dispersed samples (L = 41, W = 2, M = 0, S = 0.5) and on wider tests with off-center, narrowly dispersed samples (L = 41, W = 6, M = 1, S = 0.5).

Figures 1 through 23 interspersed throughout this chapter show the five replications of each BICAL item estimate plotted against its generating parameter, for each of twenty-three combinations of tests and samples. These plots show that the item estimates are well-balanced around the identity line and that nearly all of the estimates fall within the control lines drawn at two standard errors on either side of the identity line.

Distribution of Fit Statistics

In order to judge whether data are adequately recovered by the model it is necessary to assess the agreement between the observed data and their expectation under the model. To evaluate the fit of data to model it is useful to compute a fit statistic for each person's response to each item. This standardized squared residual is

$$z_{vi}^2 = \frac{(x_{vi} - p_{vi})^2}{p_{vi}(1 - p_{vi})} , \qquad [26]$$

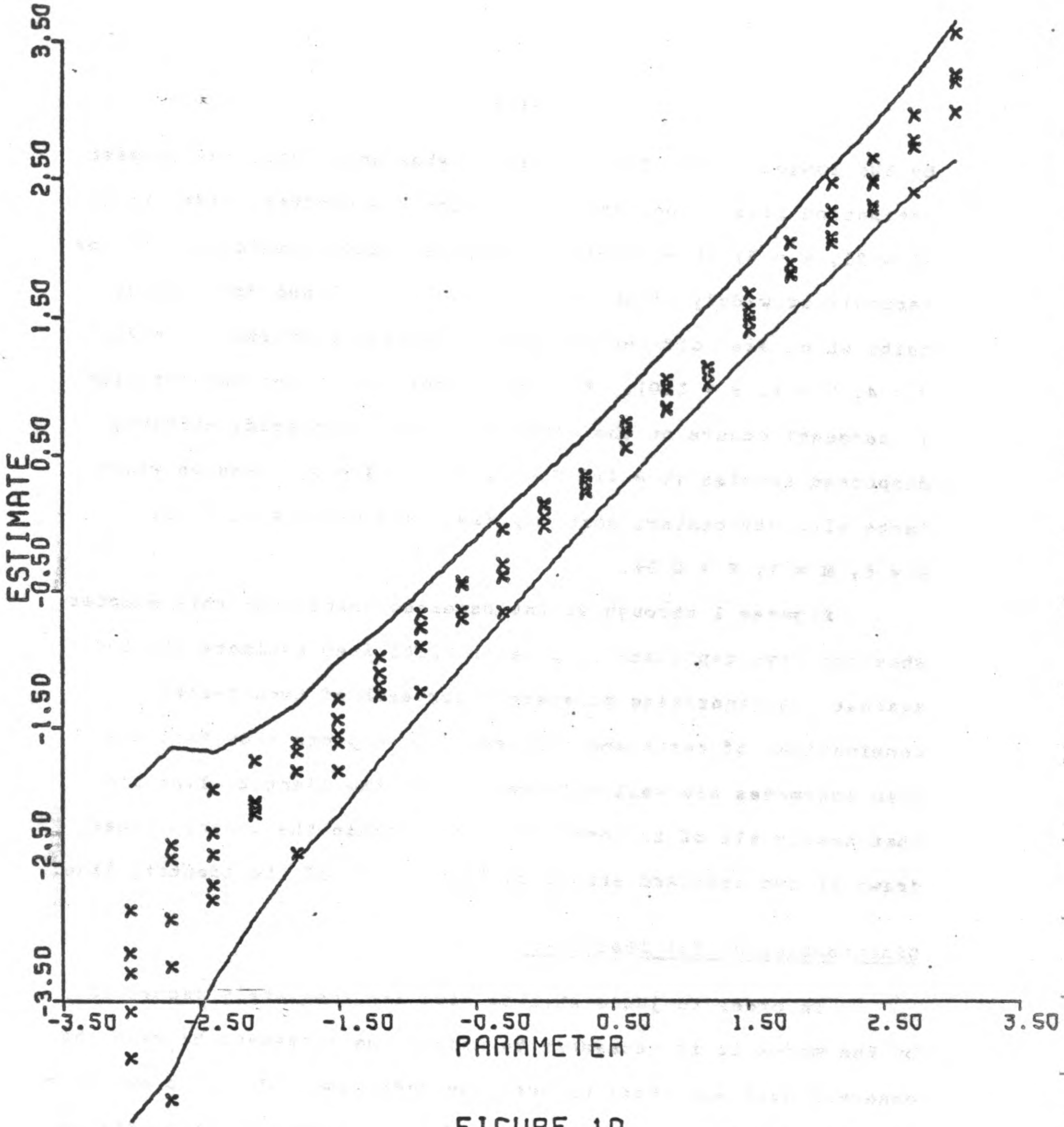

FIGURE 10

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=21 SAMPLE: M=1 S=0.5 N=400

REGRESSION: Y=1.05X X=0.94Y

TABLE 3

THE REGRESSION OF BICAL ITEM ESTIMATES ON THEIR GENERATING PARAMETERS - 21 ITEMS BY 400 PERSONS

Test H=0 L=21 Width W	Sample N=400 Mean M	Sample N=400 Std.Dev. S	Correlation Between Estimate and Parameter	Standard Deviation[1] of Param.	Standard Deviation[1] of Est.	Regression of Estimate on Parameter Slope	Regression of Estimate on Parameter Mean Square Residual[2]	Regression of Parameter on Estimate Slope	Regression of Parameter on Estimate Mean Square Residual[3]
2	0	0.5	0.985	0.608	0.615	0.996	0.0113	0.974	0.0111
2	0	1.0	0.983	0.608	0.600	0.969	0.0125	0.997	0.0128
4	0	0.5	0.995	1.217	1.215	0.994	0.0142	0.996	0.0142
4	0	1.0	0.996	1.217	1.219	0.998	0.0127	0.994	0.0127
4	0	1.5	0.994	1.217	1.248	1.019	0.0192	0.969	0.0182
6	0	1.0	0.997	1.825	1.871	1.022	0.0233	0.972	0.0221
6	0	1.5	0.997	1.825	1.877	1.025	0.0246	0.969	0.0233
4	1	0.5	0.995	1.217	1.241	1.014	0.0170	0.975	0.0163
4	1	1.0	0.995	1.217	1.274	1.041	0.0179	0.950	0.0163
6	1	0.5	0.992	1.825	1.929	1.048	0.0620	0.939	0.0555
6	1	1.0	0.996	1.825	1.841	1.006	0.0206	0.989	0.0202
6[2]	1	1.5	0.996	1.828	1.912	1.042	0.0317	0.952	0.0290

[1]Because these statistics combined five replications, the degrees of freedom used in the calculation of the standard deviations were 104 instead of 5x20 = 100. As a result, these values are .98 of the ones found in Table 2A. The ratios are comparable.

[2]These calculations were based on four replications rather than the five used in the other combinations.

[3]For samples of 400 the theoretical minimum mean square residual runs from .0100 for a zero width test exactly on target through .0225 for a rather wide test somewhat off-target.

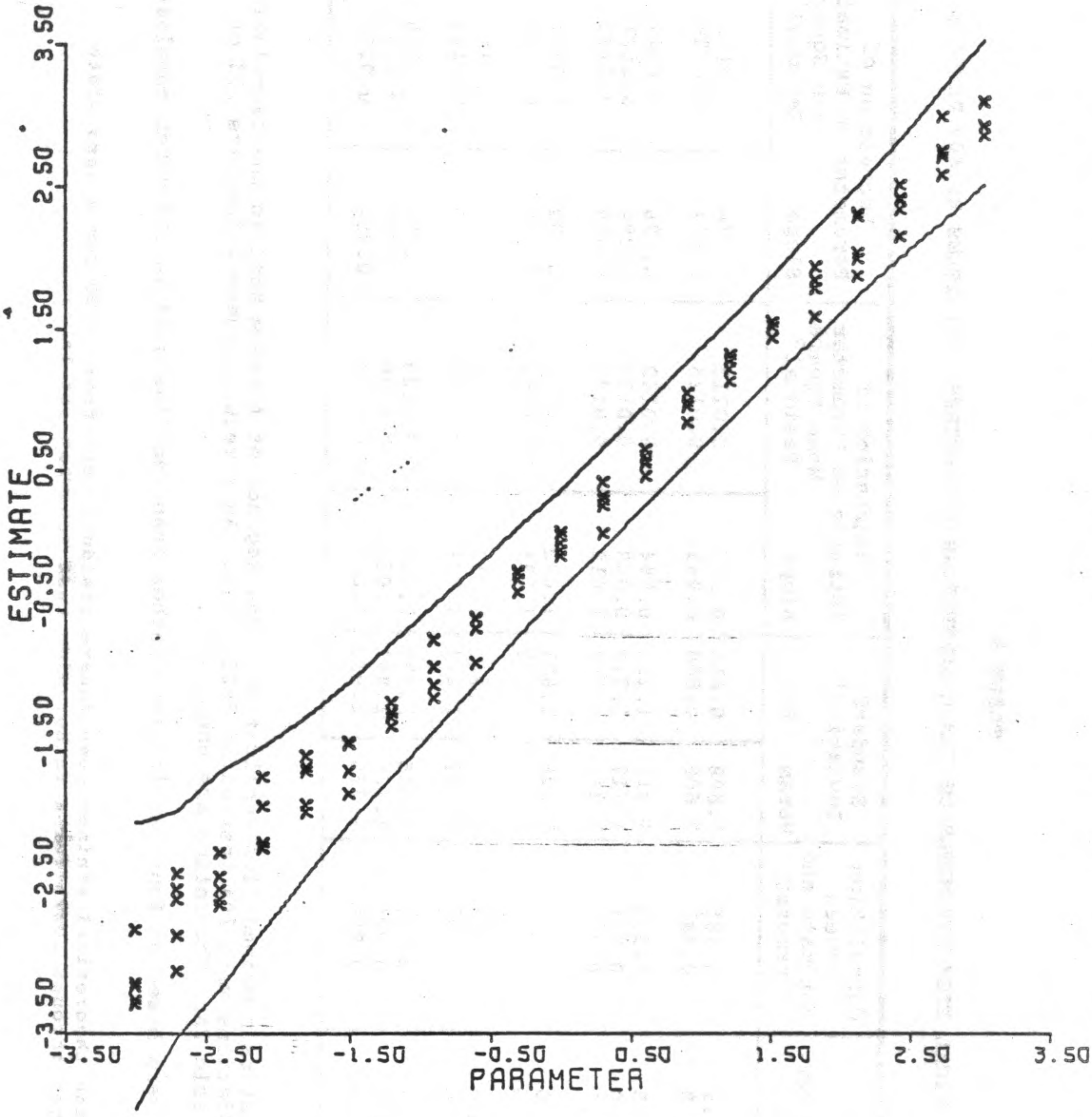

FIGURE 11

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=21 SAMPLE: M=1 S=1.0 N=400

REGRESSION: Y=1.01X X=0.99Y

TABLE 4

THE REGRESSION OF BICAL ITEM ESTIMATES ON THEIR GENERATING PARAMETERS - 41 ITEMS BY 800 PERSONS

Test H=0 L=41 Width W	Sample N=800 Mean M	Std.Dev. S	Correlation Between Estimate and Parameter	Standard Deviation[1] of Param.	Est.	Regression of Estimate on Parameter Slope	Mean Square Residual[2]	Regression of Parameter on Estimate Slope	Mean Square Residual[2]
2	0	0.5	0.993	0.593	0.602	1.009	0.0051	0.978	0.0049
2	0	1.0	0.990	0.593	0.600	1.001	0.0071	0.979	0.0070
4	0	0.5	0.997	1.186	1.200	1.009	0.0075	0.986	0.0073
4	0	1.0	0.998	1.186	1.195	1.005	0.0071	0.990	0.0070
4	0	1.5	0.997	1.186	1.191	1.001	0.0080	0.993	0.0079
6	0	1.0	0.999	1.779	1.798	1.009	0.0091	0.988	0.0089
6	0	1.5	0.998	1.779	1.803	1.012	0.0109	0.985	0.0106
4	1	0.5	0.996	1.186	1.202	1.010	0.0105	0.983	0.0102
4	1	1.0	0.997	1.186	1.182	0.993	0.0092	1.000	0.0093
6	1	0.5	0.998	1.779	1.818	1.020	0.0129	0.977	0.0124
6	1	1.0	0.998	1.779	1.787	1.002	0.0121	0.994	0.0120

[1]Because these statistics combine five replications, the degrees of freedom used in the calculation of the standard deviations were 204 instead of 5x40 = 200. As a result, these values are .99 of the ones found in Table 2B. The ratios are comparable.

[2]For samples of 800 the theoretical minimum mean square residual runs between .0050 for a zero width test exactly on target through .0112 for a rather wide test somewhat off-target.

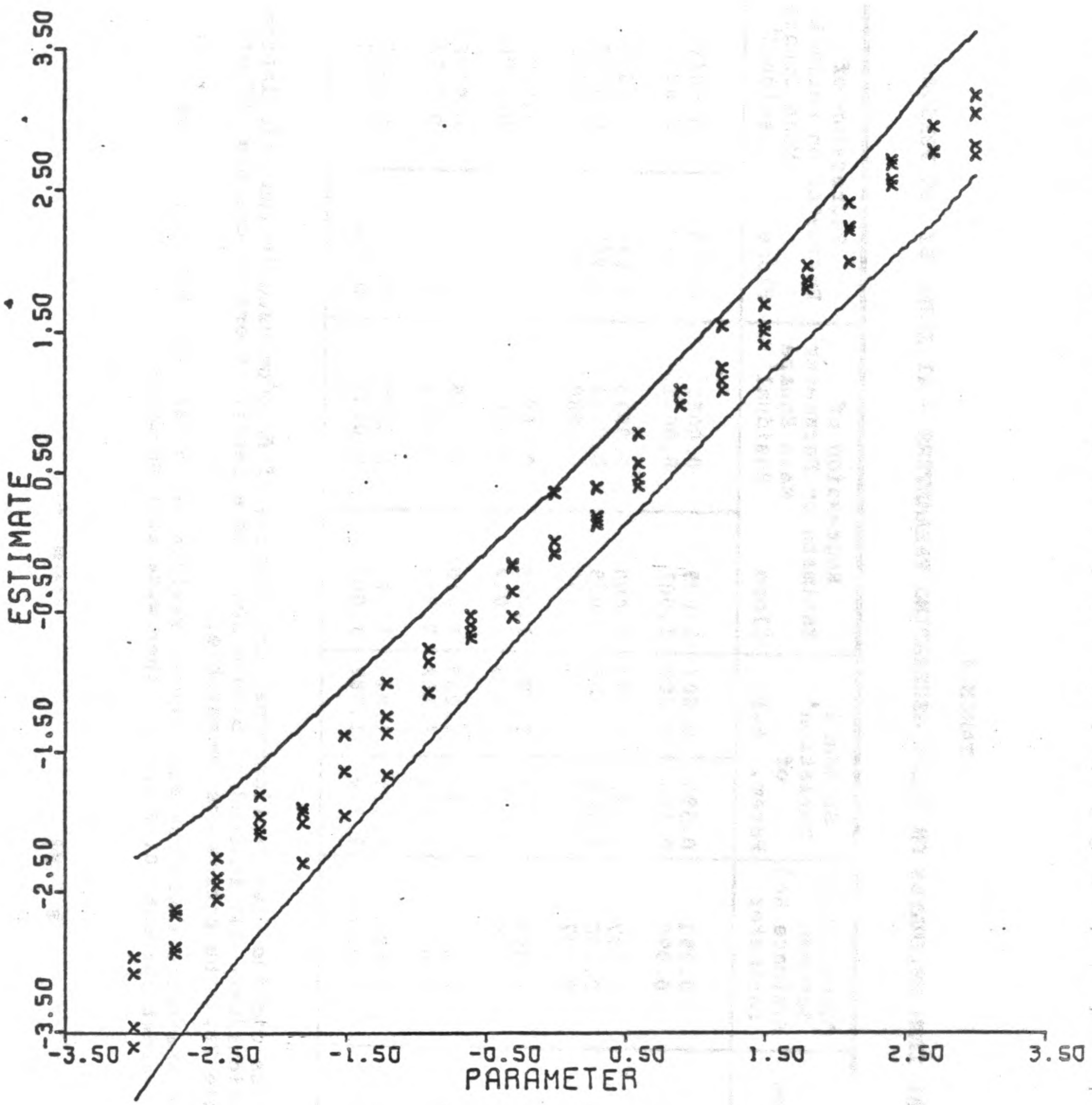

FIGURE 12

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=21 SAMPLE: M=1 S=1.5 N=400

REGRESSION: Y=1.04X X=0.95Y

where

$$P_{vi} = \frac{\exp(b_v - d_i)}{1 + \exp(b_v - d_i)} \quad .$$

It is then convenient to express these statistics in the form of mean square residuals. For the overall fit of item i this is

$$v_i = \sum_v^N z_{vi}^2 \quad \frac{L}{(N-1)\ (L-1)} \qquad [27]$$

which has an expected value of one and a variance of $2L/[(N-1)(L-1)]$.

A corresponding mean square for the fit of person v is

$$v_v = \sum_i^L z_{vi}^2 \quad \frac{N}{(N-1)\ (L-1)} \qquad [28]$$

which has an expected value of one and a variance of $2N/[(N-1)(L-1)]$.

A fit mean square for the entire test is given by

$$v = \sum\sum_{vi}^{NL} z_{vi}^2 \quad \frac{1}{(N-1)\ (L-1)} \qquad [29]$$

with an expected value of one and a variance of $2/[(N-1)(L-1)]$.

If we represent the expected value of the standard deviation of the item fit statistic v_i as $\sigma_v = \sqrt{2/df}$, and its observed value over items in any particular calibration as s_v, the ratio s_v/σ_v can become a useful part of the fit analysis, because it standardizes the dispersion of the item mean squares around an expected value of one.

The fit statistics for the various simulations are given in Tables 5 and 6. In Table 5 the observed value of the test fit statistic v is compared with its expected value of one. The

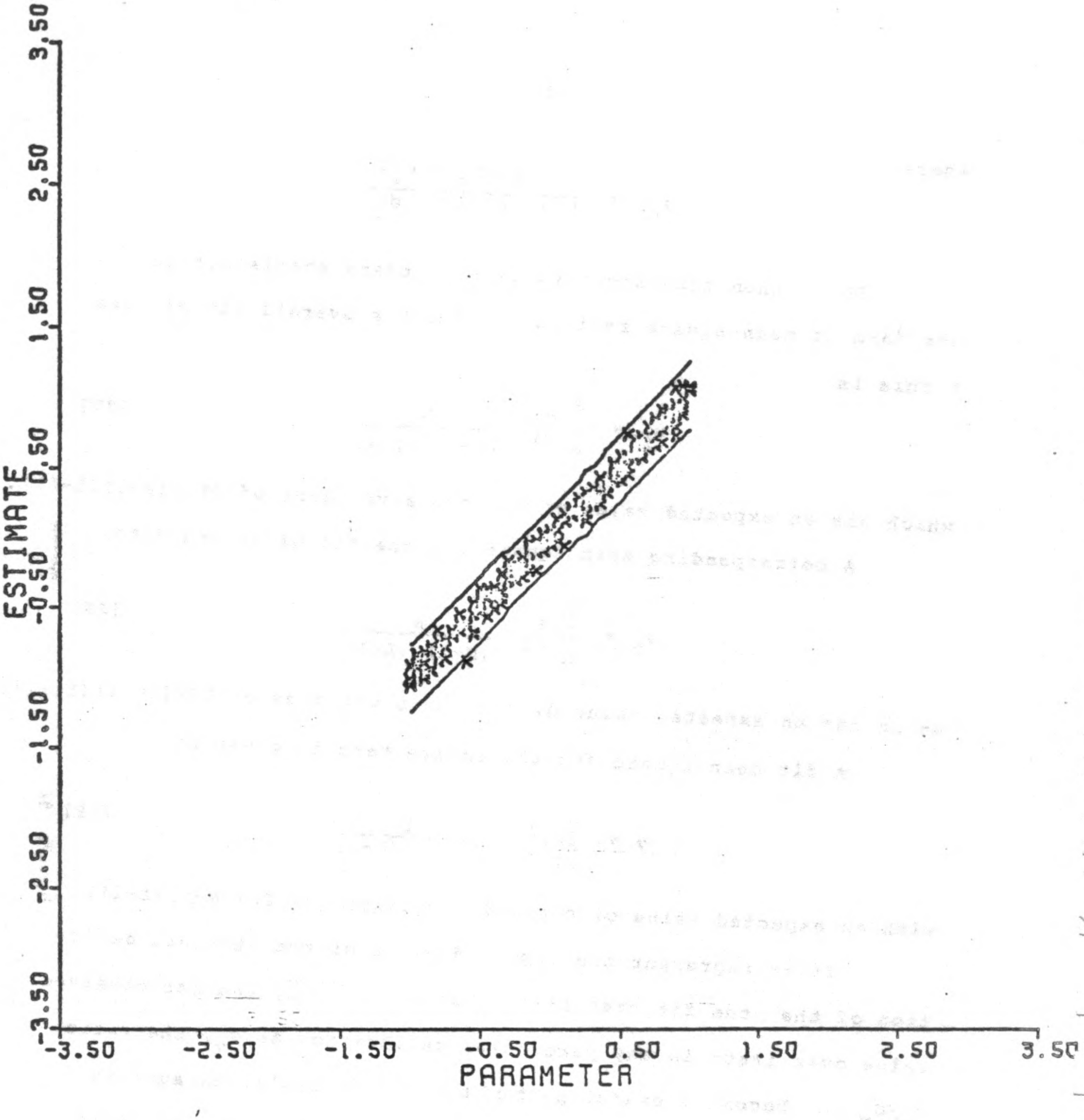

FIGURE 13

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=2 L=41 SAMPLE: M=0 S=0.5 N=800

REGRESSION: Y=1.01X X=0.98Y

fits are closest to expectation when the test is narrow (W = 2). Regardless of test length the fits drift slightly below one as the tests become wider. The departure below expectation is about the same at the different levels and dispersions of sample ability, so sample properties do not appear to have a significant influence on these fit statistics. However, the longer test (L = 41) shows less departure below expectation in its fit statistics than does the shorter test (L=21).

The standard deviations of the <u>item</u> fit statistics within tests are analyzed in Table 6. There is an inflation above expectations with short, wide tests (L = 21, W = 6). The ratio (s_v/σ_v) becomes as large as two for wider tests (W = 6), regardless of test length. This is twice the expected value of one and indicates that the item mean squares even when data fit the model can be substantially more dispersed around one than the approximate theory for the distribution of these residuals implies.

Table 6 also shows that the expected ratio of one is found on narrow tests with centered and moderately dispersed samples (W = 2, M = 0, S = 1.0) and on average width tests with off-center, narrowly dispersed samples (W = 4, M = 1, S = 0.5) for tests of both lengths. But the theoretical ratio is clearly a bit too low for evaluating the fit of wide tests (W > 4) taken by dispersed samples (S > 1.0). Obviously a relaxation in the reference value used is required when judging item fit in real data collected under such moderately extreme circumstances.

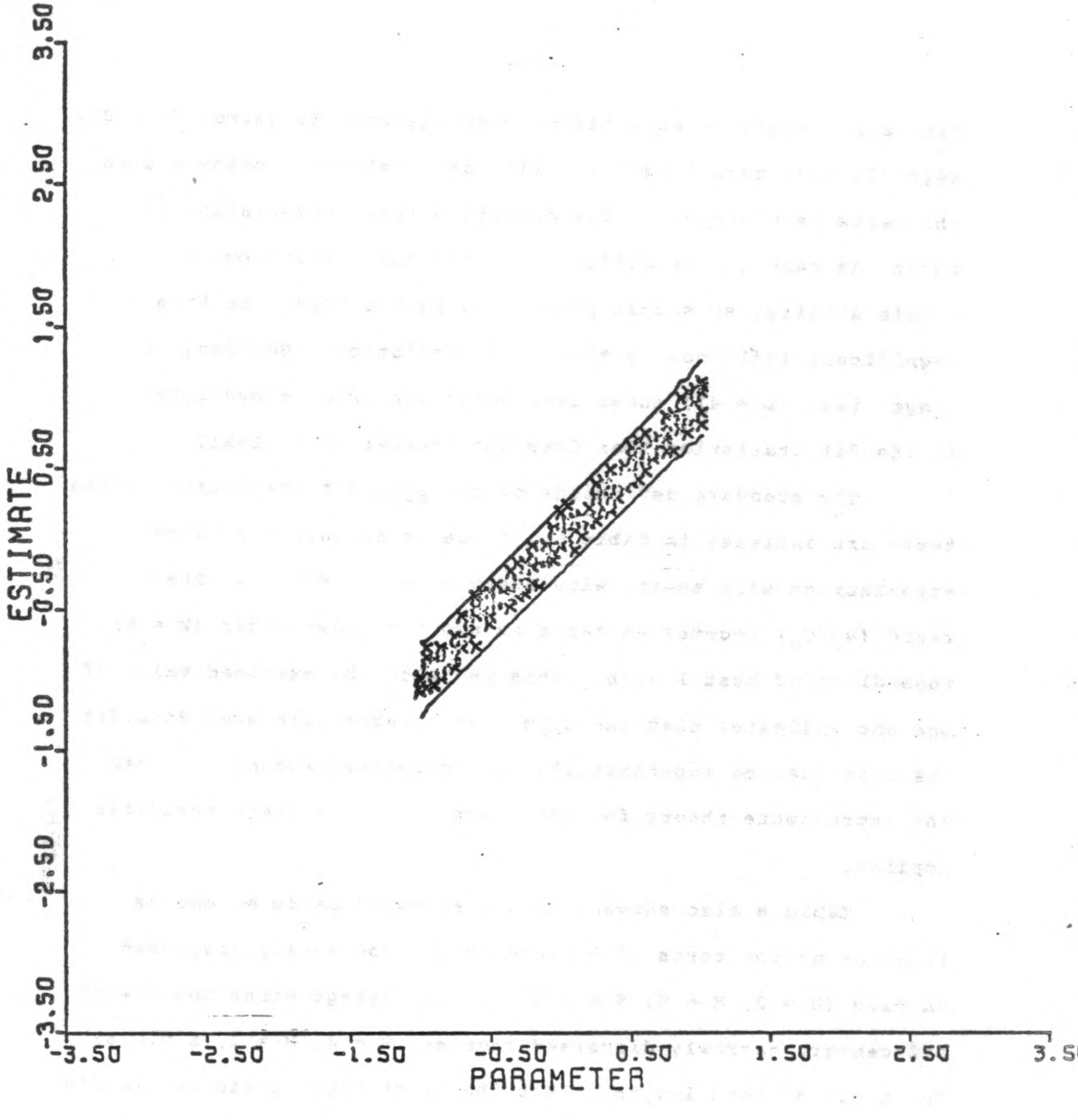

FIGURE 14

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=2 L=41 SAMPLE: M=0 S=1.0 N=800

REGRESSION: Y=1.00X X=0.98Y

TABLE 5

AVERAGE MEAN SQUARE FIT STATISTIC OVER ITEMS
(Means of five replications)

Test: H=0, W, L=21 — Sample: M, S, N=400

Average Fit Statistic V

Test Width W	M = 0 Sample Dispersion S			M = 1 Sample Dispersion S		
	0.5	1.0	1.5	0.5	1.0	1.5
1	0.99	0.99				
2	0.99	0.99	0.99	0.99	0.98	
3		0.98	0.98	0.98	0.98	0.97
4	0.97	0.96	0.97	0.96	0.97	
6		0.95	0.94	0.93	0.94	0.94

Test: H=0, W, L=41 — Sample: M, S, N=800

Average Fit Statistic V

Test Width W	M = 0 Sample Dispersion S			M = 1 Sample Dispersion S		
	0.5	1.0	1.5	0.5	1.0	1.5
2	0.99	0.99				
4	0.98	0.98	0.98	0.98	0.98	
6		0.97	0.96	0.97	0.98	0.98

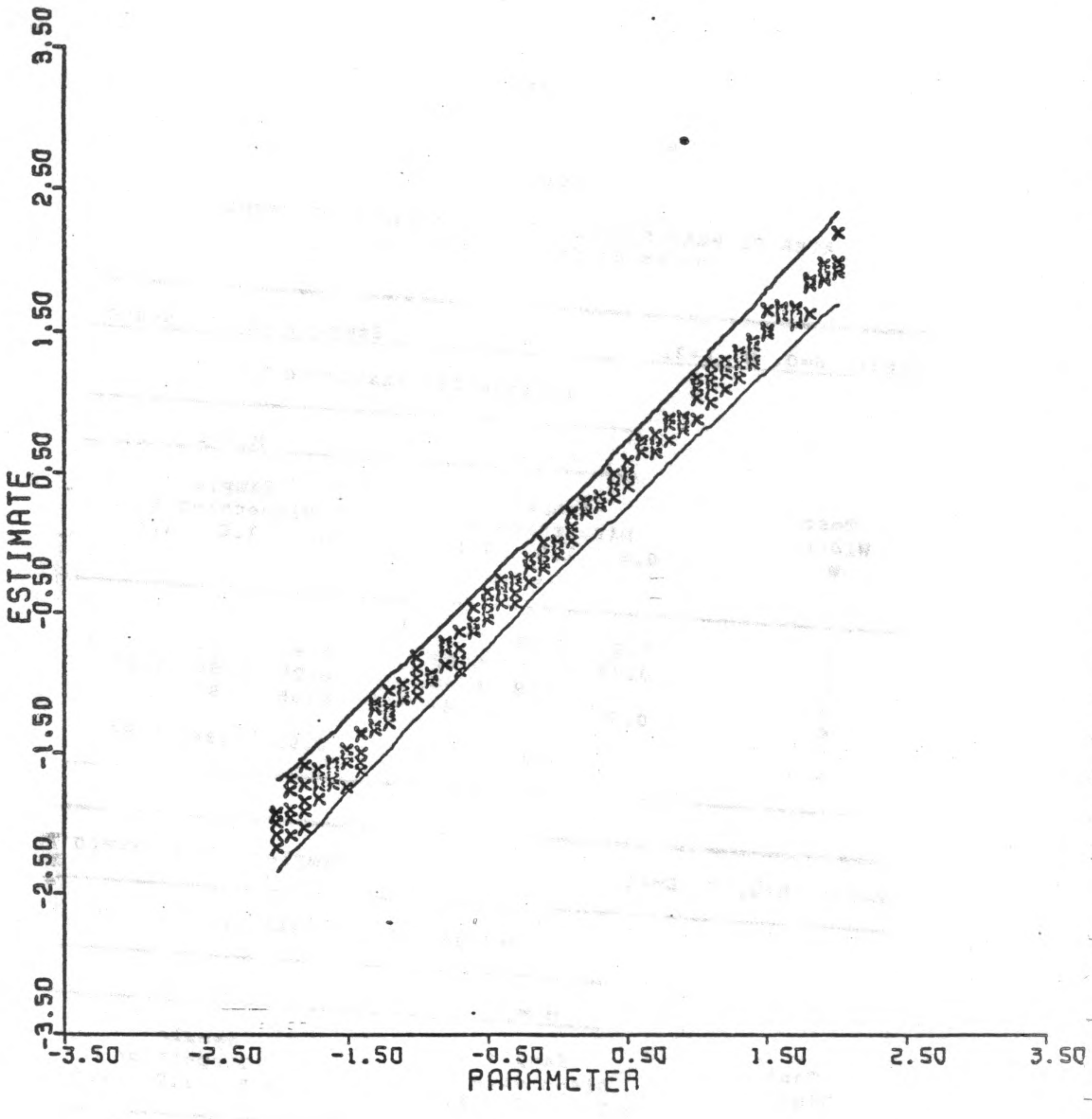

FIGURE 15

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=41 SAMPLE: M=0 S=0.5 N=800

REGRESSION: Y=1.01X X=0.99Y

TABLE 6

STANDARD DEVIATIONS OF MEAN SQUARE
FIT STATISTIC OVER ITEMS
(Means of five replications)

Test: H=0, W, L=21 — Sample: M, S, N=400

Standard Deviation of Fit Statistic s_V

Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
1	.03	.05				
2	.04	.05	.07	.04	.07	
3		.06	.07	.06	.07	.08
4	.06	.07	.09	.07	.10	
6		.14	.16	.12	.13	.17

Expectation of s_V is σ_V = .07.

