Few guidelines exist for selecting from the one and three-parameter logistic latent trait models. This study explored fit of empirical data to these two models in terms of degree of violation of model assumptions. Specifically, unidimensionality, guessing, and equality of item discrimination indices were examined. Additionally, fit statistics were explored for data which varied in both sample size and test length. Chi square statistics were used to compare fit of distributions of observed number-right scores to
number right scores predicted from latent trait theory. Using the mean of
the conditional distribution of number-right scores for a given ability
level as the criterion, the Rasch (one-parameter) model was generally found
to be superior in fit to data than the three-parameter model for the five
data sets utilized in the study. Fit of data to both models improved as
the number of items or persons increased. When short tests were constructed
from the data such that item discriminations displayed a broad range, better
fit was found for the three-parameter model. Improvement in fit for both
models was found for data fulfilling the assumption of unidimensionality.
No conclusions were drawn concerning the addition of the guessing parameter
in the three-parameter model, since guessing tended to be poorly estimated
for the samples of 1000 persons used in this research.
A COMPARISON OF THE FIT OF EMPIRICAL DATA TO TWO LATENT TRAIT MODELS

LEAH R. HUTTEN
UNIVERSITY OF MASSACHUSETTS, AMHERST

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A COMPARISON OF THE FIT OF EMPIRICAL DATA TO TWO LATENT TRAIT MODELS

LEAH R. HUTTEN
UNIVERSITY OF MASSACHUSETTS, AMHERST

LATENT TRAIT THEORY HAS SHOWN GREAT PROMISE FOR SOLVING A MULTITUDE OF MEASUREMENT PROBLEMS THAT HAVE NOT BEEN HANDLED ADEQUATELY BY CLASSICAL TEST THEORY. ONE OF THE MOST IMPORTANT GAINS TO BE MADE USING LATENT TRAIT THEORY IS IN THE FIELD OF TEST EQUATING. WITH LATENT TRAIT ABILITY ESTIMATES, IT IS POSSIBLE TO EQUATE TESTS WHICH ARE NOT PARALLEL, AND WHICH DO NOT EVEN CONTAIN THE SAME NUMBER OF ITEMS. THE NATIONAL READING TEST EQUATING STUDY (RENZ AND BASHAW, 1975) HELPED SPUR INTEREST BY PRACTITIONERS IN LATENT TRAIT ABILITY ESTIMATION. THEORETICALLY IT IS NOW POSSIBLE TO CONDUCT EVALUATIVE STUDIES ON SCHOOL CHILDREN WHO HAVE TAKEN DIFFERENT ACHIEVEMENT TESTS. A SECOND IMPROVEMENT BROUGHT ABOUT THROUGH THE USE OF LATENT TRAIT MODELS OCCURS IN THE FIELD OF TEST DEVELOPMENT. HERE, IT IS POSSIBLE TO DESIGN TESTS AT SPECIFIC DIFFICULTY LEVELS, WHICH CAN BE HIGHLY DISCRIMINATING WITHIN GIVEN ABILITY RANGES. TESTS CAN BE "TAILORED" TO STUDENTS' INDIVIDUAL NEEDS.

BECAUSE MAJOR IMPROVEMENTS IN MEASUREMENT ARE EXPECTED USING LATENT TRAIT THEORY, SCHOOL SYSTEMS AND GOVERNMENT EDUCATIONAL ORGANIZATIONS AROUND THE COUNTRY HAVE SHOWN INCREASED INTEREST IN USING LATENT TRAIT MODELS. THIS INCREASE IN INTEREST IS ALSO ATTRIBUTED TO THE THEORY'S INCREASING ACCEPTANCE BY THE MEASUREMENT COMMUNITY ITSELF, AND FINALLY, TO TECHNOLOGICAL ADVANCES IN BOTH LATENT TRAIT PARAMETER ESTIMATION AND COMPUTER METHODS. ALTHOUGH WE ARE CURRENTLY WITNESSING THE USE OF LATENT TRAIT MODELS IN A
VARIETY OF APPLIED SETTINGS (SEE, FOR EXAMPLE, HAMBLETON ET AL., 1979; RENTZ AND RENTZ, 1978). MANY BASIC RESEARCH QUESTIONS CONCERNING LATENT TRAIT THEORY HAVE NOT YET BEEN SATISFACTORILY ANSWERED. THE RESEARCH REPORTED IN THIS STUDY WAS DESIGNED TO PROVIDE NEEDED INFORMATION FOR EFFECTIVE APPLICATION OF LATENT TRAIT MODELS BY PRACTITIONERS.