Ratio s_V/σ_V

Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
1	0.4	0.7				
2	0.6	0.7	1.0	0.6	1.0	
3		0.9	1.0	0.9	1.0	1.1
4	0.9	1.0	1.3	1.0	1.4	
6		2.0	2.3	1.7	1.9	2.4

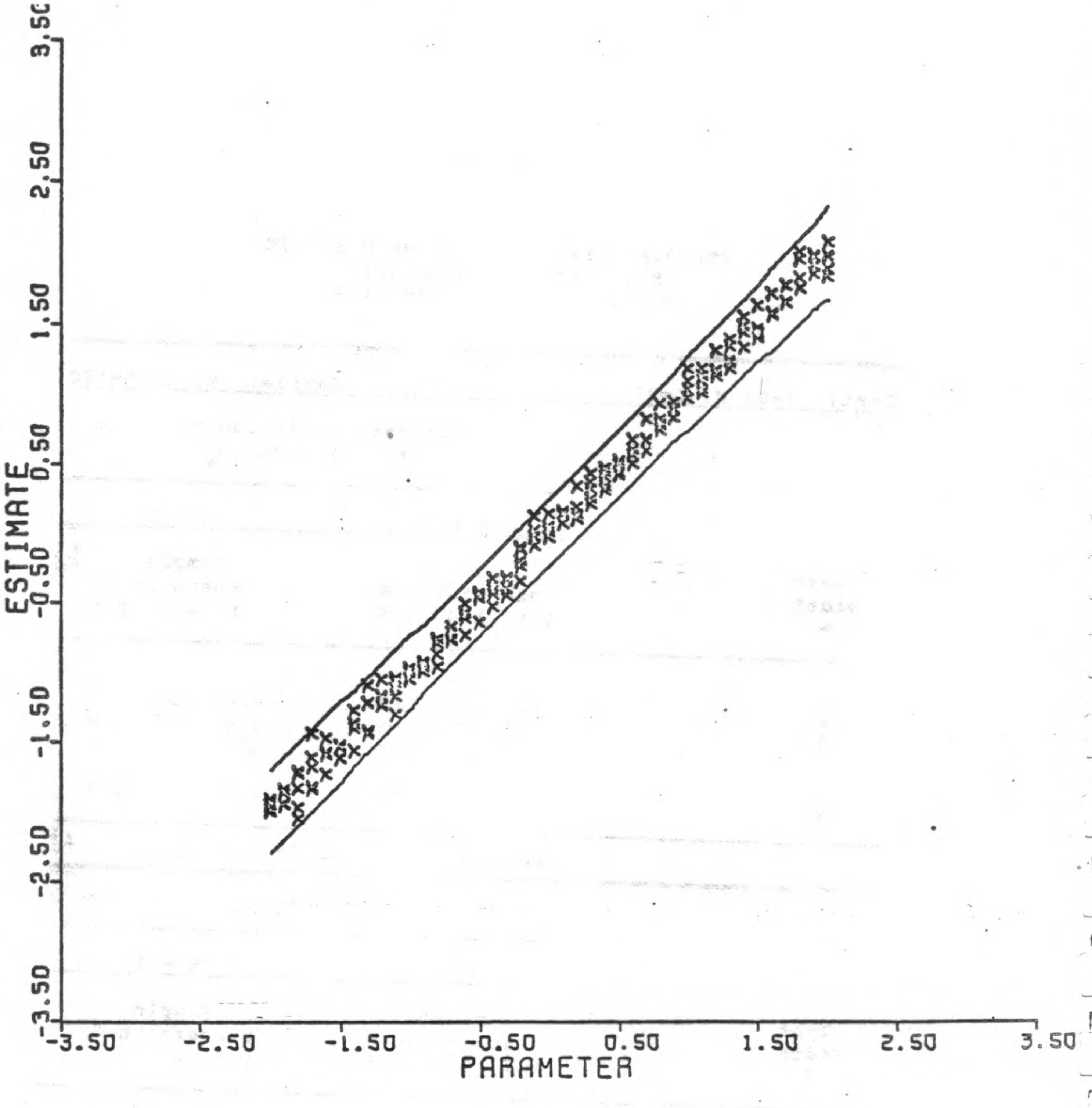

FIGURE 16

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=41 SAMPLE: M=0 S=1.0 N=800

REGRESSION: Y=1.00X X=0.99Y

TABLE 6

STANDARD DEVIATIONS OF MEAN SQUARE
FIT STATISTIC OVER ITEMS
(Means of five replications)

Continued

Test: H=0, W, L=41 Sample: M, S, N=800

Standard Deviation of Fit Statistic s_V

Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
2	.03	.05				
4	.04	.06	.08	.05	.07	
6		.08	.12	.07	.15	.13

Expectation of s_V is $\sigma_V = .05$.

Ratio s_V/σ_V

Test Width W	M = 0, Sample Dispersion S 0.5	1.0	1.5	M = 1, Sample Dispersion S 0.5	1.0	1.5
2	0.6	1.0				
4	0.8	1.2	1.6	1.0	1.4	
6		1.6	2.4	1.4	3.0	2.6

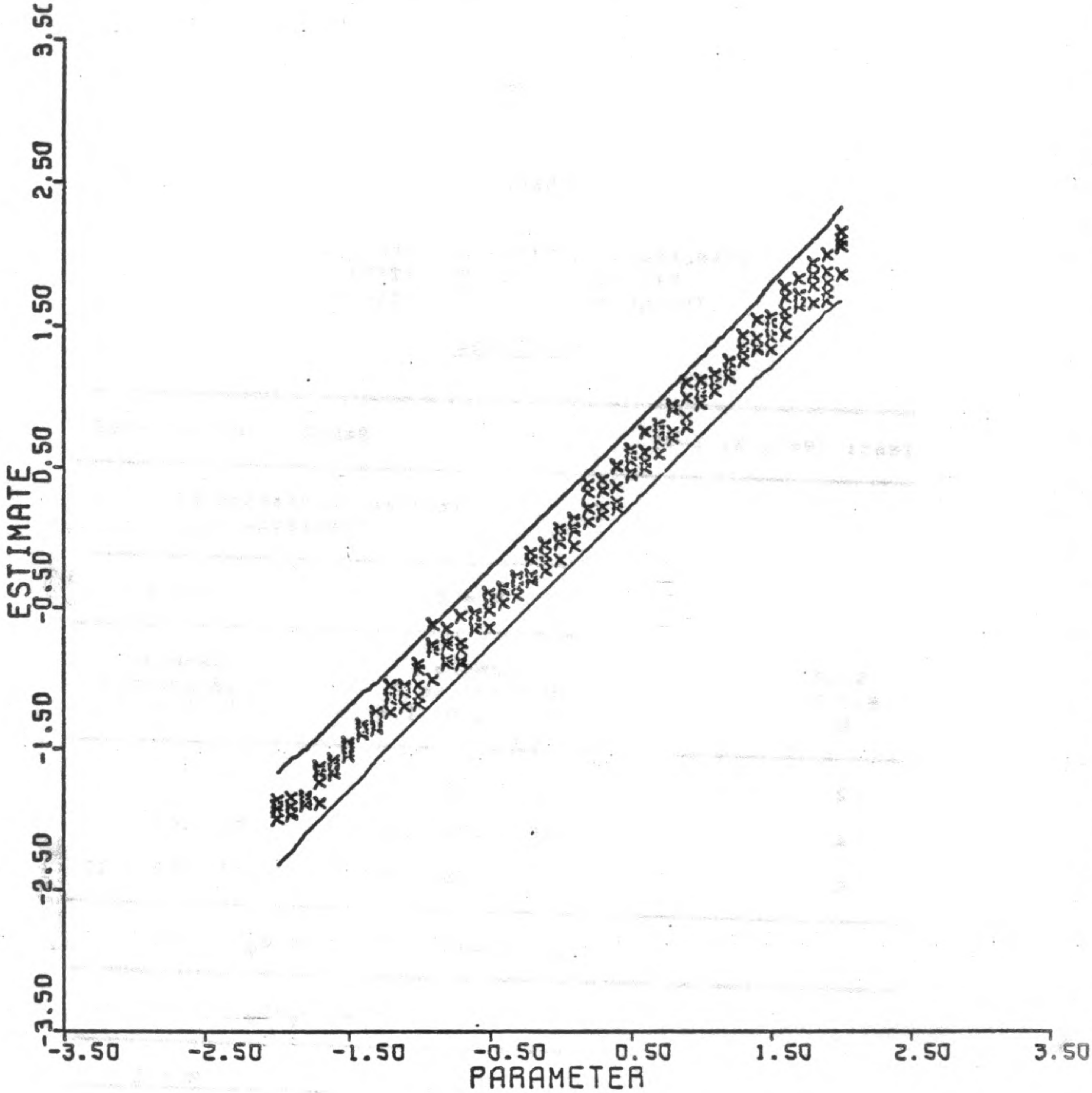

FIGURE 17

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=41 SAMPLE: M=0 S=1.5 N=800

REGRESSION: Y=1.00X X=0.99Y

Summary

The Rasch response model used by BICAL implies ideal consequences for residuals from the model. The residuals actually observed in a calibration are summarized into mean square residual fit statistics for individual items and for the test as a whole. It is unrealistic to expect the results of simulations to match the ideal consequences exactly, but one can ask, "To what extent do the results, and hence the algorithm they document, approximate these ideals?" This is an important question, as the ideals are the frame of reference from which an experimenter must judge the fit of any real data.

The simulations reviewed show that, when test and sample properties are in approximate rapport, then the expected fit statistics can be used to evaluate fit and, when fit is obtained, that good parameter estimates are also obtained. These simulations also show that when sample and/or test characteristics are pushed to extremes, residuals more widely dispersed than those anticipated by the model can result.

In serious practice genuine attempts are ordinarily made to avoid unruly situations. Should extreme conditions nevertheless arise, the experimenter can qualify the interpretation of his results in terms of the trends shown in these simulations. As sample or test spread out beyond typical values, variation among the item mean squares for data simulated to fit the model increases to twice that expected by the model. At the same time, the total mean square falls slightly below its expected

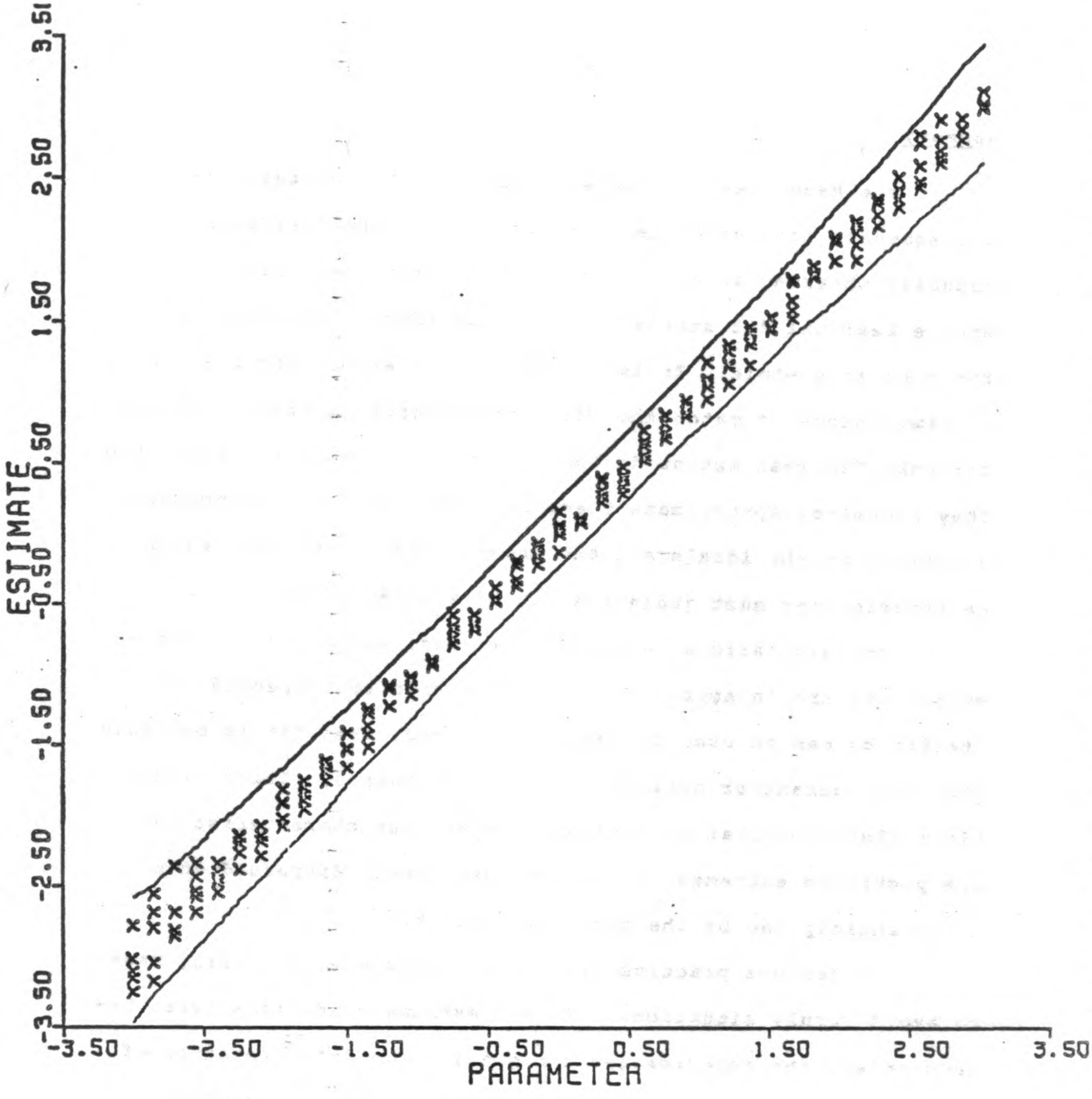

FIGURE 18

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=41 SAMPLE: M=0 S=1.0 N=800

REGRESSION: Y=1.01X X=0.99Y

value of one. When judging the fit of real data for either a wide test (W > 4) or a wide sample (S > 1.0), it would seem reasonable to be tolerant of item mean square dispersions somewhat larger than expected, but to work toward average mean squares falling slightly below one.

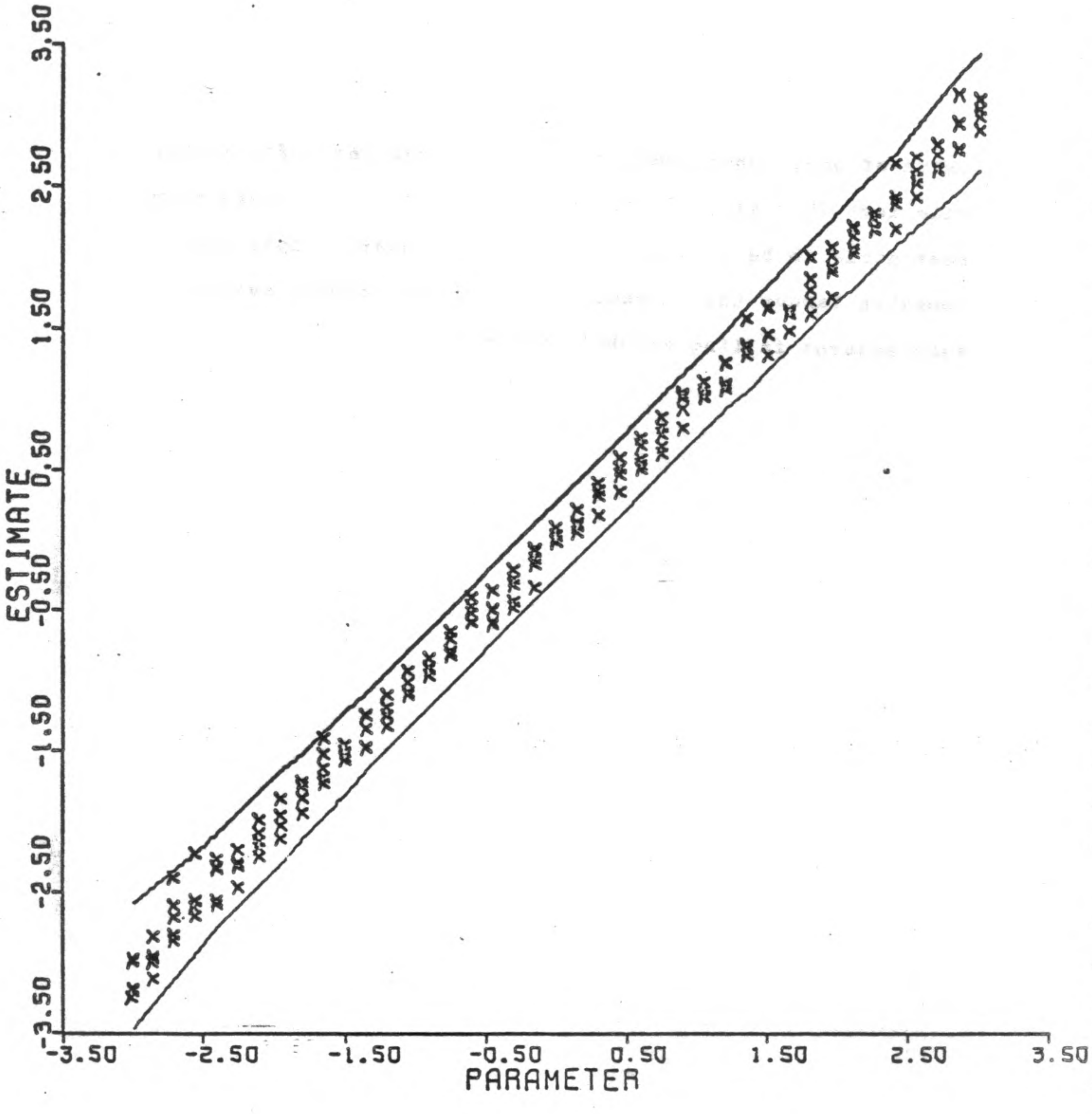

FIGURE 19

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=41 SAMPLE: M=0 S=1.5 N=800

REGRESSION: Y=1.01X X=0.99Y

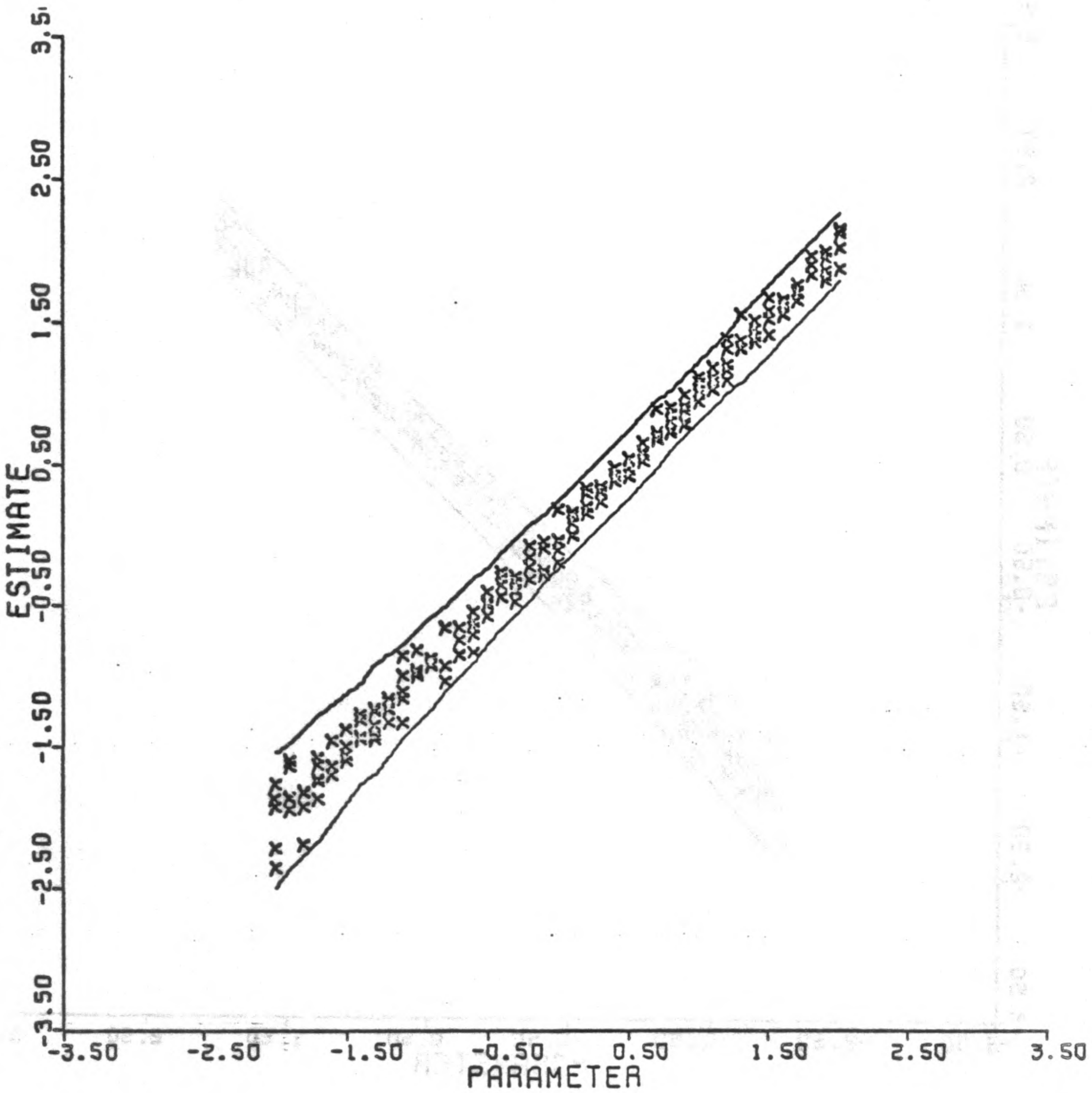

FIGURE 20

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=41 SAMPLE: M=1 S=0.5 N=800

REGRESSION: Y=1.01X X=0.98Y

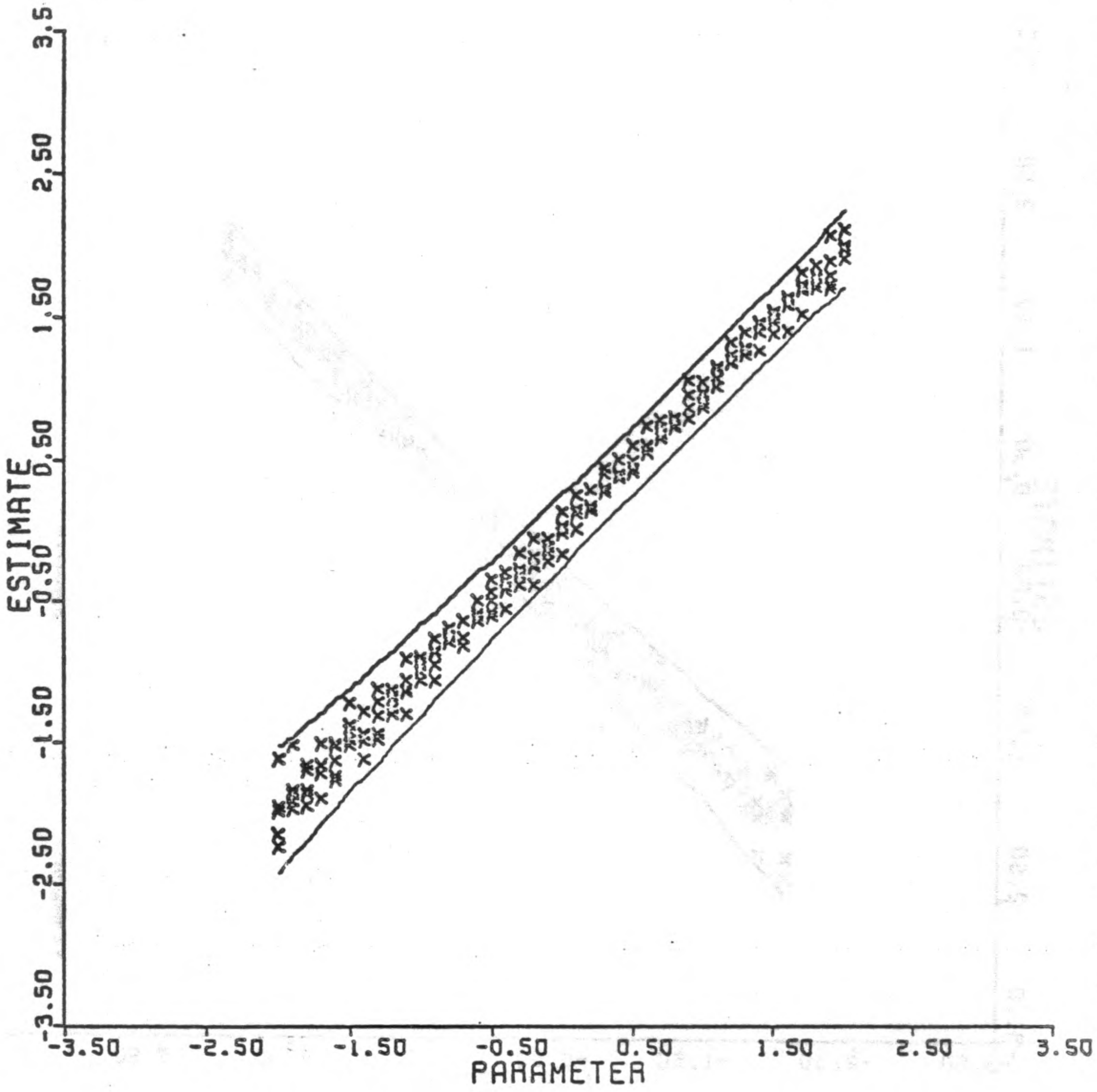

FIGURE 21

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=4 L=41 SAMPLE: M=1 S=1.0 N=800

REGRESSION: Y=0.99X X=1.00Y

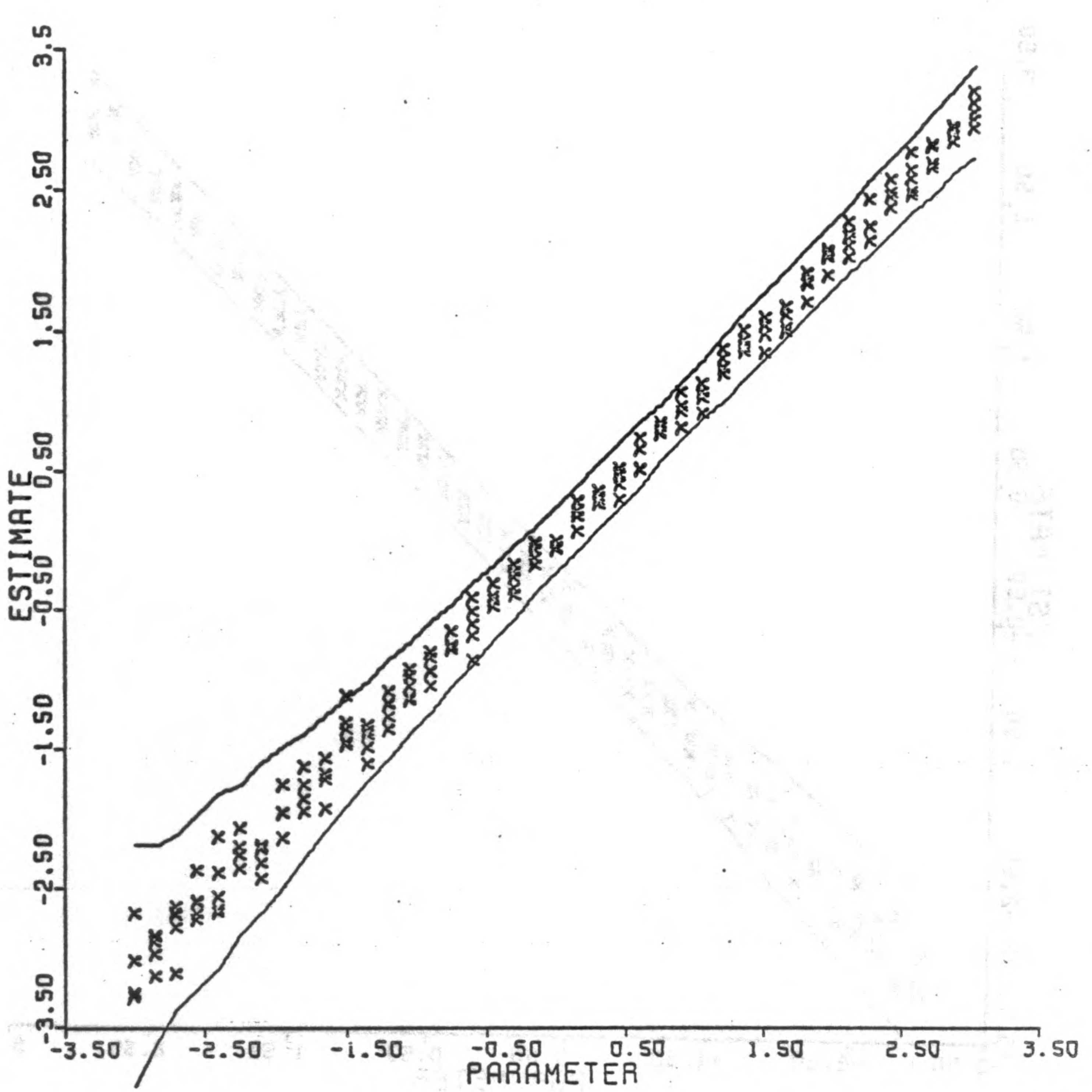

FIGURE 22

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=41 SAMPLE: M=1 S=0.5 N=800

REGRESSION: Y=1.02X X=0.98Y

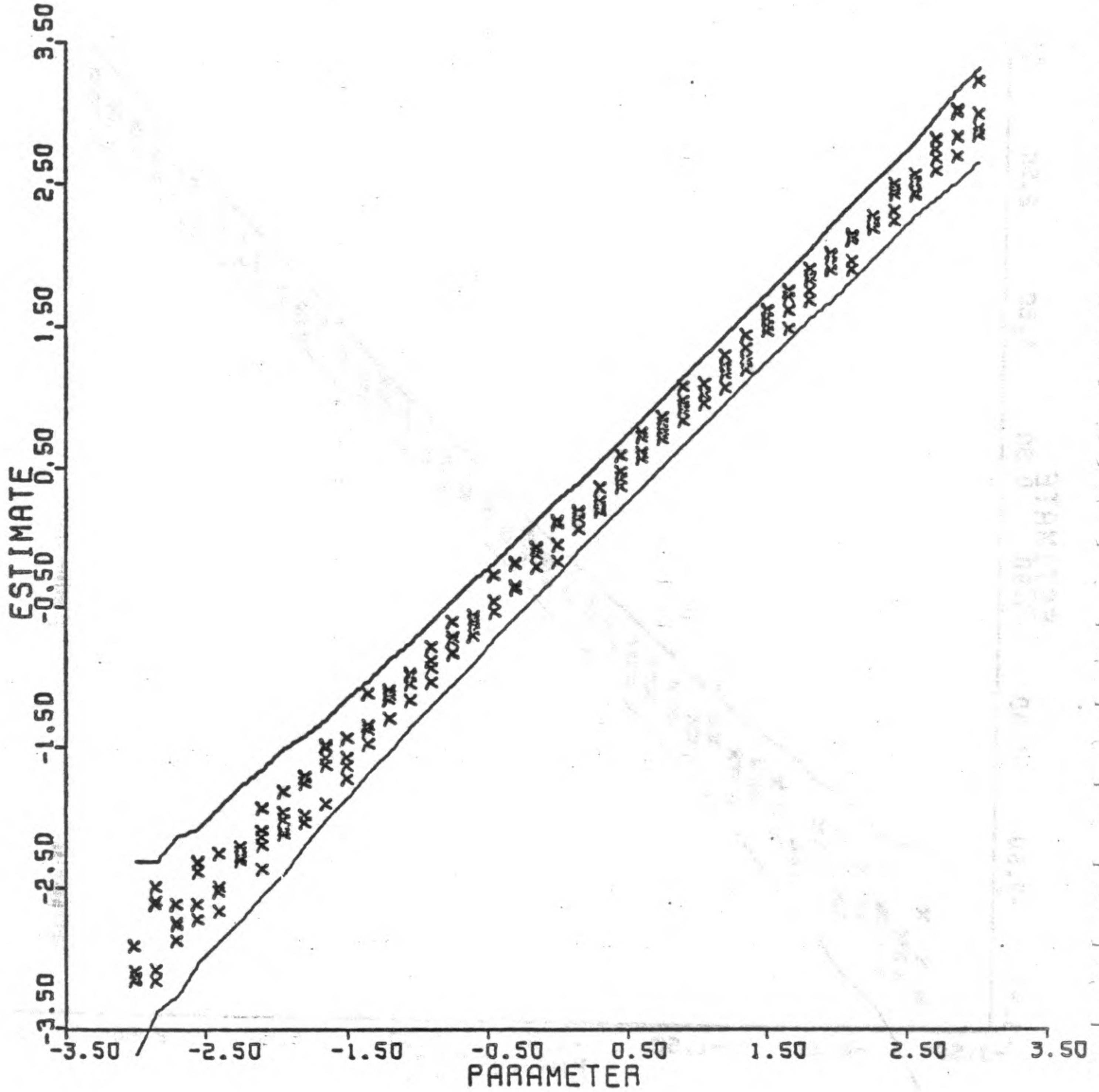

FIGURE 23

REGRESSION OF BICAL ESTIMATES ON THEIR PARAMETERS

TEST: H=0 W=6 L=41 SAMPLE: M=1 S=1.0 N=800

REGRESSION: Y=1.00X X=0.99Y

V. RASCH MODEL REFERENCES

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VI. DESCRIPTION OF PROGRAM FLOW

BICAL consists of three major sections: input, estimation, and fit. The input section reads control cards, processes the person records, stores them for a fit analysis and computes the item and person marginals for the estimation section. This involves sub-routines PAGE, REDØP and EDITD.

The estimation section is controlled by sub-routine ESTIM which includes calls to PRØX, UCØN and ABLTY. These routines calculate from the marginal person and item score distributions the estimates of ability and difficulty.

The parameter estimates from ESTIM and the person file prepared by REDØP are combined into an analysis of the fit of the data in sub-routine FITCS. This routine computes a mean square test of fit for each item and organizes the results for SMMRY, which prints the fit summary table.

Description of Major Sub-routines

Sub-routines called from the mainline are, in order of call, PAGE, REDØP, EDITD, ESTIM, GRPM and FITCS. The other routines produce special output but do not manipulate data.

PAGE (I, J, K)

Reads control cards and handles pagination.

Arguments:

I = 1: initialized program, read control cards

2: begin new page, write title and page number

3: punch header card for output item file

4: count lines written on current page; if greater than 50, begin new page

J (needed only if I = 4)

1: item difficulty table

2: item fit table

3: item fit summary table

K (needed only if I = 4)

Counts number of lines; must be initialized in calling routine.

<u>REDØP (IDATA, IB, IS, ISEL, MATX, IA, ID, DIFF)</u>

Reads person records, writes temporary file and prepares marginal distributions of ESTIM.

Subroutines called: PAGE, TRANS, SCØRE, RESIM

<u>EDITD (IB, IS, ISEL, MATX)</u>

Eliminates zero and perfect scores from item and person files.

<u>ESTIM (IS, IB, DIFF, ABIL, ISEL, MATX, KCAB)</u>

Estimates item difficulties and person abilities based on the marginal distributions given in IS and IB.

Arguments: KCAB = 1: normal approximation: PROX

2: unconditional maximum likelihood

Subroutines called: PROX, UCØN, ABLTY

GRPM (DIFF, Z, IB, ISEL, NSEL, MATX, IDATA, C, IS, ABIL, A, ID)

Rereads person file and establishes groups of equal size; computes basic fit statistics.

FITCS (Z, C, IB, ISEL, NSEL, DIFF, ABIL, IDATA, MATX, A)

Computes "among group" fit statistics and prints fit statistics.

SMMRY (DIFF, A, IDATA, IS, MATX, ISEL, C, IB)

Prints fit summary statistics in sequence, fit and difficulty orders.

The subroutines called by ESTIM are:

PROX (IS, B, DIFF, ABIL, ISEL, SE, M)

Calculates initial estimates of ability and difficulty based on Cohen's normal approximation. The estimates are returned in arrays ABIL and DIFF with standard errors in SE.

UCON (IS, IB, DIFF, ABIL, ISEL, SE)

If requested, computes corrected unconditional maximum likelihood estimates of difficulty.

ABLTY (ABIL, DIFF, SE, IB, ISEL)

Given the final difficulty estimates, computes the corresponding ability estimates for all scores. Prints the difficulty estimates summary table and the score equivalence table.

B I C A L

FORTRAN Source Listing

```
            CDC     STATEMENTS NEEDED TO MODIFY BICAL FOR CDC ARE MARKED BY CDC
            CDC    PROGRAM BICAL(INPUT,OUTPUT,PUNCH,TAPE1,
            CDC   1 TAPE5=INPUT,TAPE6=OUTPUT,TAPE7=PUNCH)
0001               DIMENSION ABIL(180),DIFF(540),IB(180),IS(180),MATX(1300)
0002               DIMENSION A(480),C(480),ID(180),IDATA(180),NSEL(180),SNAME(180)
0003               DIMENSION DLAB(12),ISEL(180),SE(180),TZ(180),Z(180),
                  1ALAB(12),ZLAB(12),XLAB(12),YLAB(12),SSW(180),SSW2(180),SI(180)
0004               DIMENSION EX(180),PB(180),STAT(28),SEA(180),WLAB(12)
0005               DATA YLAB/'F','I','T',' ','T',' ','T','E','S','T',' ',' '/
0006               DATA XLAB/'P','E','R','S','O','N',' ','A','B','L','T','Y'/
0007               DATA DLAB/'D','I','F','F','I','C','U','L','T','Y'/
0008               DATA ALAB/'D','I','S','C','R','I','M','N','T','I','O','N'/
0009               DATA ZLAB/'T','O','T','A','L',' ','T',' ','T','E','S','T'/
0010               DATA WLAB/'B','E','T','W','N',' ','T',' ','T','E','S','T'/
0011               COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
                  1,SNAME
0012               COMMON/MISC/CFIT,MGROP,MSUBJ,IBK
0013               COMMON/DCK/XTMN,XTSD,LOOP,NDEL,NDEL1
0014               COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
0015               COMMON/PFIT/ PFITS,PFITSD
0016               IBK = 0
0017               NDEL = 0
0018               WRITE(6,105)
0019             1 CALL PAGE(1,J)
0020               CALL REDOP(IDATA,IB,IS,ISEL,A,C,DIFF)
0021               LOOP = 0
0022          4    NDEL1 = NDEL
0023               IF(NDEL.GT.0)CALL PAGE(2,J)
0024               CALL EDITD(IB,IS,ISEL,MATX)
0025               CALL ESTIM(IS,IB,DIFF,SE,ABIL,ISEL,MATX,KCAB,SEA)
0026               CALL NEWTAB (ABIL,IB,DIFF,0.2,ISEL,MATX(NITEM+1))
0027               CALL PAGE(5,J)
0028               CALLGRPM(DIFF,Z,IB,ISEL,NSEL,MATX,IDATA,C,IS,ABIL,A,ID,
                  *SSW,SSW2,SEA)
0029               IF(NDEL)5,5,6
0030          6    WRITE(6,103)NDEL
0031               CALL PAGE(8,J)
0032               WRITE(6,102)PFITS,PFITSD
0033               CALL PLOT(YLAB,XLAB)
0034               WRITE(6,106) NDEL,CFIT
0035               CALL PAGE(6,J)
0036               GO TO 7
0037           5   CALL PAGE(2,J)
0038               WRITE(6,102)PFITS,PFITSD
0039               CALL PLOT(YLAB,XLAB)
0040               CALL PAGE(5,J)
0041               CALL PAGE(2,J)
0042          7    IF(NDEL.GT.0) GO TO 4
```

```
            CALL FITCS(Z,C,IB,ISEL,NSEL,DIFF,SE,ABIL,IDATA,MATX,A,SSW,SSW2,
           *TZ,PB,EX,SI)
            CALL SMMRY(DIFF,A,Z,IDATA,IS,MATX,ISEL,C,IB,SE,TZ,EX,PB,STAT,
           *SI)
            CALL PAGE(2,J)
            WRITE(6,100)STAT(4)
            XMIN = -2.5
            XMAX =  2.5
            DO 2 I=1,NITEM
            IF(ISEL(I).LE.0) GO TO 2
            XMIN = AMIN1(XMIN,DIFF(I))
            K=IDATA(NITEM)
            XMAX = AMAX1(XMAX,DIFF(I))
          2 CONTINUE
            CALL PICT(DIFF,TZ,ISEL,0.0,0.0,DLAB,ZLAB)
            CALL PAGE(2,J)
            WRITE(6,108)STAT(7)
            YMIN=-4.0
            YMAX = 12.0
            CALL PICT(DIFF,PB,ISEL,0.0,0.0,DLAB,WLAB)
            CALL PAGE(2,J)
            WRITE(6,101)STAT(2)
            YMIN=0.0
            YMAX =  2.0
            CALL PICT(DIFF,A,ISEL,0.0,1.0,DLAB,ALAB)
            XMIN =    0.0
            XMAX =    2.0
            YMIN=-10.0
            YMAX=10.0
            CALL PAGE(2,J)
            WRITE(6,104)STAT(5)
            CALL PICT(A,TZ,ISEL,1.0,0.0,ALAB,ZLAB)
            XMIN = -4.0
            XMAX = 12.0
            CALL PAGE(2,J)
            WRITE(6,107)
            CALL PICT(PB,TZ,ISEL,0.0,0.0,WLAB,ZLAB)
            GO TO 1
        100 FORMAT(/29X,'TOTAL FIT T-TEST  (Y) VERSUS DIFFICULTY (X)',2X,
           *'(CORR = ',F5.2,')')
        101 FORMAT(/33X,'DISCRIMINATION (Y) VS DIFFICULTY (X)  (CORR = ',
           *F5.2,')')
        102 FORMAT(/27X,'ABILITY BY FIT T-TEST FOR EACH PERSON (MNT =',
           *F6.2,'   SDT =',F6.2,')')
        103 FORMAT(1X,132('-')//1X,'THESE',I5,' PERSONS WILL BE OMITTED FROM R
           *ECALIBRATION')
        104 FORMAT(/27X,'TOTAL FIT T-TEST (Y) VERSUS  DISCRIMINATION (X)  (COR
           *R = ',F5.2,')')
```

```
0084              105 FORMAT(1H1/////////25X,83('*')/5(25X,'*',81X,'*'/),25X,'*',14X,'* *
                     1 * * * *  B I C A L  -  V E R S I O N  3 * * * * *',14X,'*'/5(25X,
                     2'*',81X,'*'/),
                     35(25X,'*',81X,'*'/),25X,'*',10X,'DIRECT ENQUIRIES TO:',51X,'*'/25X
                     4,'*',20X,'SUSAN R. BELL',48X,'*'/25X,'*',20X,'C/O BENJAMIN D. WRIG
                     5HT',39X,'*'/25X,'*',20X,'DEPARTMENT OF EDUCATION',38X,'*'/25X,'*',
                     620X,'UNIVERSITY OF CHICAGO',40X,'*'/25X,'*',20X,'5835 S. KIMBARK A
                     7VENUE',39X,'*'/25X,'*',20X,'CHICAGO, ILLINOIS  60637',37X,'*'/25X,
                     8'*',20X,'(312) 753-3818',47X,'*'/25X,'*',20X,'(312) 753-4013',47X,
                     8'*'/4(25X,'*',81X,'*'/),25X,'*',4X,
                     9'COPYRIGHT BY RONALD J. MEAD, BENJAMIN D. WRIGHT, AND SUSAN R. BEL
                     1L (1979)',4X,'*'/3(25X,'*',81X,'*'/),25X,83('*'))
0085              106  FORMAT(/' THE',I4,' PERSONS WITH FIT ABOVE',F6.2,' WILL BE OMITTED
                     * FROM RECALIBRATION')
0086              107 FORMAT(/34X,'TOTAL FIT T-TEST (Y) VERSUS BETWEEN FIT T-TEST (X)')
0087              108 FORMAT(/31X,'BETWEEN FIT T-TEST (Y) VS DIFFICULTY (X)  (CORR = ',
                     *F5.2,')')
0088                   END
```

```
      SUBROUTINE ABLTY(AB,D,SEC,SE,IB,ISEL,M,SEA)
      DIMENSION AB(1),D(1),SEC(1),SE(1),ISEL(1),IB(1),SEA(1)
      COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      COMMON/DCK/XTMN,XTSD
      DATA BLK/4H    /,AST/1H*/
      LLINE=0
      L=NITEM
      J=NITEM+LREC
C**CHANGE TO EXPONENTIAL SCALE
  210 CONTINUE
      L1=LREC-1
      IF(M.EQ.1) GO TO 1
C**BEGIN LOOP ON SCORE GROUPS
      DO 214 K=1,L1
C**BEGIN ITERATION LOOP
      DO 215 ITK=1,5
      IX=K+L
      SE(IX )=0.0
      DD=0.0
C**BEGIN LOOP OVER ITEMS
      DO 216 I=1,L
      IF(ISEL(I))216,216,213
  213 P=EXP(AB(K)-D(I))
      P=P/(1.0+P)
C**COMPUTE SUM OF P AND PQ
      SE(IX) = SE(IX) + P*(1.0-P)
      DD = DD + P
  216 CONTINUE
      DD=(K-DD)/SE(IX)
      AB(K)=AB(K)+DD
C**CHECK FOR CONVERGENGCE
      IF(ABS(DD)-0.05)214,215,215
  215 CONTINUE
  214 CONTINUE
      DO 9198 I=1,L1
C**FINAL ABILITIES AND STANDARD ERRORS
      IX=I+L
      AB(I)=AB(I)*(LREC-2)/L1
      SE(IX)=1.0/SQRT(SE(IX))
 9198 SEA(I) = SE(IX)
C**CHANGE TO LOG SCALE
      DO 9200 I=1,L
      IF(ISEL(I))9200,9200,9199
 9199 IX=I +L+LREC
      SEC(I)=1.0/SQRT(SEC(I))
 9200 CONTINUE
C**PRINT ABILITY TABLE
```

```
      1    WRITE(6,200)
           WRITE(6,201)
           ROOT=0.0
           LLINE = 0
           DO 4 I=1,NITEM
           IF(ISEL(I)) 4, 4, 5
      5    CALL PAGE(4,LLINE)
           IF(LLINE.GT.0) GO TO 51
           WRITE(6,200)
           WRITE(6,201)
     51    ROOT = ROOT + SE(I)*SE(I)
           IXX = I + NITEM
           IZZ = IXX + NITEM
           Y = D(IZZ)
           WRITE(6,101)I,SNAME(I),D(I),SEC(I),SE(I),D(IXX),Y
        4  CONTINUE
      9    ROOT=ROOT/(IC -1)
           ROOT=SQRT(ROOT)
           INS=0
           DG20=0.
           XTSS=0.
           XTSS2=0.
           DO 4000 NTS=1,L1
           XTSS=XTSS+IB(NTS)*AB(NTS)
   4000    INS=INS+IB(NTS)
           XTMN=XTSS/INS
           DO 4001 K=1,L1
           X = AB(K) - XTMN
           DG20=DG20 + IB(K)*X*X
           IX = K + NITEM
   4001    XTSS2=XTSS2 + SE(IX)*SE(IX)*IB(K)
           XTSS2 = DG20 - XTSS2
           DG20 = XTSS2/DG20
           IF(XTSS2.LE.0.0)GO TO 301
           XTSD=SQRT(XTSS2/INS)
           GO TO 302
    301    XTSD=0.0
    302    WRITE(6,105) ROOT
           CALL PAGE(5,J)
           CALL PAGE(2,J)
           WRITE(6,102)
           K=LREC - 1
           L1 = K
           DO 10 I=1,L1
           N=(AB(K)+6.0)*7.0
           IF(N.GT.84)N=84
           IX=K+NITEM
           WRITE(6,103)K,IB(K),AB(K),SE(IX),(BLK,J=1,N),AST
```

```
0087            10   K=K-1
0088                 WRITE(6,104)(I,I=1,6),DG20
0089                 CALL PAGE(5,J)
0090            101 FORMAT(1H ,I6,2X4H |  ,A4,3H | ,F8.3,4XF9.3,2X3F9.3,2X3H ||)
0091            102 FORMAT(/' COMPLETE SCORE EQUIVALENCE TABLE'/1X34('-'),13('-------+'
                    1)/'     RAW',10X,'LOG    STANDARD ||',20X,'TEST CHARACTERSTC CURVE'/
                   23X'SCORE COUNT ABILITY  ERRORS  ||'/1X31('-'),'||+',13('-------+'))
0092            103 FORMAT(I7,I5,2F9.2,'  ||',85A1)
0093            104 FORMAT(1X31('-'),'||+',13('-------+')/33X,'-6      -5      -4      -3
                    1    -2      -1       0',617//' PERSON SEPARABILITY INDEX',F5.2,2X,
                    2'(EQUIVALENT TO KR20)')
0094            105 FORMAT(1X74('-')/25X18HROOT MEAN SQUARE =,F9.3)
0095            200 FORMAT('0',74('-')/1H ,   8HSEQUENCE,4H |   ,4HITEM,4H |  ,3X
                    1'ITEM',6X,'STANDARD',3X9HLAST DIFF,3X,'PROX ',4X,'FIRST',5H   || )
0096            201 FORMAT(1H ,7H NUMBER,5H   |   ,4HNAME,4H |   ,10HDIFFICULTY,5X5HERROR
                    1,3X10H  CHANGE   ,3X,'DIFF ',4X,'CYCLE',5H   || /1X,74('-'))
0097                 RETURN
0098                 END
```

```
      SUBROUTINE CLEAR(XAXIS,YAXIS,KPLOT)
      COMMON /GRID/ GRID(4080)
      COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
      DATA BLK/' '/,DOT/'.'/,DASH/'-'/,PLUS/'+'/,BAR/'|'/
      L = NCOL  *    NROW  + NCOL
      DO 1 I=1,L
    1 GRID(I)=BLK
      IX = (YAXIS - YMIN)/(YMAX-YMIN) * NROW
      IF(IX.LE.0.OR.IX.GT.NROW)IX = NROW/2
      IX = NCOL *(NROW-IX) + 1
      K = L -NCOL
      DO 2 I=1,NCOL
      K= K+ 1
      GRID(IX) = DOT
      GRID(I)=DASH
      GRID(K)=DASH
    2 IX=IX+1
      IX=(XAXIS-XMIN)/(XMAX-XMIN) *NCOL
      IF(IX.LE.0.OR.IX.GT.NCOL)IX =  NCOL/2
      K=1
      K1 = NCOL
      DO 3 I=1,NROW
      IF(KPLOT.EQ.1)GRID(IX) = DOT
      GRID(K) = BAR
      GRID(K1) = BAR
      K = K + NCOL
      K1 = K1 + NCOL
    3 IX=IX+NCOL
      K = NCOL * NROW
      DO 4 I=10,NCOL,10
      GRID(I) = PLUS
      K=K+10
    4 GRID(K)= PLUS
      IX = 5*NCOL
      DO 5 I=1,L,IX
      GRID(I) = PLUS
      K=I + NCOL - 1
    5 GRID(K) = PLUS
      RETURN
      END
```

```
      SUBROUTINE EDITD(IB,IS,ISEL,MATX)
      DIMENSION IB(1),IS(1),ISEL(1)
      COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      COMMON/MISC/CFIT,MGROP,MSUBJ,IBK
      NLOW=0
      NHIGH=0
      ITCK=0
      NOUT=0
      IX=0
      IF(NGROP.LE.0) NGRUP=30
      L=LREC
      MQ=L-1
      IF(MAXSC-L)2,1,1
    1 MAXSC=MQ
C**COUNT HIGH AND LOW SCORES
    2 DO88 I=1,MQ
      IF(I-MINSC)4,6,5
    4 NLOW=NLOW+IB(I)
      GO TO 88
    5 IF(I-MAXSC)6,6,7
    6 IX=IX+IB(I)
      GO TO 88
    7 NHIGH=NHIGH+IB(I)
   88 CONTINUE
      NLOW = NLOW + IBK
      MSUBJ = NLOW + NHIGH + IX
      WRITE(6,100)MINSC,NLOW,MAXSC,NHIGH,IX,MSUBJ
      NSUBJ=IX
      WRITE(6,202)
    3 IF(NSUBJ-NGROP)99,99,21
   21 IF(MAXSC-MINSC)99,99,22
C**BEGIN EDIT LOOP
   22 DO 18 I=1,NITEM
      K=1
      IF(ISEL(I)) 18,16,8
    8 IF(IS(I))15,15,9
    9 IF(IS(I)-NSUBJ)18,10,10
C**CHECK FOR PERFECT ITEM SCORES
   10 WRITE(6,201)I,SNAME(I),IS(I)
      ITCK=ITCK+1
C**ADJUST MINSC, MAXSC, AND IB ARRAY FOR REJECTED PEOPLE
      ISI=ISEL(I)
      J2=ISI+1
      IBK = IBK + IB(1)
      DO 12 J=J2,L
      J1=J-ISI
12    IB(J1)=IB(J)
```

```
0044                 L=L-ISI
0045                 MAXSC=MAXSC-ISI
0046                 MINSC=MINSC-ISI
0047                 IF(MINSC.GT.0) GO TO 13
0048                 ISI=0
0049                 MINSC=1
0050                 DO 11 J=MINSC,MAXSC
0051            11   ISI=ISI+IB(J)
0052                 NOUT=NOUT+NSUBJ-ISI
0053                 NSUBJ=ISI
0054                 MSUBJ = ISI
0055                 K=2
0056           13    ISEL(I)=0
0057                 GO TO (18,3),K
               C**CHECK FOR ZERO ITEM SCORES
0058              15 WRITE(6,200)I,SNAME(I),IS(I)
0059                 ITCK=1+ITCK
0060                 L=L-ISEL(I)
0061                 IF(L.GT.MAXSC) GO TO 13
0062                 DO 17 J=L,MAXSC
0063                 NSUBJ=NSUBJ-IB(J)
0064                 MSUBJ = MSUBJ - IB(J)
0065                 NOUT=NOUT+IB(J)
0066                 DO 17 II=1,NITEM
0067             17  IS(II)=IS(II)-IB(J)
0068                 MAXSC=L-1
0069                 K=2
0070                 GO TO 13
0071              18 CONTINUE
               C**PRINT RESULTS OF DATA EDITTING
0072                 IF(ITCK)19,19,20
0073              19 WRITE(6,211)
0074              20 WRITE(6,210)NOUT,NSUBJ,ITCK,L,MINSC,MAXSC
0075                 IC=IC-ITCK
0076                 LREC=L
0077                 IBK = IBK - NOUT
0078                 RETURN
0079              99 WRITE(6,102) IC,NSUBJ,MAXSC,MINSC
0080             100 FORMAT(///1X,32('-')/' SUBJECTS BELOW',5X,I3,6X,I4/' SUBJECTS ABOV
                    1E',5X,I3,6X,I4/19H SUBJECTS IN CALIB.I14/1H ,32(1H-)/
                    215H TOTAL SUBJECTS,13XI5)
0081             102 FORMAT(45H0 PROBLEM ENDED BECAUSE OF 1 OF THE FOLLOWING/
                    1' ITEMS READ IN',I9/18H SUBJECTS IN RANGE I5/14H MAXIMUM SCORE
                    2I5/14H MINIMUM SCORE I5)
0082             200 FORMAT(1H ,1X,I3,5X,A4,4X,I4,3X,9HLOW SCORE)
0083             201 FORMAT(1H ,1X,I3,5X,A4,4X,I4,3X,10HHIGH SCORE)
0084             202 FORMAT(1H ,//15H REJECTED ITEMS,//7H  ITEM ,3X4HITEM,3X8HANSWERED/
                    17H NUMBER,3X4HNAME,3X9HCORRECTLY/1X35('-'))
```

```
0085            210 FORMAT(1X,35('-')/1H0,20H  SUBJECTS DELETED =,I5/21H SUBJECTS REMA
                   1INING =,I5//6X,'ITEMS DELETED =',I5/4X,'POSSIBLE SCORE  =',I5//6X,
                   2'MINIMUM SCORE =',I5/6X15HMAXIMUM SCORE =,I5)
0086            211 FORMAT(10X,'NONE')
0087                STOP
0088                END
```

```
0001          SUBROUTINE ESTIM(IS,IB,DIFF,SEC,ABIL,ISEL,SE,M,SEA)
0002          DIMENSION IS(1),IB(1),DIFF(1),SEC(1),ABIL(1),ISEL(1),SE(1)
0003          DIMENSION PROC(3),SEA(1)
0004          COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
             1,SNAME(1)
0005          DATA PROC/4HPROX,4HUCON,4HERCR/
0006          CALL PAGE(2,J)
0007          WRITE(6,199) PROC(M)
        C**NORMAL APPROXIMATION METHOD
0008          CALL PROX(IS,IB,DIFF,SEC,ABIL,ISEL,SE,M)
0009          GO TO (3,1,1),M
        C**CORRECTED UNCONDITIONAL METHOD
0010        1 CALL UCON(IS,IB,DIFF,SEC,ABIL,ISEL,SE)
0011        3 CONTINUE
        C**COMPUTE FINAL ABILITIES AND PRINT TABLE
0012          CALL ABLTY(ABIL,DIFF,SEC,SE,IB,ISEL,M,SEA)
0013      199 FORMAT(1H0,'PROCEDURE IS ',A4)
0014          RETURN
0015          END
```

```
                 SUBROUTINE FITCS(ZZ,B,IB,ISEL,NSEL,DIFF,SEC,ABIL,IDATA,MATX,A,SSW,
                *SSW2,TZ,PB,EX,SI)
                 DIMENSION IB(1),ISEL(1),NSEL(1),DIFF(1),ABIL(1),IDATA(1),MATX(1)
                 DIMENSION EXT(6),VAR(6),OBS(6),COMP(18),DISC(6),Z(6),STAT(2),
                *SSW(1),SSW2(1),SI(1),TZ(1),EX(1),PB(1)
                 DIMENSION ZZ(1),B(1),IGROP(6),A(1),TOT(6),SEC(1),SE(6)
                 COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
                1,SNAME(1)
                 PRIT=ISW(8)
                 PRIT=PRIT/100.0
                 IF(ISW(8).EQ.0) PRIT=-9999.
           C**CLEAR ARRAYS
                 LLINE=0
                 CRIT=0.1
                 DO 197 I=1,6
                 Z(I)=0.0
                 DISC(I)=0.0
                 OBS(I)=0.0
                 TOT(I)=0.0
                 SE(I)=0.0
             197 IGROP(I)=0
           C**COUNT NUMBER IN EACH SCORE GROUP
                 DO 198 I=MINSC,MAXSC
                 J=NSEL(I)
                 IF(J)198,196,196
             196 IGROP(J)=IGROP(J)+IB(I)
             198 CONTINUE
                 DO 195 I=1,18
             195 COMP(I)=0.0
                 WRITE(6,200)
                 WRITE(6,201)
                 WRITE(6,202)
           C**COMPUTE AVERAGE ABILITY FOR EACH SCORE GROUP
                 X=0.0
                 DO 181 I=MINSC,MAXSC
                 J=NSEL(I)
                 IF(J)181,181,182
             182 COMP(J)=COMP(J)+IB(I)*ABIL(I)
                 X=X+IB(I)*ABIL(I)
             181 CONTINUE
                 X=X/NSUBJ
           C**STORE AVERAGE IN LOC SEVEN TO TWELVE AND CENTER LOC ONE TO SIX AT ZER
                 DO 184 I=1,NGROP
                 COMP(I)=COMP(I)/IGROP(I)
                 COMP(I+6)=COMP(I)
             184 COMP(I)=COMP(I)-X
                 NI=LREC-1
           C**BEGIN LOOP THROUGH ITEMS
```

```
0041          DO 9 K=1,NITEM
0042          L=IDATA(K)
0043          IF(ISEL(L))9,9,1
0044        1 LL=L
0045          X=DIFF(L)
0046          DO 11 I=1,NGROP
0047          EXT(I)=0.0
0048       11 VAR(I)=0.0
      C**COMPUTE EXPECTED NUMBER NP AND VARIANCE NPQ
0049          DO 8 I=MINSC,MAXSC
0050          J=NSEL(I)
0051          IF(J)8,8,7
0052        7 P=EXP(ABIL(I)-X)
0053          P=P/(1.0+P)
0054          EXT(J)=EXT(J)+IB(I)*P
0055          VAR(J)=VAR(J)+IB(I)*P*(1.-P)
0056        8 CONTINUE
0057          PB(L)=0.0
0058          EX(L) = 0.0
0059          STAT(1)=0.0
0060          STAT(2)=0.0
      C**BEGIN LOOP THROUGH SCORE GROUPS
0061          DO 2 I=1,NGROP
      C**OBSERVED NUMBER OF CORRECT RESPONSES
0062          ISC=MATX(LL)
0063          SC=ISC
0064          VI=SQRT(VAR(I))
0065          LL = LL + NITEM
      C**STANDARDIZE THE DEVIATION
0066       12 Z(I)=(SC-EXT(I))/VI
      C**SCALE TO A SINGLE DEGREE OF FREEDOM
0067          Y=NSUBJ-IGROP(I)
      C**COMPUTE MARGINALS OF FIT TABLE
0068          TOT(I)=TOT(I)+Z(I)
0069          SE(I)=SE(I)+Z(I)*Z(I)
0070          PB(L)=PB(L)+Z(I)*Z(I)
0071          OBS(I)= SC/IGROP(I)
0072          DISC(I)=(SC-EXT(I))/IGROP(I)
      C**COMPUTE DISCRIMINATION INDEX FOR THIS ITEM
0073          XX=COMP(I)
0074          STAT(1)=STAT(1)+XX*Z(I)*VI
0075        2 STAT(2)=STAT(2)+XX*XX*VAR(I)
      C**COMPUTE ERROR IMPACT
0076          EX(L) = ZZ(L)/SSW(L)
0077          ZZ(L) = EX(L)
0078          IF(EX(L).GT.1.0) GO TO 21
0079          EX(L)=0.0
0080          GO TO 22
```

```
0081            21    EX(L) = SQRT(EX(L)) - 1.0
                C**COMPUTE BETWEEN GROUP TTEST
0082              22  SI(L)=((SSW(L) - 4*SSW2(L))/(SSW(L)*SSW(L)))
0083                  FRDM = 2/SI(L)
0084                  TZ(L) = TTEST(ZZ(L),FRDM)
0085                  SI(L) = SQRT(SI(L))
0086                  STAT(1)= STAT(1)/STAT(2) +1.0
0087                  GROP=NGROP-1
0088                  PB(L) = PB(L)/GROP
0089                  PB(L) = TTEST(PB(L),GROP)
                C**PRINT LINE OF THE FIT TABLE FOR THIS ITEM
0090                  CALL PAGE(4,LLINE)
0091                  IF(LLINE.GT.0) GO TO 25
0092                  WRITE(6,200)
0093                  WRITE(6,201)
0094                  WRITE(6,202)
0095             25   WRITE(6,302)L,SNAME(L),EX(L),PB(L),TZ(L),ZZ(L),SI(L),
                     *STAT(1),B(L)
0096                  WRITE(6,303)(OBS(LL),LL=1,NGROP)
0097                  WRITE(6,304)(DISC(LL),LL=1,NGROP)
0098                  IF(TZ(L).LE.PRIT)WRITE(3,101)L,SNAME(L),DIFF(L),SEC(L),TZ(L),PB(L)
                     *,STAT(1)
                C**STORE DISCRIMINATION INDEX
0099                  A(L)=STAT(1)
0100                9 CONTINUE
                C**COMPUTE STANDARD DEVIATION OF Z SQUARES
0101                  DO 17 I=1,NGROP
0102                  TOT(I)=TOT(I)/IC
0103             17   SE(I)=SQRT((SE(I)- IC *TOT(I)*TOT(I))/( IC -1))
0104                  DO 15 I=2,12
0105             15   IDATA(I)=0
                C**CALCULATE LIMITS OF EACH SCORE GROUP
0106                  DO 14 I=1,LREC
0107                  J=NSEL(I)*2
0108                  IF(J)14,14,13
0109             13   IDATA(J)=I
0110             14   CONTINUE
0111                  IDATA(1)=MINSC
0112                  J=2*NGROP
0113                  IDATA(J)=MAXSC
0114                  J=J-1
0115                  DO 16 I=3,J,2
0116             16   IDATA(I)=IDATA(I-1)+1
                C**PRINT BOTTOM LINES
0117                  IF(NGROP.EQ.2)WRITE(6,502)(IDATA(I),I=1,4),
                     1(COMP(I),I=7,8),(TOT(I),I=1,2),(SE(I),I=1,2),(IGROP(I),I=1,2)
0118                  IF(NGROP.EQ.3)WRITE(6,503)(IDATA(I),I=1,6),
                     1(COMP(I),I=7,9),(TOT(I),I=1,3),(SE(I),I=1,3),(IGROP(I),I=1,3)
```

```
0119             IF(NGROP.EQ.4)WRITE(6,504)(IDATA(I),I=1,8),
                1(COMP(I),I=7,10),(TOT(I),I=1,4),(SE(I),I=1,4),(IGROP(I),I=1,4)
0120             IF(NGROP.EQ.5)WRITE(6,505)(IDATA(I),I=1,10),
                1(COMP(I),I=7,11),(TOT(I),I=1,5),(SE(I),I=1,5),(IGROP(I),I=1,5)
0121             IF(NGROP.EQ.6)WRITE(6,506)(IDATA(I),I=1,12),
                1(COMP(I),I=7,12),TOT,SE,(IGROP(I),I=1,6)
0122             CALL PAGE(5,J)
0123         101 FORMAT(I4,1X,A4,1X,5F7.3)
0124         200 FORMAT(/19X,'ITEM CHARACTERISTIC CURVE',11X,'DEPARTURE FROM EXPECT
                1ED ICC',19X,'ITEM FIT STATISTICS'/1X,132('-'))
0125         201 FORMAT(1H ,12H SEQ  ITEM |,2(38H  1ST    2ND    3RD    4TH    5TH    6T
                1H  |),' * ERR   FIT T-TESTS  WTD  MNSQ  DISC  POINT')
0126         202 FORMAT(1H ,12H NUM  NAME |,6(5H GROUP),2H |,6(6H GROUP),2H |,
                1' IMPAC  BETWN  TOTAL  MNSQ  SD   INDX  BISER'/1X132('-'))
0127         302 FORMAT(1H ,I4,2X,A4,2H |,36X,2H |,36X,2H |,
                1F6.2,2F7.2,F6.2,F5.2,F6.2,F7.2)
0128         303 FORMAT(1H+,12X,6F6.2)
0129         304 FORMAT(1H+,50X,6F6.2)
0130         502 FORMAT(1H ,132('-')/' SCORE RANGE ',2(I3,'-',I2),64X,'*ERROR IMPAC
                1T = PROPORTION ERROR INCREASE'/' MEAN ABILITY',2F6.2,33X,'PLUS=TOO
                2 MANY RIGHT',28X'DUE TO THIS MISFIT'/58X'MINUS=TOO MANY WRONG'/
                3' MEAN Z-TEST',2F6.1/' SD(Z-TEST) ',2F6.1/' GROUP COUNT',2I6)
0131         503 FORMAT(1H ,132('-')/' SCORE RANGE ',3(I3,'-',I2),58X,'*ERROR IMPAC
                1T = PROPORTION ERROR INCREASE'/' MEAN ABILITY',3F6.2,27X,'PLUS=TOO
                2 MANY RIGHT',28X'DUE TO THIS MISFIT'/58X'MINUS=TOO MANY WRONG'/
                3' MEAN Z-TEST',3F6.1/' SD(Z-TEST) ',3F6.1/' GROUP COUNT',3I6)
0132         504 FORMAT(1H ,132('-')/' SCORE RANGE ',4(I3,'-',I2),52X,'*ERROR IMPAC
                1T = PROPORTION ERROR INCREASE'/' MEAN ABILITY',4F6.2,21X,'PLUS=TOO
                2 MANY RIGHT',28X'DUE TO THIS MISFIT'/58X'MINUS=TOO MANY WRONG'/
                3' MEAN Z-TEST',4F6.1/' SD(Z-TEST) ',4F6.1/' GROUP COUNT',4I6)
0133         505 FORMAT(1H ,132('-')/' SCORE RANGE ',5(I3,'-',I2),46X,'*ERROR IMPAC
                1T = PROPORTION ERROR INCREASE'/' MEAN ABILITY',5F6.2,15X,'PLUS=TOO
                2 MANY RIGHT',28X'DUE TO THIS MISFIT'/58X'MINUS=TOO MANY WRONG'/
                3' MEAN Z-TEST',5F6.1/' SD(Z-TEST) ',5F6.1/' GROUP COUNT',5I6)
0134         506 FORMAT(1H ,132('-')/' SCORE RANGE ',6(I3,'-',I2),40X,'*ERROR IMPAC
                1T = PROPORTION ERROR INCREASE'/' MEAN ABILITY',6F6.2,9X'PLUS=TOO M
                2ANY RIGHT',28X'DUE TO THIS MISFIT'/58X'MINUS=TOO MANY WRONG'/
                3' MEAN Z-TEST',6F6.1/' SD(Z-TEST) ',6F6.1/' GROUP COUNT',6I6)
0135             RETURN
0136             END
```

```
              SUBROUTINE GRAPH(XX,YY,LENG)
              DIMENSION XX(1),YY(1),CHAR(10),BLK(5)
              DATA CHAR/'1','2','3','4','5','6','7','8','9','*'/
              DATA BLK /' ','.','-','+','|'/
              COMMON /GRID/ GRID(4080)
              COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
              DO 1 I=1,LENG
              IX = ITAB(XX(I),XMIN,XMAX)
              IY = ITAB(YY(I),YMIN,YMAX)
              K=NCOL * (NROW- IPOS(IY,NROW)) + IPOS(IX,NCOL)
              J=1
              X = GRID(K)
              DO 2 KK=1,5
              IF(X.EQ.BLK(KK)) GO TO 1
       2      CONTINUE
              DO 3 KK=1,9
              IF(X.EQ.CHAR(KK)) GO TO 4
       3      CONTINUE
              KK = 9
       4      J=KK+1
       1      GRID(K) = CHAR(J)
              RETURN
              END
```

```
      SUBROUTINE GRPM(D,Z,IB,ISEL,NSEL,MATX,IDATA,B,IS,AB,A,ID,
     *SSW,SSW2,SEA)
      DIMENSION NSEL(1),IB(1),ISEL(1),MATX(1),IDATA(1),B(1),IS(1),AB(1)
      DIMENSION D(1),Z(1),ID(1),A(1),SSW(1),SSW2(1),ISTAR(180),SEA(1),
     *JY(180),JDATA(180)
      COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
      COMMON /FORM/ FMT(18),ZSTAR(180)
      COMMON/DCK/XTMN,XTSD,LOOP,NDEL,NDEL1
      COMMON/MISC/CFIT,MGROP,MSUBJ,IBK
      COMMON/PFIT/ PFITS,PFITSD
      XMIN = -5.0
      XMAX =  5.0
      YMIN = -10.0
      YMAX = 10.0
      NCOL =  80
      NROW =  50
      KOUNT=0
C**DETERMINE NUMBER OF SCORE GROUPS
   24 X=NSUBJ/MGROP
      NGROP=X
      IF(NGROP-6)22,22,21
   21 NGROP=6
22    X=NSUBJ/NGROP
      IX=NGROP*NITEM
      DO 1 I=1,IX
    1 MATX(I)=0
      DO 25 I=1,NITEM
      Z(I)=0.0
      A(I)=0.0
      SSW(I)=0.0
      SSW2(I)=0.0
      ISTAR(I) = 0
   25 B(I)=0.0
      SST=0.0
      SSTT=0.0
      PFITS = 0.0
      PFIT2 = 0.0
      DO 2 I=1,LREC
    2 NSEL(I)=0
      NSC=0
      IX=X
      L=1
C**DETERMINE GROUPINGS OF SCORES AS EQUAL AS POSSIBLE
      K=MAXSC - MINSC + 1
      IF(K.GT.NGROP) GO TO 23
      NGROP = K
```

```
            K=0
            DO 231 I=MINSC,MAXSC
            K=K+1
      231   NSEL(I)=K
            GO TO 32
      23    DO 8 I=MINSC,MAXSC
            NSC=NSC+IB(I)
            J=(NSC-IX)*2
            IF(J)7,5,4
          4 IF(J-IB(I))5,5,6
          5 NSEL(I)=L
            L=L+1
            NSC=0
            IF(L-NGROP)8,29,29
          6 L=L+1
            IF(L-NGROP)20,30,30
         20 NSC=IB(I)
          7 NSEL(I)=L
          8 CONTINUE
            NGROP = L
            GO TO 32
         29 I=I+1
            IF(I.GT.MAXSC) I=MAXSC
         30 DO 31 L=I,MAXSC
         31 NSEL(L)=NGROP
      C**READ AND SCORE SCRATCH FILE
      32    ISWT=1
            NSUBJ=0
            LOOP = LOOP + 1
            CFIT = ISW(6)/10.0  + .1
            NDEL = 0
            IF(ISW(6).EQ.0)CFIT = 100.0
            CALL CLEAR(0.0,CFIT,1)
            CFIT = CFIT - 0.1
            KLIM=ISW(4)
            NOPFLE=ISW(5)
            IF(NOPFLE)40,40,16
      16    ISWT=2
            ISW(5)=0
       40   NSC=0
            PFIT = 0.0
            READ(LOOP,END=12) (IDATA(N),N=1,NITEM),(ID(N),N=1,KLIM)
      CDC   READ(LOOP)        (IDATA(N),N=1,NITEM),(ID(N),N=1,KLIM)
      CDC   IF(EOF(1).NE.0) GO TO 12
            DO 162 N=1,NITEM
            IF(ISEL(N))162,162,161
      161   NSC=NSC+IDATA(N)
      162   CONTINUE
```

```
      SC=NSC
      IF(NSC.LE.0.OR.NSC.GE.IC) GO TO 40
      K=NSEL(NSC)-1
      ABIL = AB(NSC)
      SUM=0.0
      SUM1=0.0
      DO 14 N=1,NITEM
      IF(ISEL(N).LE.0) GO TO 14
      P=EXP(ABIL-D(N))
      P=P/(1.+P)
      X = P * (1.0 - P)
      ZSTAR(N) = (IDATA(N) - P)
      ISTAR(N) = ZSTAR(N)/SQRT(X)
      IF(ISTAR(N).GT.9) ISTAR(N)=9
      IF(ISTAR(N).LT.-9)ISTAR(N)=-9
      ZSTAR(N) = ZSTAR(N)*ZSTAR(N)
      SSW(N) = SSW(N) + X
      SUM=SUM+X
      Y = (X * X)
      SSW2(N) = SSW2(N) + Y
      SUM1 = SUM1 + Y
      PFIT = PFIT + ZSTAR(N)
   14 CONTINUE
      PFIT1 = (PFIT/SUM)
      SV = ((SUM - 4 * SUM1) / (SUM*SUM))
      FRDM = 2/SV
      PFIT = TTEST(PFIT1,FRDM)
      PFITS = PFITS + PFIT
      PFIT2 = PFIT2 + (PFIT * PFIT)
      FRDM = SQRT(SV)
      GO TO (17,9),ISWT
    9 WRITE(NUPFLE,105)(ID(N),N=1,20),NSC,AB(NSC),SEA(NSC),PFIT,FRDM,
     *PFIT1,(IDATA(N),N=1,NITEM),(ISTAR(N),N=1,NITEM)
   17 IF(LOOP.GT.1)GO TO 148
      IF(PFIT.LT.CFIT) GO TO 1449
      IF(K.LT.0) GO TO 144
      DO 141 I=1,NITEM
  141 IS(I) = IS(I) - IDATA(I)
  144 NDEL = NDEL + 1
      KOUNT=KOUNT+1
      IF(KOUNT.EQ.1)CALL PAGE(7,J)
      KNT=1
      DO 300 N=1,NITEM
      IF(ISEL(N).LE.0) GO TO 300
      JY(KNT) = ISTAR(N)
      JDATA(KNT) = IDATA(N)
      KNT = KNT + 1
  300 CONTINUE
```

```
      KNT = KNT - 1
      IF(KNT.GT.35)GO TO 302
      IF(KOUNT.EQ.1)WRITE(6,106)
      WRITE(6,101)KOUNT,(ID(N),N=1,20),PFIT1,FROM,
     *PFIT,AB(NSC),SEA(NSC),(JDATA(K3),K3=1,KNT)
      WRITE(6,102)(JY(K3),K3=1,KNT)
      GO TO 303
  302 KNT1 = LREC - 19
      IF(KOUNT.EQ.1)WRITE(6,107)
      WRITE(6,103)KOUNT,(ID(N),N=1,20),PFIT1,FROM,
     *PFIT,AB(NSC),SEA(NSC),(JDATA(K3),K3=1,10),(JDATA(K3),K3=KNT1,KNT)
      WRITE(6,104)(JY(K3),K3=1,10),(JY(K3),K3=KNT1,KNT)
  303 IB(NSC) = IB(NSC) - 1
      CALL GRAPH(ABIL,PFIT,1)
      GO TO 40
 1449 WRITE(2)(IDATA(N),N=1,NITEM),(ID(N),N=1,KLIM)
      GO TO 145
  148 IF(PFIT.LT.CFIT) GO TO 145
      KOUNT=KOUNT+1
      IF(KOUNT.EQ.1)CALL PAGE(7,J)
      KNT=1
      DO 301 N=1,NITEM
      IF(ISEL(N).LE.0) GO TO 301
      JY(KNT) = ISTAR(N)
      JDATA(KNT) = IDATA(N)
      KNT = KNT + 1
  301 CONTINUE
      KNT = KNT - 1
      IF(KNT.GT.35)GO TO 304
      IF(KOUNT.EQ.1)WRITE(6,106)
      WRITE(6,101)KOUNT,(ID(N),N=1,20),PFIT1,FROM,
     *PFIT,AB(NSC),SEA(NSC),(JDATA(K3),K3=1,KNT)
      WRITE(6,102)(JY(K3),K3=1,KNT)
      GO TO 145
  304 KNT1 = LREC - 19
      IF(KOUNT.EQ.1)WRITE(6,107)
      WRITE(6,103)KOUNT,(ID(N),N=1,20),PFIT1,FROM,
     *PFIT,AB(NSC),SEA(NSC),(JDATA(K3),K3=1,10),(JDATA(K3),K3=KNT1,KNT)
      WRITE(6,104)(JY(K3),K3=1,10),(JY(K3),K3=KNT1,KNT)
  145 CALL GRAPH(ABIL,PFIT,1)
      IF(K) 40,11,11
   11 KK=K*NITEM
      DO 140 N=1,NITEM
      KK=KK+1
      IF(ISEL(N).LE.0) GO TO 140
      MATX(KK)=MATX(KK)+IDATA(N)
      B(N)=B(N)+SC*IDATA(N)
      A(N)=A(N)+IDATA(N)*IDATA(N)
```

```
                Z(N)=Z(N)+ZSTAR(N)
          146   CONTINUE
                NSUBJ=NSUBJ+1
                SST=SST+SC
                SSTT=SSTT+SC*SC
                GO TO 40
             12 CONTINUE
                PFITSD = (PFITS*PFITS)/NSUBJ
                PFITSD = SQRT((PFIT2 - PFITSD)/(NSUBJ - 1))
                PFITS = PFITS/NSUBJ
                X=SST*SST/NSUBJ
                X=SSTT-X
                DO 13 K=1,NITEM
                IF(ISEL(K))13,13,131
          131   XY=IS(K)*SST/NSUBJ
                Y=IS(K)*IS(K)/NSUBJ
                XY= B(K)-XY
                Y= A(K)-Y
                IF(X*Y.GT.0.0) GO TO 130
                B(K) = 0.0
                GO TO 13
          130   B(K)=XY/SQRT(X*Y)
          C**SET ORDER FOR PRINTING FIT TABLE--IN SEQUENCE
          13    IDATA(K)=K
                IF(LOOP.EQ.1)END FILE 2
                REWIND 2
                REWIND 1
            101 FORMAT(I5,2X,20A1,F7.2,F5.2,F7.2,F8.2,F7.2,2X,35I2)
            102 FORMAT(63X,35I2)
            103 FORMAT(I5,2X,20A1,F7.2,F5.2,F7.2,F8.2,F7.2,2X,10I2,10X,20I2)
            104 FORMAT(63X,10I2,10X,20I2)
            105 FORMAT(20A1,I5,3F8.3,F5.2,F8.3,254I2,106I2)
            106 FORMAT(//1X,132('-')/'  SEQ  PERSON',17X,'WTD  MNSQ',2X,'TOTAL',
               *6X,'PERSON'/'  NUM  NAME',19X,'MNSQ  SD ',2X,'FIT T',2X,
               *'ABILITY ERROR',12X,'RESPONSES AND STANDARDIZED RESIDUALS'/1X,
               *132('-'))
            107 FORMAT(//1X,132('-')/'  SEQ  PERSON',17X,'WTD  MNSQ',2X,'TOTAL',
               *6X,'PERSON'/'  NUM  NAME',19X,'MNSQ  SD ',2X,'FIT T',2X,
               *'ABILITY ERROR',6X,'RESPONSES AND STANDARDIZED RESIDUALS (1ST 10 A
               *ND LAST 20 ITEMS)'/1X,132('-'))
                RETURN
                END
```

```
              SUBROUTINENEWT(D,I,AB,IB,IS,NSEL,MINSC,MAXSC,IVAL,CRIT,LIM,SUM,SE)
              DIMENSION AB(1),IB(1),NSEL(1)
      C**NEWTON-RAPHSON ITERATION ROUTINE
              TEMP=100.0
              DO 2 IK=1,LIM
              SE=0.0
              SUM=0.0
              DO 1 K=MINSC,MAXSC
              IF(IVAL) 5,5,4
            4 IF(NSEL(K)-IVAL) 1,5,1
            5 P=EXP(AB(K)-D)
              P=P/(1.+P)
              SE=SE+IB(K)*P*(1.-P)*I
              SUM=SUM+IB(K)*P*I
            1 CONTINUE
              SSM=(IS-SUM)/SE
              IF(ABS(SSM).GT.TEMP) GO TO 6
      7       TEMP =ABS( SSM)
              D=D-SSM
              IF(TEMP-CRIT)3,2,2
            2 CONTINUE
            3 RETURN
       6      WRITE(6,100)IK,IS,SUM,SE,SSM,TEMP,D
              SSM =SSM/2.0
              GO TO 7
          100 FORMAT(' CYCLE',I3,'  SCORE',I4,' EXP SCORE',F6.2,'   SE',F6.2,
             1'  CORRECTION',F6.3,'  PREV CORR',F6.3,'  DIFF',F6.3)
              END
```

```
          SUBROUTINE NEWTAB (ABIL,IB,DIFF,VAL,ISEL,SEM)
          REAL SD(11),TOP,BOT
          DIMENSION SEM(1),DIFF(1),TNAME(10),ABIL(1),IB(1),ISEL(1)
          INTEGER NI,F,LINE
          COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
         1,SNAME(180),TITL(20)
          COMMON/BCK/XTMN,XTSD
          DATA BLK/'    '/
C *** CALCULATE S.D. POINTS FOR DISPLAY ***
          VAL1 = VAL * 100.0
          DO 10 I=1,11
          J = 6-I
10        SD(I) = XTMN + (XTSD * J)
C *** SET UP COUNTERS FOR MAIN LOOP ***
          K = LREC-1
          BOT = 0.0
          TOP = 0.0
          DO 1 I=1,NITEM
          IF(ISEL(I).LE.0) GO TO 1
          TOP = AMAX1(TOP,DIFF(I))
          BOT = AMIN1(BOT,DIFF(I))
1         CONTINUE
          DO 2 JJ =1,K
          IF(IB(JJ).GT.0) GO TO 3
2         CONTINUE
3         BOT = AMIN1(BOT,ABIL(JJ))
          DO 4 J=JJ,LREC
          IF(IB(K).GT.0)GO TO 5
4         K = K-1
5         TOP = AMAX1(TOP,ABIL(K))
          KK = (TOP-BOT)/VAL + 2.0
          CALL PAGE(2,J)
          WRITE (6,100)
          NI = 0
          F = 0
          DO 18 I=1,10
 18       TNAME(I)=BLK
          TOP = (VAL - AMOD((TOP*100.0),VAL1)/100) + TOP
          BOT = TOP - VAL
          K=LREC-1
          DO 9 J=1,KK
  6       IF(K.EQ.0) GO TO 7
          IF(ABIL(K).LT.BOT) GO TO 7
          F = F + IB(K)
          K = K-1
          GO TO 6
7         DO 8 I=1,NITEM
          IF(ISEL(I).LE.0) GO TO 8
```

```
0046              IF(DIFF(I).GT.TOP.OR.DIFF(I).LT.BOT) GO TO 8
0047              NI = NI + 1
0048              IF(NI.GT.10) GO TO 8
0049              TNAME(NI) = SNAME(I)
0050          8   CONTINUE
0051          9   CALL OUTAB (ABIL,TOP,BOT,VAL,F,NI,TNAME,SD,K,SEM(K+1))
0052         91   WRITE (6,102)
0053        100   FORMAT ('0','MAP OF VARIABLE'//1X,125('-'),'||'/
                 1'   PERSON          RAW ||     MEASURE      || ITEM |',T127,'||'   /
                 2' STATS COUNT    SCORE|| MIDPOINT(S.E.)||COUNTS|  TYPICAL ITEMS   '
                 3,'(BY NAME)',T127,'||'/1X,125('-'),'||')
0054        102   FORMAT (1X,125('-'),'||')
0055              RETURN
0056              END
```

```
      SUBROUTINE OUTAB (ABIL,TOP,BOT,VAL,F,NI,TNAME,SD,KX,SEM)
      DIMENSION ABIL(1)
      REAL SD(11)
      REAL*4 TNAME(10),OUT/'    '/,BLK/'    '/,
     *POINTS(11)/'+5SD','+4SD','+3SD','+2SD','+1SD','MEAN','-1SD',
     *'-2SD','-3SD','-4SD','-5SD'/
      OUT = BLK
      DO 11 I=1,11
      IF (SD(I).GT.TOP) GO TO 11
      IF (SD(I).LE.BOT) GO TO 11
      OUT = POINTS(I)
   11 CONTINUE
      AVE=(TOP+BOT)/2
      KK = KX + 1
      IF(ABIL(KK).GT.TOP.OR. ABIL(KK).LT.BOT)GO TO 5
      IF(F.NE.0) GO TO 1
      IF(NI.NE.0) GO TO 3
      WRITE(6,101) OUT,KK,AVE,SEM,(TNAME(K),K=1,10)
      GO TO 4
    1 IF(NI.NE.0) GO TO 2
      WRITE(6,103) OUT,F,KK,AVE,SEM,(TNAME(K),K=1,10)
      GO TO 4
    3 WRITE(6,102) OUT,KK,AVE,SEM,NI,(TNAME(K),K=1,10)
      GO TO 4
    2 WRITE (6,100) OUT,F,KK,AVE,SEM,NI,(TNAME(K),K=1,10)
      GO TO 4
    5 IF(F.NE.0) GO TO 6
      IF(NI.NE.0) GO TO 7
      WRITE(6,201) OUT,AVE,SEM,(TNAME(K),K=1,10)
      GO TO 4
    6 IF(NI.NE.0) GO TO 8
      WRITE(6,203) OUT,F,AVE,SEM,(TNAME(K),K=1,10)
      GO TO 4
    7 WRITE(6,202) OUT,AVE,SEM,NI,(TNAME(K),K=1,10)
      GO TO 4
    8 WRITE(6,200) OUT,F,AVE,SEM,NI,(TNAME(K),K=1,10)
    4 NI = 0
      F = 0
      TOP = TOP - VAL
      BOT = TOP - VAL
      DO 15 I=1,10
   15 TNAME(I)=BLK
  100 FORMAT(1X,A4,I6,I8,' ||',F8.2,'(',F4.2,') ||',I4,'  |',
     110(1X,A4,3X),'||')
  101 FORMAT(1X,A4,6X,I8,' ||',F8.2,'(',F4.2,') ||',4X,'  |',
     110(1X,A4,3X),'||')
  102 FORMAT(1X,A4,6X,I8,' ||',F8.2,'(',F4.2,') ||',I4,'  |',
     110(1X,A4,3X),'||')
```

```
0044        103  FORMAT(1X,A4,I6,I8,' ||',F6.2,'(',F4.2,') ||',4X,'  |',
                 110(1X,A4,3X),'||')
0045        200  FORMAT(1X,A4,I6,8X,' ||',F8.2,'(',F4.2,') ||',I4,'  |',
                 110(1X,A4,3X),'||')
0046        201  FORMAT(1X,A4,6X,8X,' ||',F8.2,'(',F4.2,') ||',4X,'  |',
                 110(1X,A4,3X),'||')
0047        202  FORMAT(1X,A4,6X,8X,' ||',F8.2,'(',F4.2,') ||',I4,'  |',
                 110(1X,A4,3X),'||')
0048        203  FORMAT(1X,A4,I6,8X,' ||',F8.2,'(',F4.2,') ||',4X,'  |',
                 110(1X,A4,3X),'||')
0049             RETURN
0050             END
```

```
      SUBROUTINE PAGE(M,L)
      DIMENSION TITL(20)
      COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      COMMON/DCK/XTMN,XTSD,LOOP,NDEL,NDEL1
      COMMON /FORM/ FMT(18)
      COMMON/MISC/CFIT,MGRUP,MSUBJ,IBK
      DATA A/4H****/
      GO TO (1,2,5,6,7,8,9,11),M
    1 READ(5,102) TITL
      IF(TITL (1)-A)3,4,3
    3 READ(5,104) NITEM,MGRUP,MINSC,MAXSC,LREC,KCAB,(ISW(K),K=1,8)
      READ(5,102) FMT
      READ(5,102)(SNAME(N),N=1,NITEM)
      IF(ISW(2).LT.0) ISW(2) = -ISW(2)
      IF(ISW(2).EQ.0)ISW(2)=5
      NGRUP = MGRUP
      I=1
      WRITE(6,101) TITL,I
      WRITE(6,100)NITEM,NGRUP,MINSC,MAXSC,LREC,KCAB,(ISW(K),K=1,8),FMT
      IF(MINSC.EQ.0)MINSC=0.4*NITEM
      IF(MAXSC.EQ.0)MAXSC=0.9*NITEM
      IF(KCAB.EQ.0.OR.KCAB.GT.2) KCAB = 2
      IS=ISW(5)
      IF(ISW(3).EQ.0)ISW(3)=1
      IF(ISW(4).EQ.0) ISW(4) = 20
      LIM = ISW(4) - ISW(3) + 1
      IF(LIM.GT.20) ISW(4) = ISW(3) + 19
      IF(IS.EQ.0)RETURN
      GO TO 5
    2 I=I+1
      IF(NDEL1.GT.0) GO TO 10
      WRITE(6,101) TITL,I
      RETURN
   10 WRITE(6,110) TITL,NDEL1,I
      RETURN
    7 WRITE(6,106)LREC,NSUBJ,MSUBJ,XTMN,XTSD
      RETURN
    8 LSUBJ=NSUBJ+NDEL
      WRITE(6,106)LREC,LSUBJ,MSUBJ,XTMN,XTSD
      RETURN
    9 I=I+1
      WRITE(6,101) TITL,I
      WRITE(6,106)CFIT
      RETURN
   11 I = I + 1
      WRITE(6,101) TITL,I
      RETURN
```

```
0048          4      STOP
0049          5      IF(IS.EQ.0)IS=ISW(8)
0050                 WRITE(IS,102) TITL
0051                 RETURN
0052               6 IF(L-50)21,22,22
0053              21 L=L+1
0054                 RETURN
0055              22 L=0
0056                 I=I+1
0057                 WRITE(6,103)
0058                 RETURN
0059             100 FORMAT('OCONTROL PARAMETERS'//' NITEM NGROP MINSC MAXSC  LREC  KCA
                    *B KSCOR INFLE  LLIM  KLIM NUPFL C-FIT  KSIM  PRIT'/14I6//1X,
                    *'PERSON FILE FORMAT ',18A4)
0060             101 FORMAT(1H1,20A4,45X,'PAGE',I3)
0061             102 FORMAT(20A4)
0062             103 FORMAT(//10X,110('*')/53X,'TABLE CONTINUED'/1H1)
0063             104 FORMAT(14I5,4I1)
0064             106 FORMAT(1H0,I6,' ITEMS CALIBRATED ON',I7,' PERSONS'/1X,I6,
                    *' MEASURABLE PERSONS WITH MEAN ABILITY =',F7.2,'  AND STD. DEV. ='
                    *,F7.2///////)
0065             108 FORMAT('OLIST OF PERSONS WITH FIT ABOVE',F7.2)
0066             110 FORMAT(1H1,20A4,2X,'RECAL. WITH',I4,' MISFITTING PERSONS OMITTED',
                    *3X,'PG',I3)
0067                 END
```

```
      SUBROUTINE PICT(X,Y,ISEL,XAXIS,YAXIS,XLAB,YLAB)
      DIMENSION X(1),Y(1),XLAB(1),YLAB(1),ISEL(1)
      COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KLAB,ISW(11)
     1,SNAME
      COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
      CALL CLEAR(XAXIS,YAXIS,1)
      DO 5 I=1,NITEM
      IF(ISEL(I).LE.0) GO TO 5
      CALL GRAPH(X(I),Y(I),1)
    5 CONTINUE
      CALL PLOT(YLAB,XLAB)
      CALL PAGE(5,J)
      RETURN
      END
```

```
      SUBROUTINE PLOT (YLAB,XLAB)
      DIMENSION YLAB(1),XLAB(1),XVAL(11),OLAB(50)
      COMMON /GRID/ GRID(4080)
      COMMON/PLOTR/YMIN,YMAX,XMIN,XMAX,NROW,NCOL
      DATA BLK/' '/
      LC=NCOL/10
      LC1 = LC + 1
      LR=NROW/10
      VAL = XMIN
      XINC = (XMAX - XMIN)/NCOL * 10.0
      DO 10 I=1,LC1
      XVAL(I)=VAL
   10 VAL = VAL + XINC
      VAL =   YMAX
      XINC= (YMAX - YMIN)/NROW * 10.0
      LIML = 1
      LIMU = NCOL
      DO 6 K=1,NROW
    6 OLAB(K)=BLK
      K1 = (NROW - 12)/2
      K12 = K1 + 11
      KK = 0
      DO 5 K=K1,K12
      KK = KK + 1
    5 OLAB(K)=YLAB(KK)
      K=1
      WRITE(6,102)OLAB(K),VAL,(GRID(I),I=LIML,LIMU)
      DO 2 J=1,LR
      DO 1 JJ=1,9
      LIML=LIMU+1
      LIMU=LIMU+NCOL
      K=K+1
    1 WRITE(6,101)OLAB(K),(GRID(I),I=LIML,LIMU)
      LIML=LIMU+1
      LIMU=LIMU+NCOL
      K=K+1
      VAL = VAL - XINC
    2 WRITE(6,102)OLAB(K),VAL,(GRID(I),I=LIML,LIMU)
      LR=NROW - 10 * LR
      IF(LR.EQ.0) GO TO 4
      LIML=LIMU+1
      LIMU=LIMU+NCOL
    3 WRITE(6,103) (GRID(I),I=LIML,LIMU)
    4 WRITE(6,105)(XVAL(K),K=1,LC1)
      WRITE(6,104)(XLAB(K),K=1,12)
      RETURN
  101 FORMAT(9X,A1,9X,102A1)
  102 FORMAT(9X,A1,F8.2,1X,102A1)
```

```
0049        103   FORMAT(19X,102A1)
0050        104   FORMAT(53X,12A1)
0051        105   FORMAT(11X,11F10.2)
0052              END
```

```
                SUBROUTINE PROX(IS.IB.DIFF.SEC.ABIL.ISEL.SE.M)
                DIMENSION IS(1).IB(1).DIFF(1).SEC(1).ABIL(1).ISEL(1).SE(1)
                COMMON NITEM.NGRUP.MINSC.MAXSC.LREC.NSUBJ.IC.KCAB.ISW(11).
               1SNAME(1)
                L1 = LREC - 1
                DDOT = 0.0
                DO 2 I=1.NITEM
                DIFF(I)=0.0
                IF(ISEL(I))2.2.1
      1         DIFF(I)=NSUBJ - IS(I)
                DIFF(I) = ALOG(DIFF(I)/IS(I))
                DDOT = DDOT + DIFF(I)
      2         CONTINUE
                D = 0.0
                DDOT = DDOT/LREC
                DO 4 I=1.NITEM
                IF(ISEL(I))4.4.3
      3         DIFF(I) = DIFF(I) - DDOT
                D = D + DIFF(I)*DIFF(I)
                SE(I) = DIFF(I)
      4         CONTINUE
                BDOT = 0.0
                D = D/(2.89*(LREC-1))
                B = 0.0
                DO 5 J=MINSC.MAXSC
                ABIL(J) = J
                ABIL(J) = ALOG(ABIL(J)/(LREC-J))
                BDOT = BDOT + ABIL(J)*IB(J)
      5         B = B + ABIL(J)*ABIL(J)*IB(J)
                BDOT = BDOT/NSUBJ
                B=B-BDOT*BDOT*NSUBJ
                B=B/(2.89*(NSUBJ-1))
                C = B*D
                DDOT = 1.0 - C
                X = (1.0+D)/DDOT
                Y = (1.0+B)/DDOT
      7         B = SQRT(Y)
                D = SQRT(X)
                WRITE(6.101) B.D
    101         FORMAT('0DIFFICULTY SCALE FACTOR'.F6.2.
               1'   ABILITY SCALE FACTOR'.F6.2)
                DO 9 I=1.NITEM
                IF(ISEL(I))9.9.8
      8         DIFF(I) = B*DIFF(I)
                DIFF(I+NITEM) = DIFF(I)
                Z=B*NSUBJ/(IS(I)*(NSUBJ-IS(I)))
                SEC(I) = SQRT(Z)
      9         CONTINUE
```

```
0047          DO 10 J=1,L1
0048          ABIL(J) = J
0049          ABIL(J) = ALOG(ABIL(J)/(LREC-J))
0050          ABIL(J)=D*ABIL(J)
0051          Z = D*LREC/(J*(LREC-J))
0052    10    SE(J+NITEM)=SQRT(Z)
0053          RETURN
0054          END
```

```
0001           SUBROUTINE REDUP(IDATA,IB,IS,ISEL,IA,ID,DIFF)
0002           DIMENSION IDATA(1),IB(1),IS(1),ISEL(1),IA(1),ID(1)
0003           DIMENSION ISM(3),DIFF(1),IDD(20),IOPT(20),KKEY(180)
0004           COMMON /GRID/ MATX(180,21)
0005           COMMON /FORM/ FMT(18)
0006           COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
              1,SNAME(1)
0007           DATA IND/1H*/,ISM/1HS,1HI,1HN/,KBLK/' '/
0008           ISW1=ISW(2)
0009           NSUBJ=1
0010           LLIM=ISW(3)
0011           KLIM=ISW(4)
0012           DO 3 I=1,20
0013         3 IDD(I) = 0
         C**READ COLUMN SELECT CARD
0014           READ(5,101) (IA(I),I=1,LREC)
         C**READ KEY CARD
0015           READ(5,101)(ID(I),I=1,LREC)
         C**READ OPTION LABEL CARD
0016           READ(5,101) IOPT
0017           DO 23 K=1,20
0018           IF(IOPT(K).EQ.KBLK) GO TO 24
0019     23    CONTINUE
0020           K=K+1
0021     24    NOPT = K-1
         C**PRINT SUMMARY INFORMATION
0022           WRITE(6,200)
0023           WRITE(6,201)(MN,MN=1,8)
0024           WRITE(6,202)(ND,N=1,8),(IND,N=1,63)
0025           WRITE(6,204)(IA(I),I=1,LREC)
0026           WRITE(6,206)(ID(I),I=1,LREC)
0027           N=1
0028           NSC=1
0029           ISW4 = ISW(1)
0030           CALL TRANS(IA,LREC)
0031           IZERO=0
0032           IF(ISW4.NE.1) GO TO 207
0033           IZERO = IOPT(1)
0034           CALL TRANS(IZERO,1)
0035     207   CONTINUE
0036           IF(ISW4.NE.0) CALL TRANS(ID,LREC)
         C**COUNT ITEMS SELECTED
0037           DO 22 I=1,LREC
0038           KK=IA(I)
0039           IF(KK)20,22,21
0040     20    NSC=NSC+1
0041        21 ISEL(N)=ID(I)
0042           KKEY(N) = ID(I)
```

```
                IS(N)=0
                N=N+1
             22 CONTINUE
                CALL TRANS(KKEY,LREC)
                N=N-NSC
                IC=0
                DO 1 I=1,LREC
                JX=IA   (I)
                IF(JX)19,19,17
          17    IF(ISW4.NE.1)JX=1
                DO 18 J=1,JX
                IC=IC+1
          18    IB(IC)=0
           19   DO 1 J=1,21
          1     MATX(I,J)=0
                NLOW=0
                NHIGH=0
          C**READ AND WRITE FIRST SUBJECT
                READ(ISW1,FMT)(ID(I),I=1,LREC)
                WRITE(6,205)(ID(I),I=1,LREC)
                ASSIGN 95 TO ISIM
                DO 51 I=1,3
                IF(ID(I).NE.ISM(I)) GO TO 2
          51    CONTINUE
                ASSIGN 94 TO ISIM
                CALL RESIM(ID,IDATA,DIFF,KKEY,1)
              2 DO 13 I=1,NITEM
             13 IDATA(I)=0
          C**SCORE EACH ITEM
                K=1
                DO 41 I=LLIM,KLIM
                IDD(K)=ID(I)
          41    K=K+1
                K=1
          4     DO66 I=1,LREC
                IF(IA(I))665,66,6
              6 DO 64 J=1,NOPT
          C**COUNT OPTION SELECTED
                IF(ID(I)-IOPT(J))64,65,64
             64 CONTINUE
          665   J = NOPT + 1
             65 MATX(K,J) = MATX(K,J) + 1
                K=K+1
             66 CONTINUE
          C**SCORE EACH PERSON
                CALL SCORE(IDATA,ID,IA,ISEL,NSC,ISW4,IZERO)
          C**DISCARD ZERO OR PERFECT PERSON SCORES
          5     IF(NSC) 93,10,7
```

```
      7 IB(NSC)=IB(NSC)+1
        IF(NSC-IC)800,11,11
    800 IF(NSC.LT.MINSC.OR.NSC.GT.MAXSC) GO TO 93
C**WRITE SCRATCH FILE
8       WRITE(1)(IDATA(I),I=1,NITEM),(IDD(I),I=1,KLIM)
        NSUBJ=NSUBJ+1
        IF(NSC-MINSC)93,87,87
     87 IF(NSC-MAXSC)88,88,93
C**ACCUMULATE MARGINALS FOR CALIBRATION ROUTINES
     88 DO 9 I=1,NITEM
      9 IS(I)=IS(I)+IDATA(I)
93      GO TO ISIM,(94,95)
    94  CALL RESIM(ID,IDATA,DIFF,KKEY,2)
        GO TO 96
     95 CONTINUE
C**READ NEXT RECORD
        READ(ISW1,FMT,END=12)(ID(I),I=1,LREC)
CDC     READ(ISW1,FMT)          (ID(I),I=1,LREC)
CDC     IF(EOF(ISW1).NE.0) GO TO 12
C**TEST FOR END OF FILE
96      IF(ID(1)-IND)2,12,2
     10 NLOW=NLOW+1
        GO TO ISIM,(94,95)
     11 NHIGH=NHIGH+1
        GO TO ISIM,(94,95)
C**WRITE SUMMARY INFORMATION
     12 NSUBJ=NSUBJ-1
        WRITE(6,107)NITEM,NSUBJ
        WRITE(6,108)
        CALL PAGE(2,J)
C**PRINT OPTION FREQUENCY TABLE
        WRITE(6,103) IOPT
        I=1
        LLINE=0
        NOPT = NOPT + 1
        NOPT1 = NOPT - 1
        DO 114 M=1,LREC
        IF(IA(M))113,114,112
112     WRITE(6,104)I,SNAME(I),MATX(I,NOPT),ISEL(I),(MATX(I,K),K=1,NOPT1)
        I=I+1
        CALL PAGE(4,LLINE)
        IF(LLINE.EQ.0) WRITE(6,103)IOPT
        GO TO 114
113     I = I+1
    114 CONTINUE
        WRITE(6,105)
14      NSC=NLOW+NHIGH+NSUBJ
        CALL PAGE(2,J)
```

```
          WRITE(6,102) NLOW,NHIGH
          L=0
          DO725I=1,LREC
          KK=IA(I)
          IF(KK)753,725,752
      752 IF(ISW4.NE.1)KK=1
      753 L=L+1
          ISEL(L)=KK
      725 CONTINUE
          LREC=IC
          NITEM=L
          IC=N
          WRITE(6,106)N,L
          END FILE 1
          REWIND 1
      100 FORMAT(80I1)
      101 FORMAT(80A1)
      102 FORMAT(// 1X21HNUMBER OF ZERO SCORES I11/1X24HNUMBER OF PERFECT SC
         1ORES,I8)
      103 FORMAT(//10X,'ALTERNATIVE RESPONSE FREQUENCIES'//1X,120('-')/
         12X,'SEQ',1X,'ITEM',/
         22X,'NUM',1X,'NAME',3X,'UNKN',3X,'KEY',6X,20(A1,4X)/1X,120('-'))
      104 FORMAT(I5,1X,A4,2X,I4,5X,A4,'|',20I5)
      105 FORMAT(1X,120('-'))
      106 FORMAT(//' NUMBER OF ITEMS SELECTED',I4/' NUMBER OF ITEMS NAMED',I
         17)
      107 FORMAT(//'0NUMBER OF ITEMS',I5/' NUMBER OF SUBJT',I5)
      108 FORMAT(////////80X,53('*')/2(80X,'*',51X,'*'/),80X,'*',4X,
         1'* * *  B I C A L  -  V E R S I O N  3 * * *',4X,'*'/2(80X,'*',
         251X,'*'/),80X,'*',5X,'DIRECT ENQUIRIES TO:',26X,'*'/80X,'*',
         315X,'SUSAN R. BELL',23X,'*'/80X,'*',15X,'C/O BENJAMIN D. WRIGHT',
         414X,'*'/80X,'*',15X,'DEPARTMENT OF EDUCATION',13X,'*'/80X,'*',15X,
         5'UNIVERSITY OF CHICAGO',15X,'*'/80X,'*',15X,
         6'5835 S. KIMBARK AVENUE',14X,'*'/80X,'*',15X,'CHICAGO, ILLINOIS  6
         70637',12X,'*'/80X,'*',15X,'(312) 753-3818',22X,'*'/80X,'*',15X,'(3
         812) 753-4013',22X,'*'/2(80X,'*',51X,'*'/),80X,'*',2X,'COPYRIGHT BY
         9 RONALD J. MEAD, BENJAMIN D. WRIGHT,',1X,'*'/80X,'*',14X,'AND SUSA
         1N R. BELL (1979)',13X'*'/2(80X,'*',51X,'*'/),80X,53('*'))
      200 FORMAT(1H+,//1X16HCOLUMNS SELECTED/)
      201 FORMAT(1H+,3I10)
      202 FORMAT(1H ,1H1,8A1,1H0,7(9A1,1H0))
      204 FORMAT(1H ,80A1/)
      205 FORMAT(1H0,13HFIRST SUBJECT/1X80A1)
      206 FORMAT(1H0,3HKEY/1X80A1)
          RETURN
          END
```

```
      SUBROUTINE RESIM(ID,IDATA,DIFF,ISEL,M)
      DIMENSION ID(1),IDATA(1),DIFF(1),ISEL(1),ICODE(36),COM(1)
      COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      DATA JD/1H /,IND/1H*/,ICODE/1H0,1H1,1H2,1H3,1H4,1H5,1H6,1H7,1H9,
     11H9,1HA,1HB,1HC,1HD,1HE,1HF,1HG,1HH,1HI,1HJ,1HK,1HL,1HM,1HN,1HO,
     21HP,1HQ,1HR,1HS,1HT,1HU,1HV,1HW,1HX,1HY,1HZ/
      GO TO (1,4),M
    1 READ(5,101) WIDTH,ISUBJ,GMEAN,SD,ISED
      IF(ISED.GT.0)ISEED=ISED
      WRITE(6,105)ISUBJ,WIDTH,GMEAN,SD,ISEED
      WIDTH= WIDTH/(NITEM-1)
      AB=0.
      P=0.
      DO 10 I=1,NITEM
      AB=AB+ISEL(I)
      P = P-1
   10 CONTINUE
      DIFF(1)=WIDTH*(1.+P/AB)
      DD=DIFF(1)*DIFF(1)
      NN=ISEL(1)
      I=1
      WRITE(6,102)I,DIFF(I)
      DO 2 I=2,NITEM
      DIFF(I)=DIFF(I-1)+WIDTH
      DD=DD + DIFF(I)*DIFF(I)
      NN = NN + ISEL(I)
      WRITE(6,102)I,DIFF(I)
    2 DIFF(I-1)=EXP(DIFF(I-1))
      DIFF(NITEM)=EXP(DIFF(NITEM))
      DD=SQRT(DD/(NN-1))
      WRITE(6,106) DD
      DO 3 I=1,150
    3 ID(I)=JD
      ICNT=0
      ABM=0.
      ABM2=0
    4 IF(ICNT.LT.ISUBJ) GO TO 5
      ID(I)=IND
      ABM2=SQRT((ABM2-ABM*ABM/ICNT)/(ICNT-1))
      ABM=ABM/ICNT
      WRITE(6,104)ICNT,ABM,ABM2
      RETURN
    5 ICNT=ICNT+1
      CALL GGUN(ISEED ,1,COM)
CDC   CALL GGNOR(ISEED,1,COM)
C  GGUN GENERATES NORMALL VARIATES WITH MEAN 0 AND VARIANCE 1.
C        ISEED IS THE SEED FOR THE GENERATOR WHICH IS READ FROM
```

```
C                 SIMULATION DESCRIPTION CARD.
C              '1' INDICATES ONLY ONE DEVIATE IS TO BE REURNED.
C             COM IS AN ARRAY IN WHICH THE RANDOM NUMBER IS RETURNED.
            ABL=SD*COM(1)+GMEAN
            ABN=ABN+ABL
            ABM2=ABM2+ABL*ABL
            AB=EXP(ABL)
            DO 8 I=1,NITEM
            IX=ISEL(I)
            IF(IX.EQ.0) GO TO 8
            P = AB/DIFF(I)
C   NEITHER GGUN NOR GGU3 ARE INCLUDED IN THE RASCH SOURCE DECK.
C   THEY ARE PART OF 'SYS2.IMSL' PACKAGE AT THE UNIVERSITY OF CHICAGO.
            P=P/(1.+P)
            NSC=0
            DO 7 J=1,IX
            CALL GGU3(ISEED,1,COM)
CDC         CALL GGUB(ISEED,1,COM)
C   GGU3 GENERATES UNIFORM RANDOM NUMBERS. THE ARGUMENT LIST IS
C              IS IDENTICAL TO 'GGUN.'
            IF(COM(1)-P)6,6,7
      6     NSC = NSC +1
    7       CONTINUE
            ID    (I)=ICODE(NSC+1)
    8       CONTINUE
            IF(ISW(7).NE.0)WRITE(6,103)ICNT,ABL,(ID(I),I=1,NITEM)
      101 FORMAT(F5.0,I5,2F5.0,I10)
      102 FORMAT(' ITEM NUMBER',I5,' DIFFICULTY=',F7.3)
      103 FORMAT(' SUBJECT NUMBER',I5,' ABILITY ',F6.3,' RESPONSES ',80A1)
      104 FORMAT(/1H0,I5,' SUBJECTS SIMULATED.  MEAN ABILITY ='
         1,F6.3,' STANDARD DEVIATION =',F6.3)
      105 FORMAT('0SIMULATION OF ',I5,' SUBJECTS',/,' TARGET VALUES --'
         1,'TEST WIDTH =',F6.3,/,' ABILITY MEAN =',F6.3,' STANDARD',
         2' DEVIATION =',F6.3,/,' SEED FOR RN GENERATOR =  ',I10,/)
      106 FORMAT(/'0',9X,'STANDARD DEVIATION',F7.2)
            RETURN
            END
```

```
      SUBROUTINE SCORE(IDATA,ID,ISEL,KEY,NSC,M,NZ)
      DIMENSION IDATA(1),ID(1),ISEL(1),KEY(1)
      COMMON  NITEM,NGROUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      DATA BLK/1H /,AST/1H*/
      MM=M+1
      NSC=0
      J=0
      GO TO (9,1,14,19,24),MM
    1 CALL  TRANS(ID,LREC)
      DO 5 I=1,LREC
      K=ISEL(I)
      IF(K)4,5,2
    2 IF(K-ID(I))6,3,3
    3 ID(I) = ID(I) - NZ
      NSC=NSC+ID(I)
    4 J=J+1
      IDATA(J)=ID(I)
    5 CONTINUE
      RETURN
    6 WRITE(6,101)(ID(K),K=1,LREC)
      WRITE(6,102)(BLK,K=1,I),AST
      NSC=-1
      RETURN
    9 J=1
      DO 13 I=1,LREC
      K=ISEL(I)
      IF(K)12,13,10
   10 IF(ID(I)-KEY(J))12,11,12
   11 NSC=NSC+1
      IDATA(J)=1
   12 J=J+1
   13 CONTINUE
      RETURN
   14 CALL  TRANS(ID,LREC)
      J=1
      DO 18 I=1,LREC
      K=ISEL(I)
      IF(K)17,18,15
   15 IF(ID(I)-KEY(J))16,16,17
   16 NSC=NSC+1
      IDATA(J)=1
      J=J+1
      GO TO 18
   17 IDATA(J)=0
      J=J+1
   18 CONTINUE
      RETURN
```

```
19      CALL  TRANS(ID,LREC)
        J=1
        DO 23 I=1,LREC
        K=ISEL(I)
        IF(K)22,23,20
20      IF(ID(I)-KEY(J))22,21,21
21      NSC=NSC+1
        IDATA(J)=1
        J=J+1
        GO TO 23
22      IDATA(J)=0
        J=J+1
23      CONTINUE
        RETURN
24      CONTINUE
C**THIS SPACE RESERVED FOR USER SUPPLIED LOGIC.
  101 FORMAT(1X,'ILLEGAL CODE.   CASE OMITTED'/(1X80I1))
  102 FORMAT(81A1)
        RETURN
        END
```

```
      SUBROUTINE SMMRY(DIFF,A,Z,IDATA,IS,MATX,ISEL,B,IB,SE,TZ,EX,PB,
     *STAT,SI)
      DIMENSION DIFF(1),ISEL(1),IDATA(1),MATX(1),IS(1),A(1),B(1),IB(1)
      DIMENSION XX(7),STAT(1),AVG(7),Z(1),SE(1),EX(1),TZ(1),PB(1),
     *SI(1)
      COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      LLINE=0
C**CLEAR NECESSARY ARRAYS
      DO 97 I=1,NITEM
      IF(ISEL(I))97,97,95
   95 K=1
   97 CONTINUE
      DO 98 I=1,7
98    AVG(I)=0.0
      DO 99 I=1,28
   99 STAT(I)=0.0
      DIF = 0.0
      CALL PAGE(2,J)
      DO 1 I=1,NITEM
      IS(I) = -IS(I)
    1 IB(I)=1000.0*TZ(I)
C**FIND DIFFICULTY AND FIT ORDERS
      CALL SRT(IS,IDATA)
      CALL SRT(IB,IS)
C**PRINT HEADINGS
      WRITE(6,100)
C**PRINT TABLE WITH I EQ SEQ ORDER, J EQ DIFF ORDER AND K EQ FIT ORDER
      I1=0
      I2=0
      DO22 I=1,NITEM
      IF(ISEL(I).LE.0) GO TO 22
 11   I1=I1+1
      J=IDATA(I1)
      IF(ISEL(J).LE.0.AND.I1.LE.NITEM) GO TO 11
12    I2=I2+1
      K=IS(I2)
      IF(ISEL(K).LE.0.AND.I2.LE.NITEM) GO TO 12
      CALL PAGE(4,LLINE)
      IF(LLINE.EQ.0)WRITE(6,100)
      WRITE(6,101)I,SNAME(I),DIFF(I),SE(I),A(I),TZ(I),J,SNAME(J),
     1DIFF(J),A(J),TZ(J),K,SNAME(K),DIFF(K),EX(K),PB(K),TZ(K),Z(K),
     2SI(K),A(K),B(K)
      XX(1)=DIFF(I)
      XX(2)=A(I)
      XX(3)=TZ(I)
      XX(4) = PB(I)
      XX(5) = Z(I)
```

```
0040            XX(6) = SI(I)
0041            XX(7) = SE(I)
0042            KL=1
0043            IF(ISEL(I))22,22,5
0044          5 DO 2 K=1,7
0045            AVG(K)=AVG(K)+XX(K)
0046            DO 2 L=1,K
0047            STAT(KL)=STAT(KL)+XX(K)*XX(L)
0048          2 KL=KL+1
0049            D2 = XX(1) * XX(1)
0050            S2 = XX(7) * XX(7)
0051            DIF = DIF + (D2-S2)
0052         22 CONTINUE
0053            KL=1
0054            X=   IC  -1
      C**COMPUTE MEANS, STANDARD DEVIATIONS AND CORRELATIONS
0055            DO 3 I=1,7
0056            AVG(I)=AVG(I)/ LREC
0057            DO 3 J=1,I
0058            STAT(KL)=(STAT(KL)-LREC *AVG(I)*AVG(J))/(LREC-1)
0059          3 KL=KL+1
0060            KL=1
0061            DO 4 I=1,7
0062            K=(I*(I+1))/2
0063            XX(I)=SQRT(STAT(K))
0064            DO 4 J=1,I
0065            IF((XX(I)*XX(J)).NE.0.0)STAT(KL)=STAT(KL)/(XX(I)*XX(J))
0066          4 KL=KL+1
0067            DIF = AMAX1(DIF,0.0)
0068            IF(DIF.GT.0.0)DIF = SQRT(DIF/(LREC-1))
0069            WRITE(6,102)(AVG(I),I=1,4),AVG(3),AVG(5),AVG(6),DIF,(XX(I),I=2,4),
               *XX(3),XX(5),XX(6)
0070            CALL PAGE(5,J)
0071        100 FORMAT(/15X'SERIAL ORDER',22X,'DIFFICULTY ORDER',34X,'FIT ORDER',
               1/1X132('-')/2X,'SEQ ITEM',3X,'ITEM',2X,' STD',4X,'DISC',3X,' FIT
               *|',' SEQ ITEM',3X,'ITEM',3X,'DISC',3X,' FIT   |',
               1' SEQ ITEM    ITEM  ERR     FIT T-TESTS  WTD  MNSQ  DISC POINT'
               2/2X,'NUM NAME',3X,'DIFF',2X,'ERROR',3X,'INDX',3X,'TTEST |',
               *1X,'NUM NAME',3X,'DIFF',3X,'INDX',3X,'TTEST |',
               3' NUM NAME    DIFF IMPAC  BETWN  TOTAL  MNSQ  SD    INDX BISER'
               */1X,132('-'))
0072        101 FORMAT(I5,1XA4,4F7.2,2X1H|,I4,1XA4,3F7.2,2X1H|,I4,1XA4,F7.2,F6.2,
               *2F7.2,F6.2,F5.2,2F6.2)
0073        102 FORMAT(1X,132(1H-)/6X'MEAN',F7.2,7X,2F7.2,58X,2F7.2,F6.2,F5.2/
               *6X,'S.D.',F7.2,7X,2F7.2,58X,2F7.2,F6.2,F5.2)
0074            RETURN
0075            END
```

```
 0001                 SUBROUTINE SRT(MATX,IDATA)
 0002                 DIMENSION MATX(1),IDATA(1)
 0003                 COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
                     1,SNAME(1)
                C**SORT CONTENTS OF MATX, STORE ORDER IN IDATA
 0004                 DO 1 I=1,NITEM
 0005               1 IDATA(I)=I
 0006                 DO 2 I=1,NITEM
 0007                 DO 30 J=I,NITEM
 0008                 IX=IDATA(I)
 0009                 JX=IDATA(J)
 0010                 IF(MATX(JX)-MATX(IX))3,30,30
 0011               3 IDATA(I)=JX
 0012                 IDATA(J)=IX
 0013              30 CONTINUE
 0014               2 CONTINUE
 0015                 RETURN
 0016                 END
```

```
0001               SUBROUTINE TRANS(IA,LENG)
0002               DIMENSION IA(1),ICODE(36)
0003               COMMON  NITEM,NGROP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
                  1,SNAME(1)
0004               DATA ICODE/1H0,1H1,1H2,1H3,1H4,1H5,1H6,1H7,1H8,1H9,1HA,1HB,1HC,1HD
                  1,1HE,1HF,1HG,1HH,1HI,1HJ,1HK,1HL,1HM,1HN,1HO,1HP,1HQ,1HR,1HS,1HT,
                  21HU,1HV,1HW,1HX,1HY,1HZ/,BLK/1H /,IAMP/1H&/
0005               DO 18 I=1,LENG
0006               K=IA(I)
0007               IF(K.NE.BLK) GO TO 14
0008               IA(I)=0
0009               GO TO 18
0010         14    IF(K.NE.IAMP) GO TO 15
0011               IA(I)=-1
0012               GO TO 18
0013         15    DO 17 J=1,36
0014               IF(K-ICODE(J))17,16,17
0015         16    IA(I)=J-1
0016               GO TO 18
0017         17    CONTINUE
0018               IA(I)=0
0019         18    CONTINUE
0020               RETURN
0021               END
```

```
      SUBROUTINE UCON(S,R,D,SEC,AB,ISEL,SE)
      INTEGER R(1),S(1),ISEL(1)
      DIMENSION D(1),AB(2),SE(1),SEC(1)
      COMMON  NITEM,NGRUP,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISW(11)
     1,SNAME(1)
      L=NITEM
      L1=LREC-1
      DX=LREC
      DX=DX/L1
      DO 199 I=1,L
      IF(ISEL(I).LE.0) GO TO 199
      D(I) = D(I)*DX
  199 CONTINUE
      DO 2000 IT=1,10
      NITER = IT
      CRIT=0.0
      CEN=0.0
      DO 201 I=1,L
      IF(ISEL(I)) 201,201,200
  200 CONTINUE
      CALLNEWT(D(I),ISEL(I),AB,R, S(I),NSEL,MINSC,MAXSC,0.,.05,10,DD,P)
      CEN=CEN+D(I)
      SEC(I)=P
  201 CONTINUE
      CEN=CEN/LREC
      DO 212 I=1,L
      IF(ISEL(I)) 212,212,211
  211 D(I)=D(I)-CEN
      CRIT=CRIT+ABS(D(I)-SE(I))
  212 CONTINUE
      IF(IT.GT.1) GO TO 205
      DO 204 I=1,L
      IF(ISEL(I))204,204,202
  202 D(I+2*NITEM)=D(I)/DX
  204 CONTINUE
  205 IF((CRIT/IC)-0.025)330,1999,1999
 1999 DO 214 K=MINSC,MAXSC
      DO 215 ITK=1,5
      IX=K+L
      SE(IX )=0.0
      DD=0.0
      DO 216 I=1,L
      IF(ISEL(I))216,216,213
  213 P=EXP(AB(K)-D(I))
      P=P/(1.0+P)
      SE(IX)=SE(IX)+P*(1.0-P)
      DD=DD+P
  216 CONTINUE
```

```
            DD=(K-DD)/SE(IX)
            AB(K)=AB(K)+DD
            IF(ABS(DD)-0.05)214,215,215
        215 CONTINUE
        214 CONTINUE
            DO 2000I=1,L
            IF(ISEL(I)) 2000,2000,2001
       2001 SE(I)=D(I)
       2000 CONTINUE
     330    DD=LREC-1
            DD=DD/LREC
            IT=LREC-1
            DO 332 I=1,L
            IF(ISEL(I)) 332,332,333
        333 IX = IX + 1
            SE(I)=D(I)-SE(I)
     332    D(I)=D(I)/DX
            WRITE(6,100)NITER
        100 FORMAT(' NUMBER OF ITERATIONS = ',I3)
            RETURN
            END
```

```
      FUNCTION IPOS(I,N)
      FAL=1000.0/N
      IPOS = I/FAL + 1
      IPOS=MIN0(IPOS,N)
      IPOS=MAX0(IPOS,1)
      RETURN
      END
```

```
0001          FUNCTION ITAB(X,XMIN,XMAX)
0002          ITAB = 1000.0 * (X - XMIN) / (XMAX - XMIN)
0003          RETURN
0004          END
```

```
0001      FUNCTION TTEST(V,F)
0002      TTEST=0.0
0003      IF(V.LE.0.0) RETURN
0004      IF(F.LE.0.0) RETURN
0005      X = 3
0006      A = X * SQRT(F/2.0)
0007      B = V**(1.0/X)
0008      TTEST= A * B - A + 1.0 / A
0009      RETURN
0010      END
```

VII. AN ILLUSTRATION OF BICAL OUTPUT

The data for illustrating the program's application come from the administration of the 18-item Knox Cube Test, a subtest of the Arthur Point Scale (Arthur, 1947), to 35 children in Grades 2 to 7. This tiny data matrix was chosen to illustrate BICAL because it can be analyzed by hand (as it is in Chapter 2 of Best Test Design). This simplicity makes it easy to see how BICAL works. We also wanted to show how Rasch item analysis can be useful for the smallest problems. BICAL, however, can handle much larger problems. It has been used with tests as large as 1000 items and samples as large as 15,000 persons. To increase the capacity of BICAL beyond the items it is now dimensioned to handle you need only increase the dimensions assigned to its major arrays.

The Knox Cube Test implies a single latent trait. Success requires the application of visual attention and short-term memory to a simple sequencing task. The test uses five one-inch cubes. Four of the cubes are fixed two inches apart on a board, and the fifth is used to tap a series on the other four. The four attached cubes will be referred to, from left to right, as "1," "2," "3," and "4." In the version of the test used for this example, there are 18 such series progressing from a two-step sequence (1-4) and (2-3) to a seven-step

```
KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 238                                         PAGE  1

CONTROL PARAMETERS

NITEM NGROP MINSC MAXSC  LREC  KCAB KSCOR INFLE  LLIN  KLIN NUPFL C-FIT  KSIN  PRIT
   18    10     1    17    20     2     0     5     1     2     0    20     0     0

PERSON FILE FORMAT (20A1)

COLUMNS SELECTED
         1         2         3         4         5         6         7         8
1*********0*********0*********0*********0*********0*********0*********0*********0
  11111111111111111111

KEY
  11111111111111111111

FIRST SUBJECT
01111111110C00000000


NUMBER OF ITEMS     18
NUMBER OF SUBJT     35
```

```
*****************************************************************
*                                                               *
*      * * *  B I C A L  -  V E R S I O N  3 * * *              *
*                                                               *
*    DIRECT ENQUIRIES TO:                                       *
*              SUSAN R. BELL                                    *
*              C/O BENJAMIN D. WRIGHT                           *
*              DEPARTMENT OF EDUCATION                          *
*              UNIVERSITY OF CHICAGO                            *
*              5835 S. KIMBARK AVENUE                           *
*              CHICAGO, ILLINOIS  60637                         *
*              (312) 753-3818                                   *
*              (312) 753-4013                                   *
*                                                               *
*  COPYRIGHT BY RONALD J. MEAD, BENJAMIN D. WRIGHT,             *
*          AND SUSAN R. BELL (1979)                             *
*                                                               *
*****************************************************************
```

sequence (4-1-3-4-2-1-4).

The 18 tapping series are given in Table 7. These are the 18 "items" of the test. Note that Items 1 and 2 require a two-step sequence; Items 3 through 6, a three-step sequence; Items 7 through 10, a four-step sequence; Items 11, 12 and 13, a five-step sequence; Items 14 through 17, a six-step sequence; and Item 18, a seven-step sequence.

The responses of the 35 students to a single administration of the 18 items of this Knox Cube Text are given in Table 8 in the form of a person-by-item data matrix. A correct response by a person to an item is recorded as a "1," and an incorrect response as a "0." The items are listed across the top of the table in the order of their administration.

Person scores, the number of correct responses achieved by each subject, are given at the end of each row in the last column on the right. Item scores, the total number of correct responses to each item, are given at the bottom of each column.

Inspection of Table 8 shows that the order of administration is very close to the order of difficulty. Items 1, 2 and 3 are answered correctly by all students. A second, slightly greater level of difficulty is observed in Items 4 through 9. Then, Items 10 and 11 show a sharp increase in difficulty. Items 12 through 17 are answered correctly by only a few subjects, and no one succeeds on Item 18. Only 12 persons score successfully at last once on Items 12 through 17, and only five of these students do one or more of the six-tap items successfully.

ALTERNATIVE RESPONSE FREQUENCIES

SEQ NUM	ITEM NAME	UNKN	KEY	0	1
1	1101	0	1	0	35
2	1102	0	1	0	35
3	1103	0	1	0	35
4	1104	0	1	3	32
5	1105	0	1	4	31
6	1106	0	1	5	30
7	1107	0	1	4	31
8	1108	0	1	8	27
9	1109	0	1	5	30
10	1110	0	1	11	24
11	1111	0	1	23	12
12	1112	0	1	29	6
13	1113	0	1	28	7
14	1114	0	1	32	3
15	1115	0	1	34	1
16	1116	0	1	34	1
17	1117	0	1	34	1
18	1118	0	1	35	0

TABLE 7

TAPPING ORDER FOR THE
KNOX CUBE TEST

ITEM LABEL	TAPPING ORDER						
1	1	4					
2	2	3					
3	1	2	4				
4	1	3	4				
5	2	1	4				
6	3	4	1				
7	1	4	3	2			
8	1	4	2	3			
9	1	3	2	4			
10	2	4	3	1			
11	1	3	1	2	4		
12	1	3	2	4	3		
13	1	4	3	2	4		
14	1	4	2	3	4	1	
15	1	3	2	4	1	3	
16	1	4	2	3	1	4	
17	1	4	3	1	2	4	
18	4	1	3	4	2	1	4

```
NUMBER OF ZERO SCORES           0
NUMBER OF PERFECT SCORES        0

NUMBER OF ITEMS SELECTED  18
NUMBER OF ITEMS NAMED     18

-----------------------------------
SUBJECTS BELOW        1           0
SUBJECTS ABOVE       17           0
SUBJECTS IN CALIB.               35
-----------------------------------
TOTAL SUBJECTS                   36

REJECTED ITEMS

 ITEM      ITEM     ANSWERED
NUMBER     NAME     CORRECTLY
--------------------------------------
   1       1101        35   HIGH SCORE
   2       1102        35   HIGH SCORE
   3       1103        35   HIGH SCORE
  18       1118         0   LOW SCORE
--------------------------------------

    SUBJECTS DELETED =     1
 SUBJECTS REMAINING =     34

       ITEMS DELETED =     4
     POSSIBLE SCORE  =    14

       MINIMUM SCORE =     1
       MAXIMUM SCORE =    13
```

TABLE 8

ORIGINAL RESPONSES OF 35 PERSONS TO 18 ITEMS ON THE KNOX CUBE TEST

PERSON LABEL	ITEM LABEL 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	PERSON SCORE
1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	7
2	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
3	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	0	10
4	1	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	6
5	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
6	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
7	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	14
8	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
9	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
10	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	11
11	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	8
12	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	8
13	1	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0	10
14	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	11
15	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	13
16	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	10
17	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	9
18	1	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	11
19	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	9
20	1	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	11
21	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	12
22	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	12
23	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	0	12
24	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	1	1	0	14
25	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	5
26	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
27	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	7
28	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	10
29	1	1	1	1	1	1	0	0	1	1	1	0	0	1	0	0	0	0	10
30	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	9
31	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	10
32	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	11
33	1	1	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	6
34	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	12
35	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
ITEM SCORE	35	35	35	32	31	30	31	27	30	24	12	6	7	3	1	1	1	0	

PROCEDURE IS UCON

DIFFICULTY SCALE FACTOR 1.31 ABILITY SCALE FACTOR 2.10
NUMBER OF ITERATIONS = 7

SEQUENCE NUMBER	ITEM NAME	ITEM DIFFICULTY	STANDARD ERROR	LAST DIFF CHANGE	PROX DIFF	FIRST CYCLE
4	1104	-4.186	0.816	-0.025	-3.865	-3.557
5	1105	-3.648	0.709	-0.023	-3.294	-3.042
6	1106	-3.220	0.647	-0.021	-2.876	-2.649
7	1107	-3.648	0.709	-0.023	-3.294	-3.042
8	1108	-2.241	0.547	-0.015	-2.007	-1.803
9	1109	-3.220	0.647	-0.021	-2.876	-2.649
10	1110	-1.498	0.489	-0.009	-1.368	-1.193
11	1111	0.760	0.456	0.006	0.647	0.632
12	1112	2.135	0.556	0.015	1.767	1.728
13	1113	1.861	0.529	0.014	1.518	1.508
14	1114	3.214	0.705	0.022	2.805	2.616
15	1115	4.564	1.076	0.027	4.321	3.817
16	1116	4.564	1.076	0.027	4.321	3.817
17	1117	4.564	1.076	0.027	4.321	3.817

ROOT MEAN SQUARE = 0.022

14 ITEMS CALIBRATED ON 34 PERSONS
34 MEASURABLE PERSONS WITH MEAN ABILITY = -0.16 AND STD. DEV. = 1.45

Table 9 shows the control cards used for this BICAL analysis:

Card 1, the Title Card, supplies identifying information about the analysis being done. This information is printed at the top of each page of output.

Card 2, the Input Description Card, describes how the data is to be presented and handled. The data for this example are described as follows:

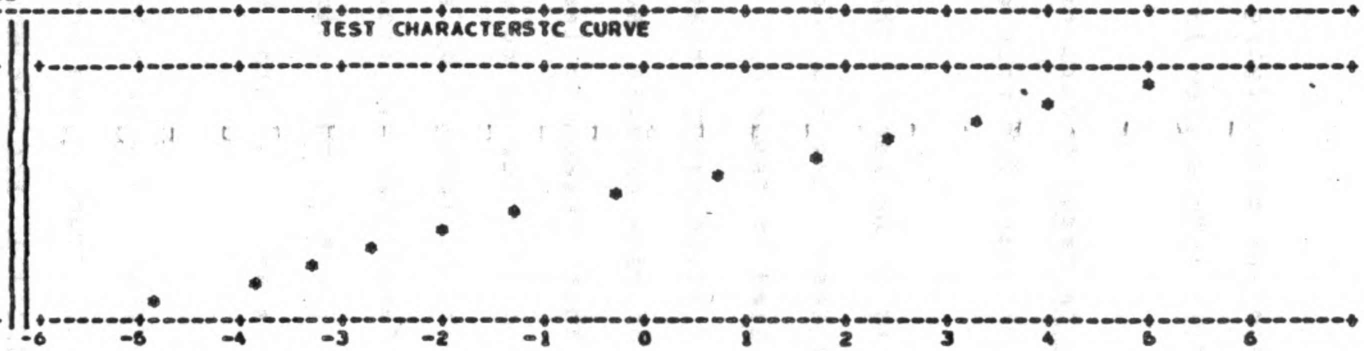
NITEM is the number of items to be read. There are NITEM = 18 items in the Knox Cube Test, that is, each person has 18 responses to be read, as described in Table 8.

NGROP governs the number of score groups that will be formed for analyzing item fit. For this example, NGROP = 10, so BICAL attempts to form groups that average at least 10 persons each. The program format allows for up to six group. However, if the total number of persons divided by six is less than NGROP (as in this example), fewer than six groups will be formed. The value of NGROP will also halt the estimation of parameters if, after editing, there are fewer than NGROP persons remaining in the entire sample.

MINSC and MAXSC define the range of scores to be included in the calibration sample. For this problem, we intend that only persons scoring at least MINSC = 1, but not more than MAXSC = 17 be included. This option is useful because extremely high and extremely low scorers frequently behave abnormally on tests. Extreme scorers can be excluded by setting MINSC well above 1 and MAXSC somewhat below (NITEM-1). The particular

COMPLETE SCORE EQUIVALENCE TABLE

RAW SCORE	COUNT	LOG ABILITY	STANDARD ERRORS
13	0	5.09	1.14
12	0	4.11	0.95
11	2	3.31	0.92
10	1	2.53	0.93
9	4	1.71	0.96
8	5	0.81	1.03
7	12	-0.22	1.07
6	3	-1.19	0.97
5	2	-1.96	0.86
4	2	-2.61	0.81
3	2	-3.21	0.81
2	1	-3.86	0.88
1	0	-4.73	1.10



PERSON SEPARABILITY INDEX 0.68 (EQUIVALENT TO KR20)

14 ITEMS CALIBRATED ON 34 PERSONS
34 MEASURABLE PERSONS WITH MEAN ABILITY = -0.16 AND STD. DEV. = 1.45

TABLE 9

CONTROL CARDS FOR ANALYZING KNOX CUBE TEST DATA WITH BICAL3

Card Number	Card Name	Card Format	Sample from Knox Cube Test Data
1	Title Card	(20A4)	KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 23B
2	Input Description	(14I5)	___18___10____1___17___20____2____0____5____1____2___10___20
3	Variable Format	(20A4)	(20A1)
4	Item Names	(20A4)	IT01IT02IT03IT04IT05IT06IT07IT08IT09IT10IT11IT12IT13IT14IT15IT16IT17IT1
5	Column Select	(80A1)	__111111111111111111
6	Key	(80A1)	__111111111111111111
7	Options Labels	(20A1)	01
	(Data Cards)		
8	End of Data	(A1)	*
9	End of Job	(A4)	****

MAP OF VARIABLE

PERSON STATS	COUNT	RAW SCORE	MEASURE MIDPOINT(S.E.)	ITEM COUNTS	TYPICAL ITEMS (BY NAME)		
			4.50(1.14)	3	IT15	IT16	IT17
			4.30(1.14)				
+3SD		12	4.10(0.95)				
			3.90(0.95)				
			3.70(0.95)				
			3.50(0.95)				
	2	11	3.30(0.92)	1	IT14		
			3.10(0.92)				
			2.90(0.92)				
+2SD			2.70(0.92)				
	1	10	2.50(0.93)				
			2.30(0.93)				
			2.10(0.93)	1	IT12		
			1.90(0.93)	1	IT13		
	4	9	1.70(0.96)				
			1.50(0.96)				
+1SD			1.30(0.96)				
			1.10(0.96)				
	5	8	0.90(1.03)				
			0.70(1.03)	1	IT11		
			0.50(1.03)				
			0.30(1.03)				
			0.10(1.03)				
MEAN			-0.10(1.03)				
	12	7	-0.30(1.07)				
			-0.50(1.07)				
			-0.70(1.07)				
			-0.90(1.07)				
	3	6	-1.10(0.97)				
			-1.30(0.97)				
			-1.50(0.97)	1	IT10		
-1SD			-1.70(0.97)				
	2	5	-1.90(0.86)				
			-2.10(0.86)				
			-2.30(0.86)	1	IT08		
			-2.50(0.86)				
	2	4	-2.70(0.81)				
			-2.90(0.81)				
-2SD			-3.10(0.81)				
	2	3	-3.30(0.81)	2	IT06	IT09	
			-3.50(0.81)				
			-3.70(0.81)	2	IT05	IT07	
	1	2	-3.90(0.88)				
			-4.10(0.86)	1	IT04		
			-4.30(0.86)				

14 ITEMS CALIBRATED ON 34 PERSONS
34 MEASURABLE PERSONS WITH MEAN ABILITY = -0.16 AND STD. DEV. = 1.45

scores to be excluded need to be thought through for each application, however, because their choice depends on the way extreme scores might occur. In achievement testing with multiple choice items it is usually desirable to set the lower limit well above the guessing level, because persons who are guessing are not providing useful information about item difficulty.

LREC is the number of columns to be read in the input person record. For this example, the first LREC = 20 positions of each person record need to be read. The Column Select Card which follows specifies the 18 columns that contain the 18 item responses.

KCAB selects the calibration technique. The KCAB = 2 used in this example selects the corrected unconditional method, UCON. The UCON method is chosen for this problem because of the small sample size and the bimodal distribution of the item difficulties.

KSCORE specifies how the data are to be scored. KSCORE = 0 indicates that these data are to be scored dichotomously according to the correct answers provided on the Key Card.

INFLE specifies the logical unit number of the person input file. INFLE = 5 indicates that the data input is from Unit 5, i.e. from cards.

LLIM indicates the start of the identification field in the person input record. For this example, the start of the ID field is column LLIM = 1.

KLIM specifies the end of the identification field in the person input record. KLIM = 2 in this case, indicates that the

LIST OF PERSONS WITH FIT ABOVE 2.00

SEQ NUM	PERSON NAME	WTD MNSQ	MNSQ SD	TOTAL FIT T	PERSON ABILITY	PERSON ERROR	RESPONSES AND STANDARDIZED RESIDUALS
1	13	3.76	0.78	2.40	-0.22	1.07	1 1 0 0 1 1 1 1 1 0 0 0 0 0
							0 0-4-5 0 0 0 1 3 0 0 0 0 0
2	29	3.73	0.78	2.38	-0.22	1.07	1 1 1 0 0 1 1 1 0 0 1 0 0 0
							0 0 0-5-2 0 0 1 0 0 6 0 0 0

THESE 2 PERSONS WILL BE OMITTED FROM RECALIBRATION

end of the ID field is in column 2.

NUPFL specifies the logical unit number of the output person file. NUPFL = 10 indicates that this person output file will be put on Unit 10. For each valid person record this output file will contain the person's identification field defined by LLIM and KLIM, the person's raw score, ability estimate in logits, its standard error, the person's total t fit, mean square standard deviation, weighted mean square, observed response pattern and corresponding standardized residuals. Whenever NUPFL is not equal to zero appropriate JCL must be provided (see Section 8).

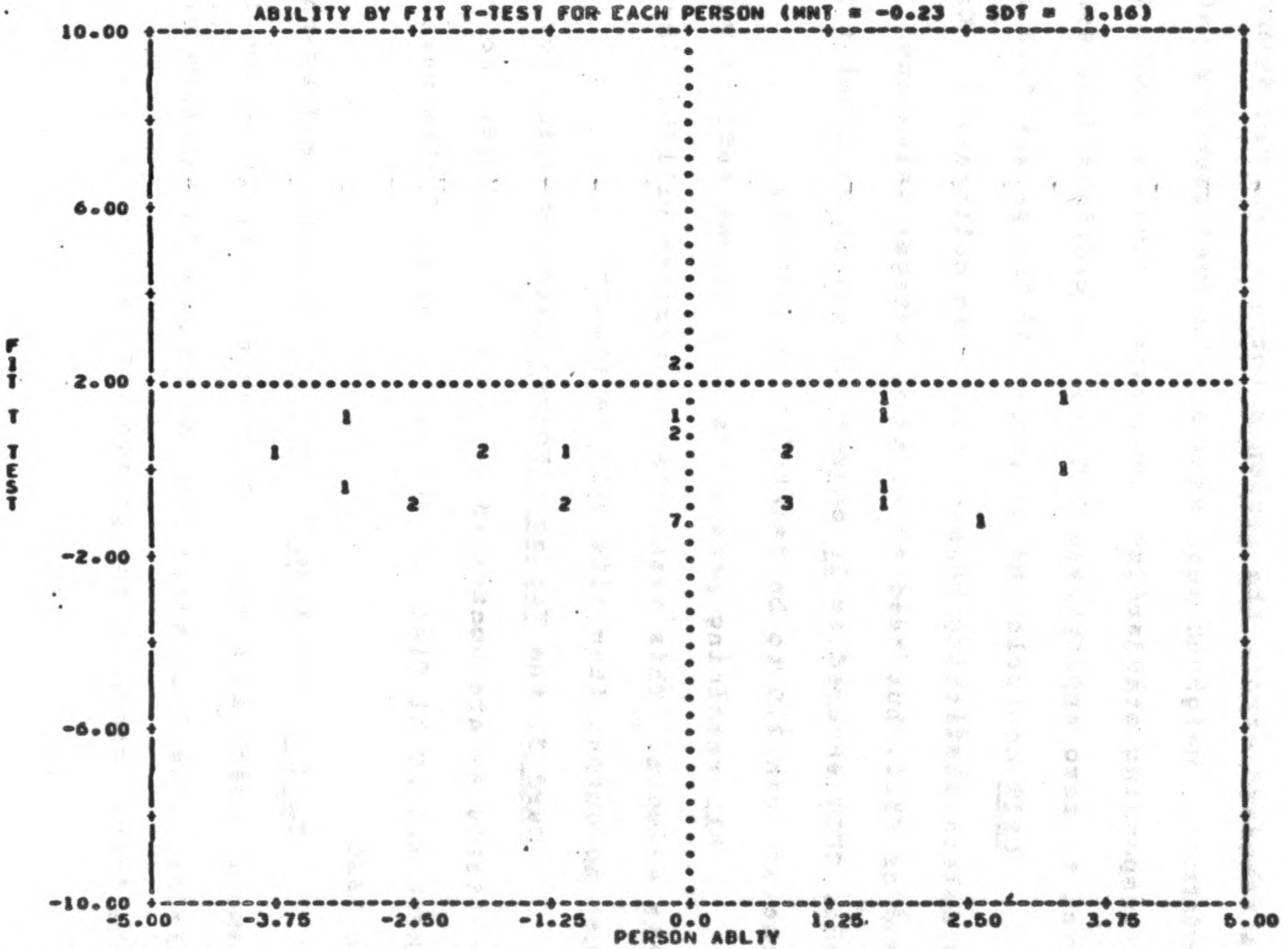
CFIT controls the screening of the person file in order to delete misfitting persons from item calibration. CFIT is used as F5.1, but read as I5 so an integer value must be input. Thus, CFIT entered as 20 causes persons whose total t fit is greater than 2.0 to be deleted as misfitting.

All remaining parameters will assume default values for this example. This means that no persons will be simulated and that no output item file will be written.

Card 3, the Variable Format Card, provides for as many A1 fields as are contained in the person record. For this example, there are 20 A1 fields. The number of A1 fields must be equal to LREC.

Card 4, the Item Names Card, provides a four-character name for each item read. In this example, there are 18 such fields. The item names must be entered in the same order as the items appear in the person record.

ABILITY BY FIT T-TEST FOR EACH PERSON (MNT = -0.23 SDT = 1.16)



THE 2 PERSONS WITH FIT ABOVE 2.00 WILL BE OMITTED FROM RECALIBRATION

14 ITEMS CALIBRATED ON 34 PERSONS
34 MEASURABLE PERSONS WITH MEAN ABILITY = -0.16 AND STD. DEV. = 1.46

Card 5, the Column Select Card, makes it possible to drop misfitting items from recalibration without changing any other control cards. Any character other than blank or zero indicates that the column it marks contains an item included in the item count (which is 18 on this Input Description Card).

Card 6, the Key Card, provides the correct answers for all 18 items. It is read in the same format as the Column Select Card. The meaning of this card for this example is that for all items the correct answer is 1.

Card 7, the Options Labels Card, defines up to 20 multiple choice alternatives. The same 20 values will be applied to all items. The occurrence frequency of each of the specified values is accumulated for each item. For this example, the table printed will show the number of times persons responded either 0 or 1 to each item.

Interpretation of BICAL Output for Knox Cube Test Data

These remarks are intended to illustrate the interpretation of BICAL output and not to provide a comprehensive analysis of these data.

Page 1 of the output shown lists the control cards just discussed. This provides a check that the analysis performed is the one intended. In addition, the first person input record and the total number of persons suitable for calibration are shown in order to verify that the data was read correctly. The number of persons suitable for recalibration excludes those persons with zero or perfect scores.

SUBJECTS BELOW	1	0
SUBJECTS ABOVE	13	0
SUBJECTS IN CALIB.		32
TOTAL SUBJECTS		32

REJECTED ITEMS

ITEM NUMBER	ITEM NAME	ANSWERED CORRECTLY
	NONE	

SUBJECTS DELETED = 0
SUBJECTS REMAINING = 32

ITEMS DELETED = 0
POSSIBLE SCORE = 14

MINIMUM SCORE = 1
MAXIMUM SCORE = 13

Page 2 gives the alternative response frequency table specified by the Options Labels Card. This table can accommodate up to 20 response values. Each item is identified on the left by a sequence number assigned to it by BICAL in the order in which test items are read, and also by its four-character item name, specified in the Item Names Card. An "unknown value" column records the count of all values encountered other than the ones specified. In this example, there are no unknowns for any of the 18 items of the Knox Cube Test.

Page 2 enables you to examine the observed responses for obvious disturbances to the test plan and will often suggest possible exaplanations for gross misfits. The distribution of responses over multiple-choice distractors, for example, can reveal the undue influence of particular distractors. The effects of insufficient time show in a piling up of responses in the unknown column toward the end of a test. The effects of widespread inexperience in test taking show in a piling up of unknown responses in the first one or two items of a test.

The "key" column records the value specified as correct. As this table shows, the Knox Cube Test was entered in scored form. The appropriate key, therefore, is the vector of "1"'s shown in the key column of the table.

Examination of Page 2 reveals that the first three items are answered correctly by all 35 persons and that Item 18 is not answered correctly by anyone. It can also be seen that there is a rapid shift from a majority of correct responses to a majority of incorrect responses between Items 9 and 11. Looking

PROCEDURE IS UCON

DIFFICULTY SCALE FACTOR 1.37 ABILITY SCALE FACTOR 2.27
NUMBER OF ITERATIONS = 10

SEQUENCE NUMBER	ITEM NAME	ITEM DIFFICULTY	STANDARD ERROR	LAST DIFF CHANGE	PROX DIFF	FIRST CYCLE
4	IT04	-4.847	0.852	0.0	-3.894	-3.587
5	IT05	-4.244	0.759	0.0	-3.292	-3.044
6	IT06	-4.244	0.759	0.0	-3.292	-3.044
7	IT07	-5.708	1.094	0.0	-4.888	-4.415
8	IT08	-2.879	0.654	0.0	-2.193	-1.978
9	IT09	-3.742	0.709	0.0	-2.850	-2.625
10	IT10	-1.483	0.570	0.0	-1.264	-1.054
11	IT11	1.511	0.528	0.0	0.896	0.975
12	IT12	3.012	0.625	0.0	2.127	2.064
13	IT13	2.349	0.571	0.0	1.560	1.569
14	IT14	4.435	0.838	0.0	3.526	3.218
15	IT15	5.260	1.088	0.0	4.521	3.974
16	IT16	5.260	1.088	0.0	4.521	3.974
17	IT17	5.260	1.088	0.0	4.521	3.974

ROOT MEAN SQUARE = 0.0

14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

back to Table 7 shows that this shift occurs when the task moves from a series of four taps to a series of five taps.

Page 3 reviews the editing process. It summarizes the work of the editing routine, which successively removes person records with zero or perfect scores and items answered correctly by all persons or not answered correctly by any persons until all such persons and items are detected and set aside. This editing process determines the final matrix of persons-by-item responses that is analyzed.

In this example, there are no persons with zero or perfect (18) scores initially, that is on the incoming test of 18 items. If there were, these persons would be excluded from all subsequent analyses and would not appear in this or any subsequent table. Since none of these persons score below 1 or above 17, there are 35 persons to be examined by the editing process for possible use in the calibration sample.

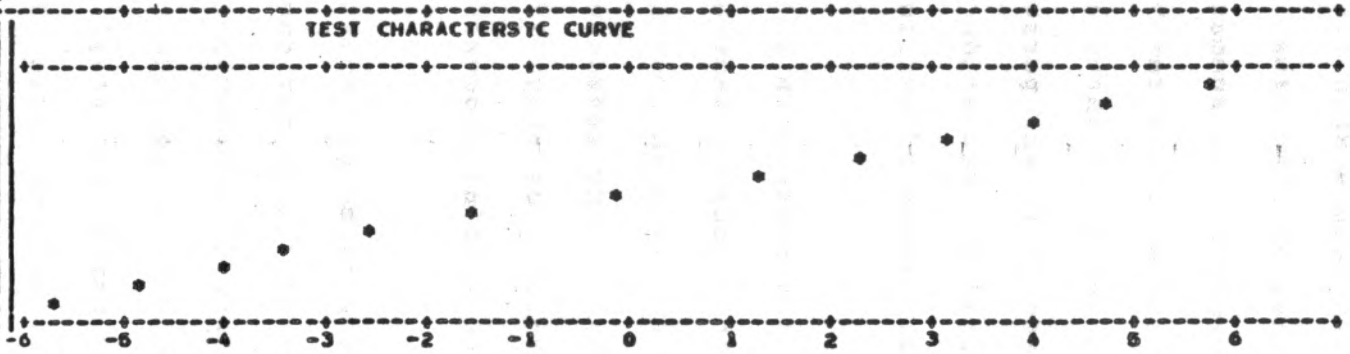
Items 1, 2 and 3 are then removed by the editing process because they are answered correctly by all 35 persons. Item 18 is also removed because no one answers it correctly. After this item editing Person 35 must also be removed because the only items they answer correctly are the three "too easy" items already removed in the previous item editing cycle, Items 1, 2 and 3. After editing is completed, the remaining calibration sample consists of 34 persons calibrating 14 items. The minimum score is still 1, but the maximum score is now 13.

Page 4 contains the difficulty estimates and the related standard errors of calibration for each of the 14 items calibrated.

COMPLETE SCORE EQUIVALENCE TABLE

RAW SCORE	COUNT	LOG ABILITY	STANDARD ERRORS
13	0	5.61	1.13
12	0	4.85	0.94
11	2	4.06	0.92
10	1	3.26	0.95
9	4	2.39	1.00
8	5	1.36	1.13
7	10	-0.07	1.34
6	3	-1.52	1.13
5	2	-2.52	0.96
4	2	-3.29	0.88
3	2	-3.99	0.87
2	1	-4.72	0.92
1	0	-5.67	1.14

TEST CHARACTERSTC CURVE



PERSON SEPARABILITY INDEX 0.76 (EQUIVALENT TO KR20)

14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

These are the values needed for any future application of the items. The mean item difficulty is arbitrary and is always set equal to zero by the program. At the top of the page are the difficulty and ability expansion factors by which the initial log odds estimates are scaled for the normal approximation method, PROX.

In addition to the difficulty estimates and their standard errors, the table displays: (1) the magnitude of improvement in the last iteration of UCON (an indication of the rate of convergence); (2) the difficulty estimate that is returned by PROX; and (3) the improvement in this estimate after one iteration of UCON. These intermediate estimates are displayed to provide experience with how PROX compares to UCON, so that you can learn when the much less expensive PROX estimates are good enough for your purposes. In this example, there are no significant differences between the PROX and UCON estimates.

<u>Page 5</u> gives the conversion of person scores to estimated person ability measures and the standard error of measurement associated with each score. This table also shows the number of persons in the sample obtaining each of the thirteen raw scores. The accompanying test characteristic curve pictures the range of ability covered by these thirteen scores and shows the extent to which the relation between score and measure is nonlinear.

A "Person Separability Index" is given at the bottom of the page. This index is equivalent to the familiar KR20 test reliability coefficient. It is calculated by forming the ratio of the sample sum of squared measure error to the sample sum of

MAP OF VARIABLE

PERSON STATS	COUNT	RAW SCORE	MEASURE MIDPOINT(S.E.)	ITEM COUNTS	TYPICAL ITEMS (BY NAME)		
			5.30(1.13)	3	IT15	IT16	IT17
			5.10(1.13)				
		12	4.90(0.94)				
			4.70(0.94)				
			4.50(0.94)	1	IT14		
			4.30(0.94)				
	2	11	4.10(0.92)				
+2SD			3.90(0.92)				
			3.70(0.92)				
			3.50(0.92)				
	1	10	3.30(0.95)				
			3.10(0.95)	1	IT12		
			2.90(0.95)				
			2.70(0.95)				
			2.50(0.95)				
	4	9	2.30(1.00)	1	IT13		
			2.10(1.00)				
+1SD			1.90(1.00)				
			1.70(1.00)				
			1.50(1.00)	1	IT11		
	5	8	1.30(1.13)				
			1.10(1.13)				
			0.90(1.13)				
			0.70(1.13)				
			0.50(1.13)				
			0.30(1.13)				
			0.10(1.13)				
MEAN	10	7	-0.10(1.34)				
			-0.30(1.34)				
			-0.50(1.34)				
			-0.70(1.34)				
			-0.90(1.34)				
			-1.10(1.34)				
			-1.30(1.34)				
	3	6	-1.50(1.13)	1	IT10		
			-1.70(1.13)				
			-1.90(1.13)				
-1SD			-2.10(1.13)				
			-2.30(1.13)				
	2	5	-2.50(0.96)				
			-2.70(0.96)				
			-2.90(0.96)	1	IT08		
			-3.10(0.96)				
	2	4	-3.30(0.88)				
			-3.50(0.88)				
			-3.70(0.88)	1	IT09		
	2	3	-3.90(0.87)				
-2SD			-4.10(0.87)				
			-4.30(0.87)	2	IT05	IT06	
			-4.50(0.87)				
	1	2	-4.70(0.92)				
			-4.90(0.92)	1	IT04		
			-5.10(0.92)				
			-5.30(0.92)				
			-5.50(0.92)				
		1	-6.70(1.14)	1	IT07		

14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

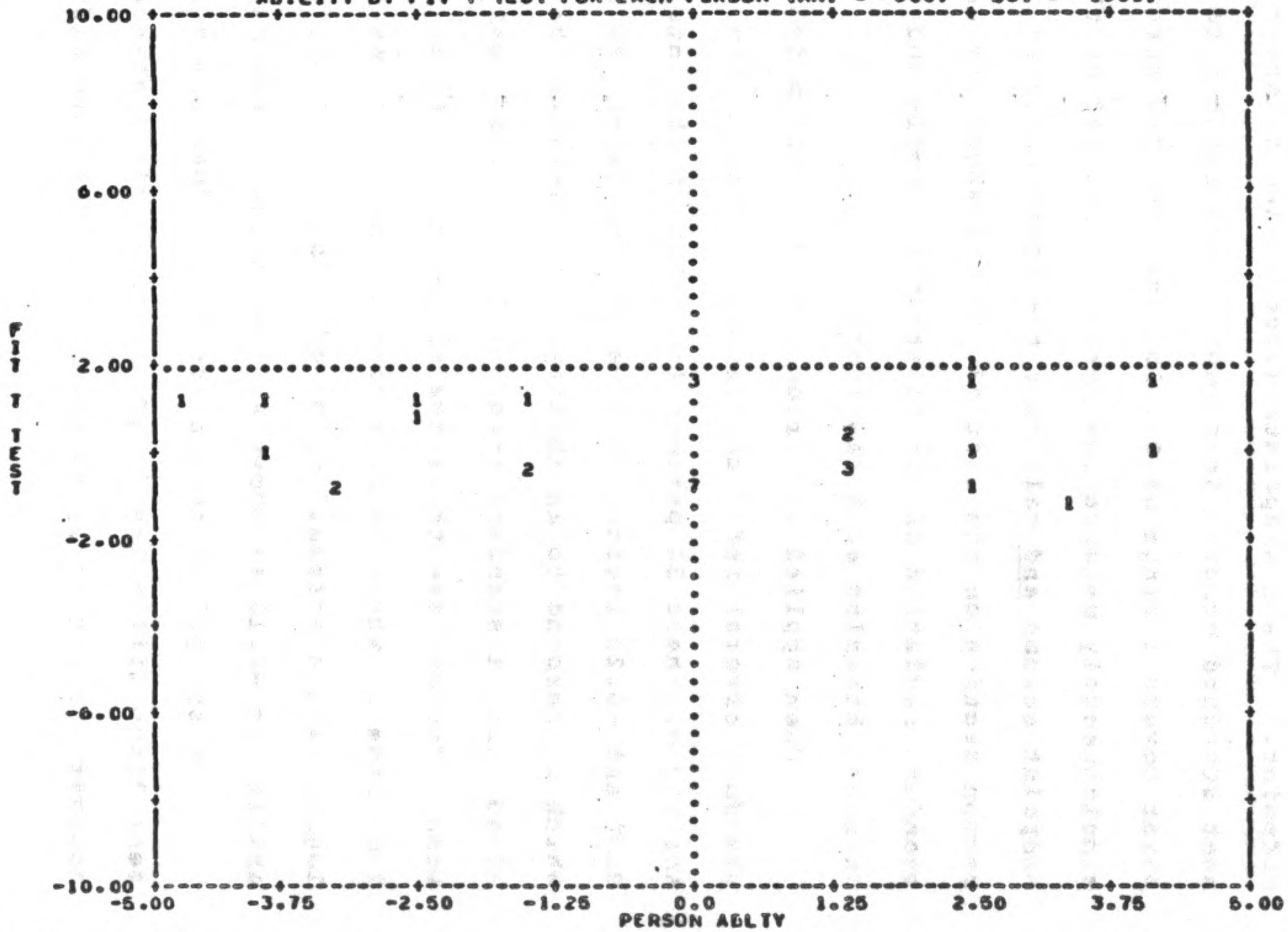
squared measure deviations and subtracting this ratio from one.

Page 6 displays a map of the KCT variable defined by these tapping items. This map shows the distributions of items and persons along the variable defined by these data. The map is marked out vertically by its central column labelled "measure midpoint." These midpoints (accompanied by their person measurement standard errors) increment by 0.2 logits, so that each midpoint covers a range of 0.2 logits. The "measure midpoints" simultaneously measure the persons tabulated on the left of the midpoint column and calibrate the items named on the right. The person section on the left of the map shows the ability mean and standard deviation of the calibrating sample and the number of persons obtaining each raw score.

When applied to persons the "measure midpoints" (and their standard errors) refer to "person ability." Thus the mean ability of these 34 persons is marked in the interval between 0.00 and -0.20 logits. Twelve persons, with raw scores of 7, which correspond to an ability in the interval between -0.20 and -0.40 (with a standard error of 1.14), stand just below this mean. You can see these twelve persons at their raw score of 7 on Page 5, where their estimated ability is exactly - 0.25 logits with a standard error of 1.14. The exact sample mean ability is -0.18 as shown at the bottom of the map.

When applied to the items, the "measure midpoints" represent "item difficulty." (The parenthetical standard errors, however, do not apply to the items. For item difficulty

ABILITY BY FIT T-TEST FOR EACH PERSON (MNT = -0.07 SDT = 1.01)



14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

standard errors consult Page 4 or 15.) Thus Items 15, 16 and 17 all have difficulties between 4.60 and 4.40 logits. You can see on Page 4 that Items 15, 16 and 17 all have estimated difficulties of exactly 4.564 with standard errors of 1.076.

Further examination of the map of this variable shows that Items 15, 16 and 17 are the hardest items, standing three standard deviations above the sample mean. No persons come near these items in ability, indicating that these items are much too hard for this sample. There also appears to be a bimodal distribution of item difficulties. Items 4 through 10 are easy and Items 11 through 17 are hard. There is a gap of approximately 0.8 logits between Items 10 and 11. This gap was noted earlier in the response frequency table on Page 2 where it appears as a rapid shift in response frequency between Items 10 and 11, from a majority of correct responses to a majority of incorrect responses.

Page 7 lists persons whose "total t fit" falls above the value of CFIT specified on the Input Description Card. These "misfitting" persons are eliminated from subsequent analyses. This page will not appear if no persons fall above the specified CFIT criterion. Also, if CFIT is specified as blank or 0, no persons are eliminated and this page does not appear in the output.

In this person list each person is identified on the left, first by a sequence number assigned to them by BICAL in the order in which persons are found to misfit and second by a person ID defined by LLIM and KLIM on the Input Description Card.

KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 23B RECAL. WITH 2 MISFITTING PERSONS OMITTED

		ITEM CHARACTERISTIC CURVE						DEPARTURE FROM EXPECTED ICC						ITEM FIT STATISTICS						
SEQ NUM	ITEM NAME	1ST GROUP	2ND GROUP	3RD GROUP	4TH GROUP	5TH GROUP	6TH GROUP	1ST GROUP	2ND GROUP	3RD GROUP	4TH GROUP	5TH GROUP	6TH GROUP	* ERR IMPAC	FIT T-TESTS BETWN	FIT T-TESTS TOTAL	WTD MNSQ	MNSQ SD	DISC INDX	POINT BISER
4	IT04	0.80	1.00	1.00				-0.03	0.01	0.00				0.02	-1.34	0.25	1.04	0.53	1.09	0.40
5	IT05	0.70	1.00	1.00				-0.05	0.02	0.00				0.10	-1.05	0.62	1.21	0.42	1.11	0.42
6	IT06	0.70	1.00	1.00				-0.05	0.02	0.00				0.05	-1.05	0.39	1.11	0.42	1.11	0.47
7	IT07	0.90	1.00	1.00				-0.01	0.00	0.00				0.0	-1.70	-0.01	0.78	0.84	1.07	0.41
8	IT08	0.40	1.00	1.00				-0.10	0.06	0.01				0.0	-0.13	-1.85	0.44	0.36	1.19	0.76
9	IT09	0.60	1.00	1.00				-0.06	0.02	0.00				0.0	-0.76	-0.74	0.71	0.38	1.13	0.61
10	IT10	0.30	0.70	1.00				0.05	-0.10	0.03				0.13	-0.09	0.94	1.29	0.32	0.96	0.57
11	IT11	0.0	0.20	0.67				-0.02	0.03	0.01				0.02	-1.12	0.25	1.04	0.26	1.06	0.59
12	IT12	0.0	0.10	0.33				-0.00	0.06	-0.02				0.05	-0.44	0.41	1.10	0.35	0.96	0.42
13	IT13	0.0	0.0	0.58				-0.01	-0.08	0.10				0.0	0.10	-0.80	0.75	0.30	1.21	0.59
14	IT14	0.0	0.0	0.17				-0.00	-0.01	0.02				0.19	-1.32	0.67	1.43	0.55	1.09	0.24
15	IT15	0.0	0.0	0.08				-0.00	-0.00	0.01				0.0	-1.68	0.08	0.84	0.85	1.07	0.33
16	IT16	0.0	0.0	0.08				-0.00	-0.00	0.01				0.0	-1.68	0.08	0.84	0.85	1.07	0.33
17	IT17	0.0	0.0	0.08				-0.00	-0.00	0.01				0.0	-1.68	0.08	0.84	0.85	1.07	0.33

SCORE RANGE	1- 6	7- 7	8-13
MEAN ABILITY	-2.89	-0.07	2.31
MEAN Z-TEST	-0.2	0.1	0.2
SD(Z-TEST)	0.3	0.5	0.2
GROUP COUNT	10	10	12

PLUS=TOO MANY RIGHT
MINUS=TOO MANY WRONG

*ERROR IMPACT = PROPORTION ERROR INCREASE DUE TO THIS MISFIT

14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

The program format allows up to 20 characters of ID to be printed for each person. If KLIM-LLIM+1 is greater than 20, then the first 20 characters are printed as person identification.

Next, weighted mean squares, their accompanying standard errors and a "total t fit" are listed for each misfitting person. Then, the misfitting person's ability and its standard error are given. Finally, each persons's individual item responses and the corresponding standardized residuals are shown.

The standardized residuals are truncated and signed for easy reading. Valuesoutside ± 9 are printed as ± 9. A large negative residual indicates that a person missed an item you could expect them to answer correctly and a large positive residual indicates that the person correctly answered an item you could expect them to fail. The larger the residual the more unexpected the response. In particular, the odds against any observed response are given by the square of the residual listed beneath it.

The response pattern expected for each person is a string of 1's on easy items followed by a string of 0's on hard items, with a few adjacent and alternating 1's and 0's on items near the person's ability. In this example, two persons were eliminated. Person 13 passed Items 4 and 5, missed Items 6 and 7, passed Items 8 through 12, and then failed the remaining items. Person 29 passed Items 4, 5 and 6, missed Items 7 and 8, passed Items 9, 10 and 11, failed Items 12 and 13, and then passed Item 14 before missing the remaining items. The locations of their surprising responses, three unexpected failures each, are marked

KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 238 RECAL. WITH 2 MISFITTING PERSONS OMITTED

SERIAL ORDER

SEQ NUM	ITEM NAME	ITEM DIFF	STD ERROR	DISC INDX	FIT TTEST
4	I104	-4.85	0.85	1.09	0.25
5	I105	-4.24	0.76	1.11	0.62
6	I106	-4.24	0.76	1.11	0.39
7	I107	-5.71	1.09	1.07	-0.01
8	I108	-2.88	0.65	1.19	-1.85
9	I109	-3.74	0.71	1.13	-0.74
10	I110	-1.48	0.57	0.96	0.94
11	I111	1.51	0.53	1.06	0.25
12	I112	3.01	0.62	0.96	0.41
13	I113	2.35	0.57	1.21	-0.80
14	I114	4.44	0.64	1.09	0.87
15	I115	5.28	1.09	1.07	0.08
16	I116	5.28	1.09	1.07	0.08
17	I117	5.28	1.09	1.07	0.08
	MEAN	-0.00		1.09	0.04
	S.D.	4.18		0.07	0.74

DIFFICULTY ORDER

SEQ NUM	ITEM NAME	ITEM DIFF	DISC INDX	FIT TTEST
7	I107	-5.71	1.07	-0.01
4	I104	-4.85	1.09	0.25
6	I106	-4.24	1.11	0.39
5	I105	-4.24	1.11	0.62
9	I109	-3.74	1.13	-0.74
8	I108	-2.88	1.19	-1.85
10	I110	-1.48	0.96	0.94
11	I111	1.51	1.06	0.25
13	I113	2.35	1.21	-0.80
12	I112	3.01	0.96	0.41
14	I114	4.44	1.09	0.87
15	I115	5.28	1.07	0.08
16	I116	5.28	1.07	0.08
17	I117	5.28	1.07	0.08

FIT ORDER

SEQ NUM	ITEM NAME	ITEM DIFF	ERR IMPAC	FIT T-TESTS BETWN	FIT T-TESTS TOTAL	WTD MNSQ	MNSQ SD	DISC INDX	POINT BISER
8	I108	-2.88	0.0	-0.13	-1.85	0.44	0.36	1.19	0.76
13	I113	2.35	0.0	0.10	-0.80	0.75	0.30	1.21	0.59
9	I109	-3.74	0.0	-0.76	-0.74	0.71	0.38	1.13	0.61
7	I107	-5.71	0.0	-1.70	-0.01	0.78	0.84	1.07	0.41
16	I116	5.28	0.0	-1.68	0.08	0.84	0.85	1.07	0.33
17	I117	5.28	0.0	-1.69	0.08	0.84	0.85	1.07	0.33
15	I115	5.28	0.0	-1.68	0.08	0.84	0.85	1.07	0.33
4	I104	-4.85	0.02	-1.34	0.25	1.04	0.53	1.09	0.40
11	I111	1.51	0.02	-1.12	0.25	1.04	0.26	1.06	0.58
6	I106	-4.24	0.05	-1.05	0.39	1.11	0.42	1.11	0.47
12	I112	3.01	0.05	-0.44	0.41	1.10	0.35	0.96	0.42
5	I105	-4.24	0.10	-1.05	0.62	1.21	0.42	1.11	0.42
14	I114	4.44	0.19	-1.32	0.87	1.43	0.55	1.09	0.24
10	I110	-1.48	0.13	-0.09	0.94	1.29	0.32	0.96	0.57
				-1.00	0.04	0.96	0.52		
				0.64	0.74	0.26	0.23		

14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

by the large negative residuals in the output. For example, the odds against Person 13 failing Item 7 are 36 to 1. This is the main cause of this person's misfit.

Page 8 is a plot of "total t fit" against ability for each person. The mean and standard deviation of "total t fit" over all calibrated persons is given at the top of the page. Examination of the plot above the chosen CFIT line of 2.00 shows the two persons who misfit at this cut-off level. These are the persons listed in the Table on Page 7, and are the persons deleted from the subsequent item calibration.

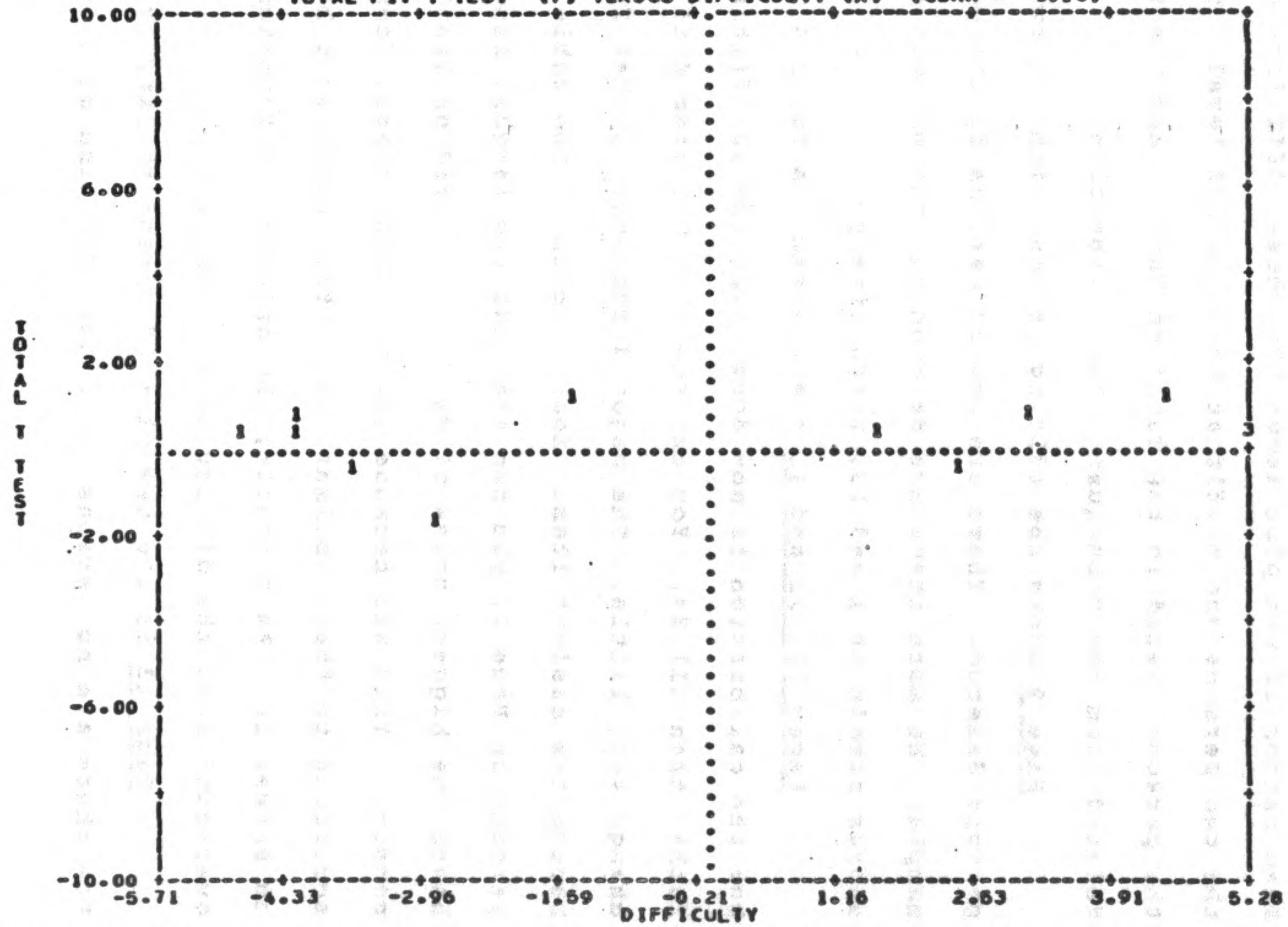
Page 9 shows the editing process with the two misfitting persons deleted. There are now 32 persons in the calibration sample. No more items are deleted and the minimum and maximum scores remain at 1 and 13, respectively.

Pages 10, 11 and 12 are the same as Pages 4, 5 and 6, but the calibration is now done using the 32 "fitting" persons rather than all 34. You can see that the item difficulties change very little. The major difference is that Item 7 has now become the easiest item. Looking back to the table of misfitting persons on Page 7, you can see that the largest residuals, and hence the biggest cause of misfit, occurred on Item 7 for both persons. This was because these persons missed Item 7 when according to their estimated abilities they could be expected to answer it. As a result, the original calibration slightly over-estimated the difficulty of Item 7.

Page 13 is the new plot of person ability by "total t fit." Now there are no persons above the CFIT line of 2.00. If there

KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 238 RECAL. WITH 2 MISFITTING PERSONS OMITTED PG 16

TOTAL FIT T-TEST (Y) VERSUS DIFFICULTY (X) (CORR = 0.15)



14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

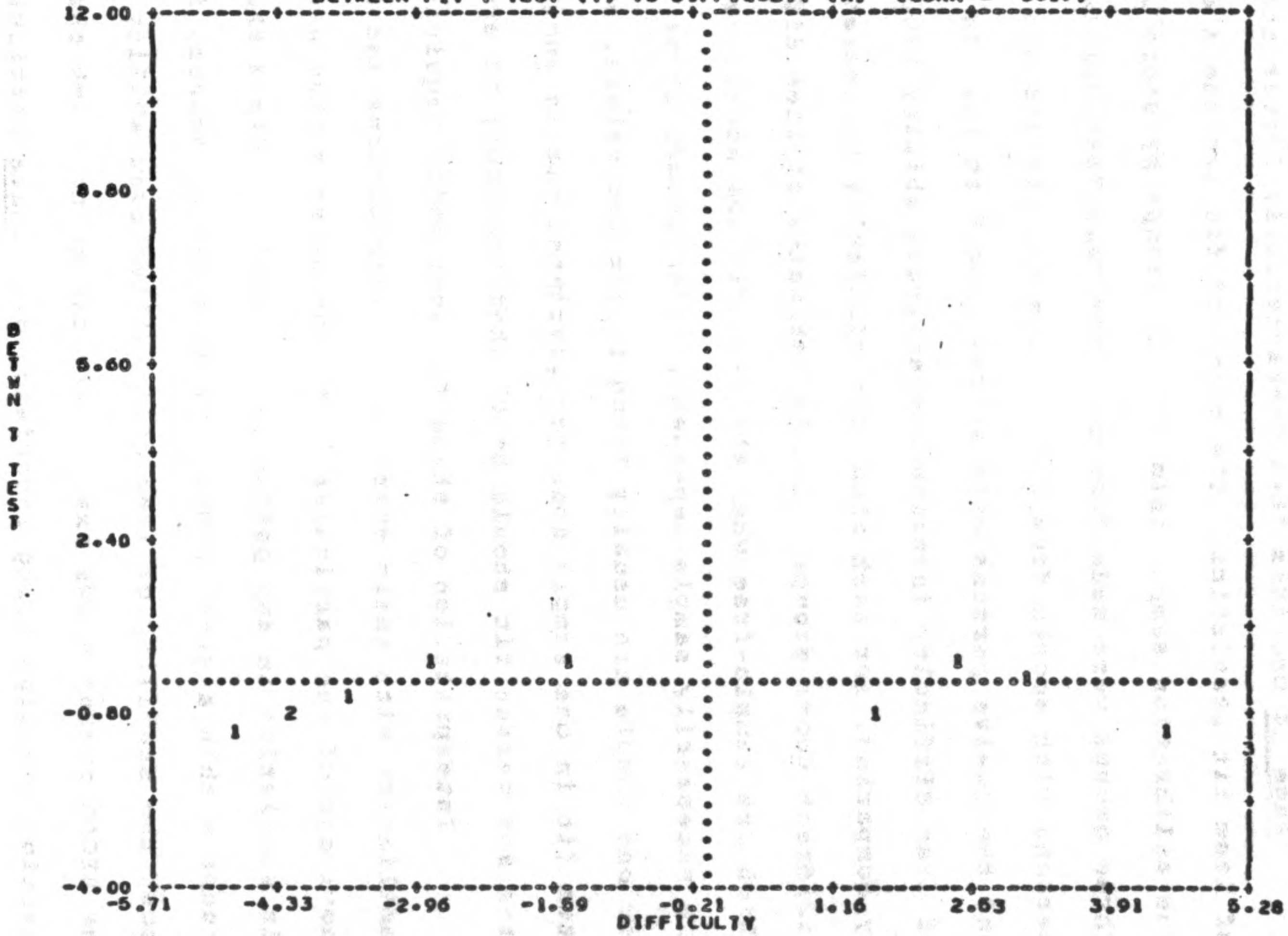
were any new misfitting persons, they would be listed on a page preceding this one in the same format as Page 7, but this second group of misfitting persons would not be deleted from the item calibration, because elimination of misfitting persons is done only once.

Page 14 provides Item Characteristic Curves and a variety of item fit statistics. The tests of fit include a division of the calibration sample into ability groups by score level. Three groups were made from the Knox Cube Test sample, the ten persons with scores from 1 to 6, the ten persons who scored 7, and the twelve persons with scores from 8 to 13. An evaluation of item difficulty invariance over these ability groups is made by comparing, for each item, its difficulty estimates over the different score groups. Unlike estimates of item difficulty, which are sample-free when the data fit the model, tests of fit are necessarily sample-dependent. Even though items that fit for one sample are usually found to fit for others, successful item fit in one sample does not guarantee fit in another. Both item and person fit should be checked routinely in every application.

Interpretation of these fit statistics requires both familiarity with their statistical distributions and detailed knowledge of the particular items and persons that generated the fit statistics in any particular situation. Since the ability groups within a given sample are arranged by scores, information about the stability of item difficulties over ability is explicit. The BICAL output shows exactly the extent to which the items in question are displaying invariance over these particular ability groups.

KNOX CUBE TEST COMPUTER OUTPUT EXAMPLE FOR BICAL MANUAL - ESL 238 RECAL. WITH 2 MISFITTING PERSONS OMITTED

BETWEEN FIT T-TEST (Y) VS DIFFICULTY (X) (CORR = -0.19)



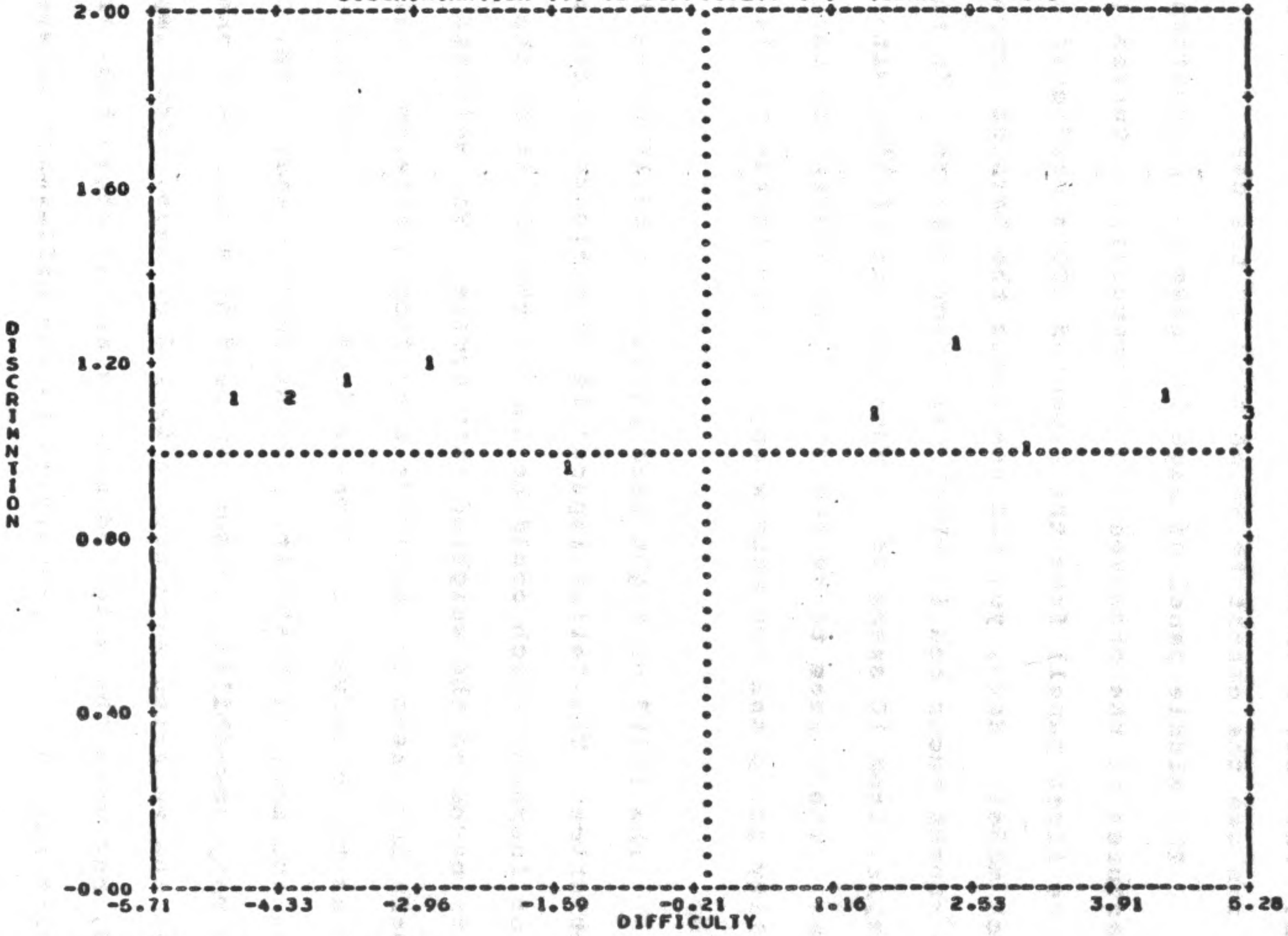
14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

The left-hand Item Characteristic Curve panel provides the proportion of correct answers to each item given by each ability group. The score range, mean ability and count of persons for each group are given at the bottom of this panel. The proportion correct is expected to increase from left to right, that is, from less able to more able score groups, and you can see the extent to which this is the case.

The middle panel of Page 14 shows the proportional departures of the observed Item Characteristic Curves (as shown in the first panel) from the expected ICC's predicted by the Rasch model. Here, you can see where the largest proportional departures occur and in which direction they go. In this example, Item 10 seems to be somewhat out of line with the other items. There seem to be too many right answers in the lowest ability group and too many wrong answers in the middle ability group.

The third or right-hand panel on Page 14 gives item fit statistics. The "error impact" is an estimate of the proportional error increase which could be due to the misfit of the item. It is based on the weighted mean square. The weighted mean square increases in magnitude away from a reference value of 1.0 as the observed ICC departs from the expected ICC, that is, when too many high-ability persons fail an easy item, or when too many low-ability persons succeed on a difficult one. Thus, when the weighted mean square is 1.0 or less, error impact is 0.0, but when the weighted mean square is above 1.0, error impact increases in proportion to the difference between the

DISCRIMINATION (Y) VS DIFFICULTY (X) (CORR = -0.18)



14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

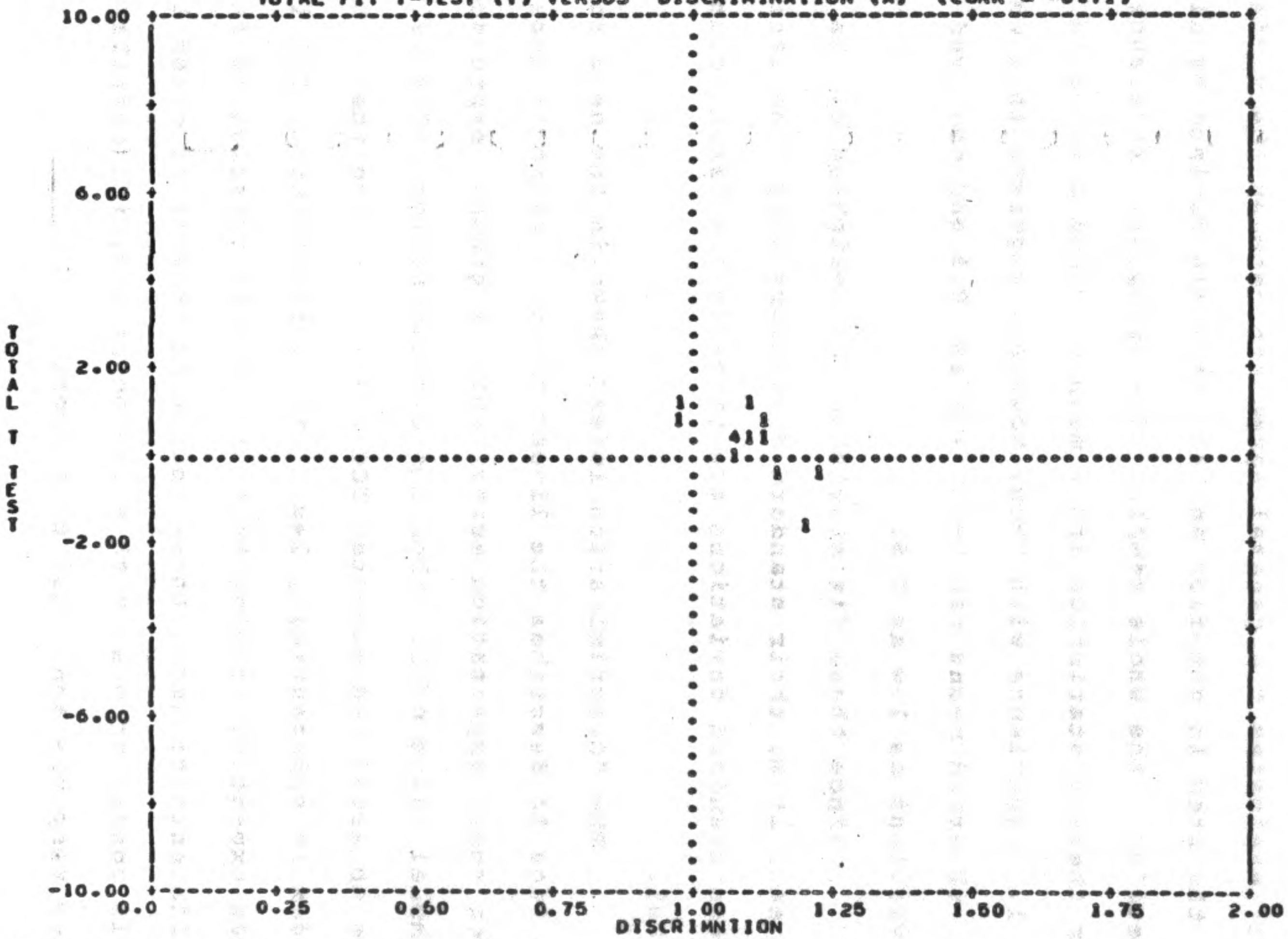
square root of the weighted mean square and one. You can see that Items 10 and 14 have the most misfit according to their error impact.

The "between group t" evaluates the agreement between the observed Item Characteristic Curve and the best fitting Rasch model curve, as estimated by the ability groups. The "total t fit" evaluates the general agreement between the variable defined by the item in question and the variable defined by all other items over the whole sample. The asymptotic reference values for these t-statistics are a mean of 0 and a standard deviation of 1. Experience with them, however, suggests that when items fit observed means can be as low as -0.5 and observed standard deviations as low as 0.6.

Since these fit statistics are weighted by the information on each item, their standard deviations vary from item to item. These standard deviations are given in the fifth column of this panel.

The "discrimination index" shown in the next to last column on Page 14 describes the linear trend of residual departures from model expectation across ability groups, expressed around a model value of 1. When the discrimination index is near 1, the observed and expected ICC's are close together. When the index is substantially less than 1, the observed ICC is flatter than expected, meaning that the item in question is failing to differentiate among these abilities as well as other items do. This condition goes with a low point biserial correlation between item response and total test score.

TOTAL FIT T-TEST (Y) VERSUS DISCRIMINATION (X) (CORR = -0.71)



14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

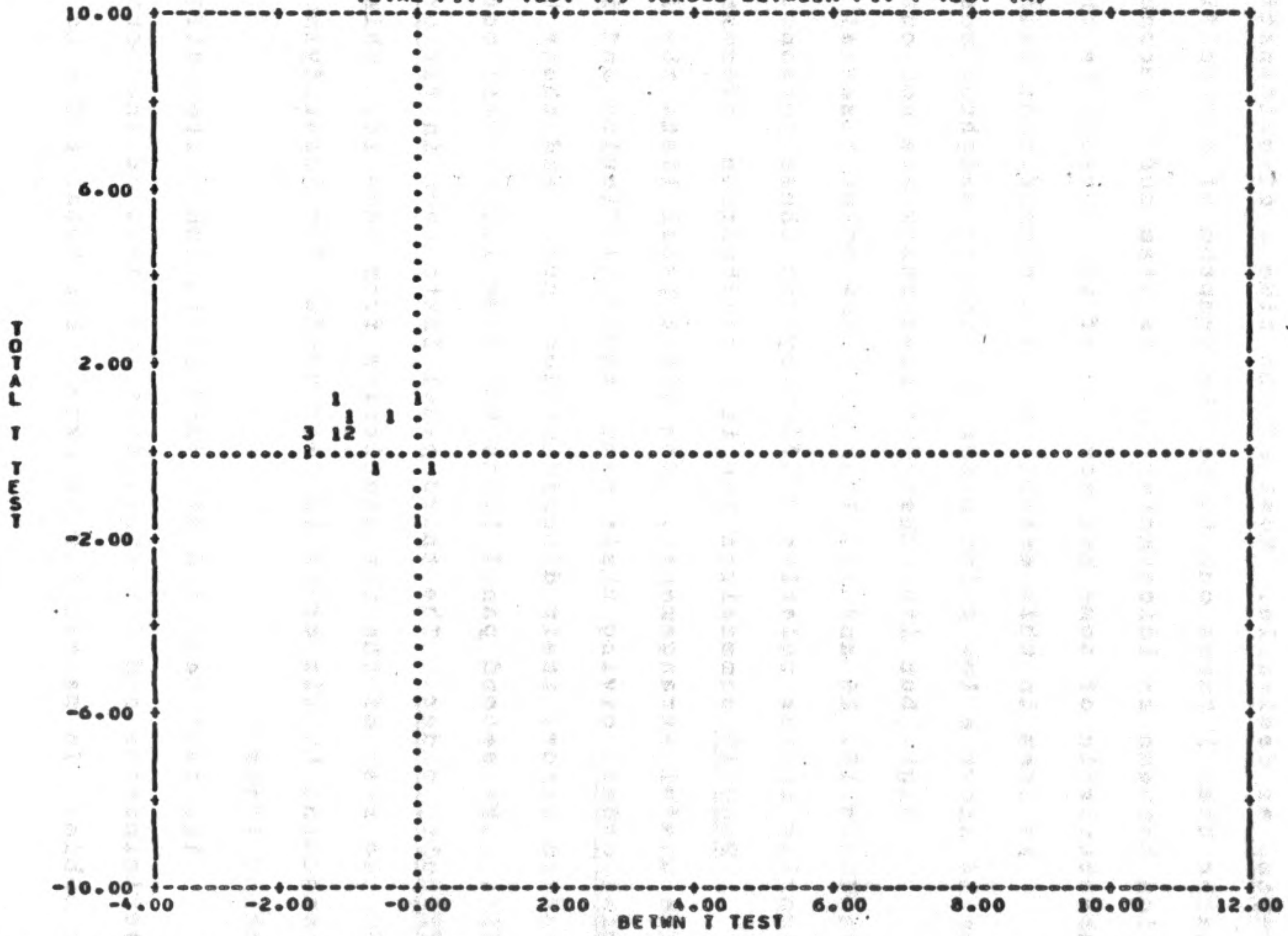
When the discrimination index is substantially greater than 1, then the observed ICC is steeper than the average best fitting logistic curve for all items. This gives the item the appearance of differentiating abilities more effectively than the average items in the test. But the substantive cause of this seeming advantage must be tracked down before it can be accepted as desirable. Most of the time a discrimination index greater than 1 turns out to be the symptom of a specific interaction between an idiosyncrasy of the item and a secondary characteristic of some but not all of the persons in the sample.

No item in this example shows a significant misfit. Item 14 shows a low point biserial and its weighted mean square is high, but its other fit statistics are not out of line. Like Items 15, 16 and 17, Item 14's low point biserial is due primarily to its relative difficulty for these persons.

Page 15 summarizes the item calibration information in three useful arrangements. The first panel lists the items in serial order, giving their name, their difficulty and its standard error, their discrimination index, and their total t fit. The second panel lists the same items again but now in difficulty order. The third panel lists them in fit order and adds the rest of the fit statistics from Page 14. This final arrangement by fit order is very useful for identifying misfitting items.

The test mean and standard deviation of item difficulty, discrimination and fit statistics are given at the bottom of the table. In particular we expect the total t fit to have a

TOTAL FIT T-TEST (Y) VERSUS BETWEEN FIT T-TEST (X)



14 ITEMS CALIBRATED ON 32 PERSONS
32 MEASURABLE PERSONS WITH MEAN ABILITY = -0.06 AND STD. DEV. = 2.02

mean near 0 and a standard deviation near 1. You can see that in this example the mean of 0.22 is slightly high and the standard deviation of 0.77 is rather low. These items are not quite as spread out in misfit as expected.

Pages 16, 17, 18, 19 and 20 are two-way plots of the four main statistics given for each item on Page 15; difficulty, between fit t, total fit t and discrimination. There is no new information in these plots, but examining them is a convenient way to detect interesting patterns in the relationships among the various item statistics.

VIII. BICAL CONTROL CARDS

Card Position	Card Name	Format and Description
* 1	Title Card	(20A4) Descriptive heading to be printed at the top of each page of output.
* 2	Input Description Card	(14I5)

C C	Label	Definition
* 1 - 5	NITEM	Total number of items to be read before deletions. This is equal to the number of non-zero entries on the Column Select Card and is the number of item names expected.
6 - 10	NGROP	1) Used to terminate execution when editing reduces the sample size below NGROP, and 2) Used to determine the number of score groups used for item fit analysis. BICAL tries to allocate (sample size)/6 persons to each of 6 score groups. If (sample size)/6 is less than NGROP, then BICAL forms less than 6 score groups. The default value for NGROP is 25. It is unwise to set NGROP less than 10.

* required

11 - 15	MINSC	The <u>minimum score</u> to be included in the calibration sample. Any persons scoring below MINSC are eliminated from calibration. MINSC must be at least 1, but not more than MAXSC-1. The default value for MINSC is 0.4*NITEM.
16 - 20	MAXSC	The <u>maximum score</u> to be included in the calibration sample. Any persons scoring above MAXSC are eliminated from calibration. MAXSC must be at least MINSC+1, but not more than NITEM-1. The default value for MAXSC is (0.9)*NITEM.
* 21 - 25	LREC	<u>Number of columns in the input person record to be scanned</u>. LREC must be large enough to cover all columns containing items and also to skip any extra cards in the person record.
* 26 - 30	KCAB	<u>Calibration code</u>: 1 = Normal approximation method, <u>PROX</u>. Can be used with long tests and symmetrical distributions. b,2 = Corrected unconditional maximum likelihood estimation, <u>UCON</u>. Should be used with short tests and skewed distributions.

* required

31 - 35	KSCORE	Scoring code: b,0 = Score dichotomously according to the Key Card. 1 = DO NOT USE. 2 = Score dichotomously, correct if $X \leq$ Key. 3 = Score dichotomously, correct if $X \geq$ Key.
36 - 40	INFLE	Logical unit number of input person file. b,0 = Unit 5 (cards).
41 - 45	LLIM	Start of person identification field in person input record. The default value for LLIM is 1.
46 - 50	KLIM	End of person identification field in person input record. The default value for KLIM is 20. If KLIM - LLIM + 1 exceeds 20, then only the first 20 characters are used to identify the person.
51 - 55	NUPFL	Logical unit number of output person file. b,0 = No file is output.

For each valid person record this output file contains:

1 - 20: The person's identification defined by LLIM and KLIM.

21 - 25: Their raw score.

* required

26 - 33: Their ability in logits.
34 - 41: The standard error of ability.
42 - 49: Total t fit.
50 - 54: Mean square standard deviation
55 - 62: Weighted mean square.
63 - end: Their response pattern and then their standardized response residuals (I2 format).

If NUPFL ≠ b,0 then, appropriate JCL must be provided. The following JCL is appropriate for the UC IBM 370:

```
//FTuuF001 DD DSN=$acct.sub.filename,UNIT=SYSDA,
//  DISP=(NEW,CATLG),DCB=(RECFM=FB,LRECL=xxx,
//  BLKSIZE=yyyy),SPACE=(TRK,(5,1))
```

where: uu = NUPFL
xxx = 64 + (4*NITEM) minimum=80
yyyy = some multiple of xxx

56 - 60	CFIT	Controls the screening of the person file before recalibration. CFIT is read in I5 format, but the program changes the input value to F5.1 by dividing CFIT by 10.

Example: CFIT = 20 is used as CFIT = 2.0.

b,0 = No persons will be deleted for misfit.
GT 0 = Persons whose total t fit is greater than CFIT/10 will be deleted for misfit.

* required

61 - 65	KSIM	If KSIM greater than 0 print simulated persons. Only use when BICAL simulates persons instead of reading data.
66 - 70	PRIT	Controls output of the item statistic file. PRIT is read in I5 format, but the program changes the input value to F5.2 by dividing PRIT by 100.

Example: PRIT = 200 is used as PRIT = 2.00.

b,0 = No item file created.

GT 0 = An item file is created containing items whose total t fit is less than PRIT/100.

The contents of the file for each item are:

1 - 4: Local sequence number assigned by BICAL.
6 - 9: Item name from Item Names Card.
15 - 21: Item difficulty in logits.
22 - 28: Standard error of calibration.
29 - 32: Total t fit.
36 - 42: Between score groups t fit.
43 - 49: Discrimination index.

This file is <u>always</u> put on Unit 3.
If PRIT ≠ b,0 then, appropriate JCL must be provided. The following JCL is appropriate for the UC IBM 370:

<u>If the file is to be punched on cards</u>:

```
//FT03F001 DD SYSOUT=B
```

<u>If the file is to be saved on disk</u>:

```
//FT03F001 DD DSN=$acct.sub.filename,UNIT=SYSD
//   DISP=(NEW,CATLG),DCB=(RECFM=FB,LRECL=80,
//BLKSIZE=4560),SPACE=(TRK,(5,1))
```

Card Position	Card Name	Format and Description
* 3	Variable Format Card	Format card that provides as many A1 fields as contained in the person record. The number of A1 fields must be equal to LREC. Example: (80A1) Only <u>one</u> format card is allowed.
* 4	Item Names Card(s)	(20A4) Provides a four-character alphanumeric name for each of the NITEM items. These names must be entered in the order in which the items appear in the person record.
* 5	Column Select Card(s)	(80A1) Indicates how the data is to be used. It must be a record identical in size and format to a person record. b,0 = Skip this column. 1 = Include the item in this column. An item name field <u>must</u> be provided for this item. & = Delete the item in this column. This code differs from b,0 in that it indicates the presence of an item which is included in the total number of items, NITEM, and also has an item name field provided for it on the Item Names Card(s).

		The reason for this code is to make it easy to delete misfitting items on successive runs of the data, without changing NITEM and the Item Names Card(s).
* 6	Scoring Key Card(s)	(80A1) A record identical in size and format to each person record. This card corresponds to a perfect person record.
* 7	Options Labels Card	(20A1) Identifies up to 20 multiple choice alternatives for each item. Example: ABCDE The number of times each option is chosen will be counted for each item.
8	Data Cards	The input person file is placed here if the file is on cards.
9	End of Data Card(s)	* in column 1. As many of these cards as there are cards in a person record must be provided. Only used if input is from cards.
10	Simulation Header Card	SIMULATE in columns 1-8. Causes the program to simulate persons rather than read data. If included it <u>must</u> be followed by Card 11.

* required

11 Simulation Task Description Card (F5.0,I5,2F5.0,I10)

C C	Label	Definition
* 1 - 5	WIDTH	Range of difficulties to be generated.
* 6 - 10	ISUBJ	Number of persons to be generated.
* 11 - 15	GMEAN	Mean ability of population sampled.
* 16 - 20	SD	Standard deviation of ability.
21 - 30	ISED	Seed for random number generator. Should only be coded for first generation in each run.

* 12 End of Job Card **** in columns 1-4. Program will keep recycling looking for new problems until this card is encountered. As many jobs as desired may be stacked by repeating Cards 1 - 11.

* required

University of Chicago JCL:

```
*     //valid UC job card, RE=129K
*     //  EXEC PGM=BICAL7
*     //STEPLIB DD DSN=$2DD130.S05.PRODUCT,DISP=SHR
*     //FT01F001 DD UNIT=SYSCR,DISP=NEW,SPACE=(TRK,(5,1))
*     //FT02F001 DD Unit=SYSCR,DISP=NEW,SPACE=(TRK,(5,1))
      //FT03F001 DD appropriate JCL as discussed under PRIT
      //FTxxF001 DD alternative input file description
      //FTuuF001 DD alternative output file description as
           discussed under NUPFL
*     //FT06F001 DD SYSOUT=A,DCB=(RECFM=FA,BLKSIZE=133)
*     //FT05F001 DD *
```

The FT05F001 card is followed by the BICAL control cards.

Cards FT03F001, FTxxF001, and FTuuF001 are not always required:

Include FT03F001 if you want an item file output. Appropriate JCL is discussed under PRIT.

Include FTxxF001 if the input person records are not on cards. The xx should be replaced by the value of INFLE coded on the Input Description Card (CC 36 - 40).

Include FTuuF001 if a new person file is to be output. The uu should be replaced by the value of NUPFL coded on the Input Description Card (CC 51 - 55).