PURPOSE

THE PRIMARY QUESTION ADDRESSED IN THIS STUDY WAS HOW WELL DO EMPIRICAL DATA FIT THE ONE AND THREE-PARAMETER LOGISTIC LATENT TRAIT MODELS, THE MODELS OF MOST CURRENT INTEREST IN THE MEASUREMENT COMMUNITY. ALTHOUGH THERE ARE MANY CLAIMS THAT BOTH ACHIEVEMENT AND APTITUDE DATA FIT RASCH (ONE-PARAMETER) MODELS, AND EQUALLY STRONG CLAIMS CONCERNING FIT OF DATA TO THE THREE-PARAMETER LOGISTIC MODEL, LITTLE RESEARCH HAS ADDRESSED THE QUESTION OF COMPARABLE MODEL FIT. THREE QUESTIONS SEEM ESPECIALLY IMPORTANT:

1. SHOULD THE PRACTITIONER SELECT THE RASCH MODEL WITH ONE TYPE OF DATA, AND THE BIRNBAUM (THREE-PARAMETER) MODEL FOR OTHER KINDS OF DATA?

2. IS THERE IMPROVEMENT IN MODEL-DATA FIT FOUND BY USING THE THREE-PARAMETER MODEL, RATHER THAN THE RASCH MODEL?

3. HOW CAN PRACTITIONERS DETERMINE WHICH TEST MODEL (THE ONE OR THREE-PARAMETER MODEL) BEST SUIT THEIR DATA?

ANSWERS TO THE ABOVE QUESTIONS HAVE BEEN SOUGHT PRIMARILY THROUGH SIMULATION STUDIES. THERE IS INSUFFICIENT EVIDENCE FAVORING ONE OR THE OTHER LATENT TRAIT MODELS FROM RESEARCH USING EMPIRICAL DATA. WHAT FOLLOWS ARE SOME RESULTS

THE RESULTS FROM THIS STUDY PROVIDE AN INDICATION OF THE ADEQUACY OF LATENT TRAIT THEORY FOR EXPLAINING TEST BEHAVIOR. THE RESULTS INCLUDE EVIDENCE ON WHICH OF THE ONE OR THREE-PARAMETER LOGISTIC MODELS BEST SUIT VARIOUS TYPES OF DATA. HOPEFULLY, THE INFORMATION PROVIDED HERE CAN SERVE AS A GUIDE FOR PRACTITIONERS IN SELECTING LATENT TRAIT MODELS FOR USE IN TEST CONSTRUCTION AND TEST ANALYSIS.
RESEARCH QUESTIONS

ITEM DISCRIMINATION AND GUESSING

The Rasch Model is based on the premises that item discrimination is equal for all items and that guessing does not occur. Two questions arise in this connection: 1) How can one determine if these assumptions are fulfilled in a data set? And 2) Can data fit the Rasch model even when these assumptions are violated? It is difficult to assume that guessing does not take place on multiple-choice tests, and yet the Rasch model is considered robust with respect to this condition (Nezlek, 1976). A number of practical procedures have been suggested to determine the extent of guessing on items. Unfortunately, most methods obscure the possibility that guessing may be as much person or ability related as item related (Jenema, 1974). In this case, neither the Rasch or the three-parameter model would be an adequate description of test behavior. Practical methods are utilized in this study to explore the extent of guessing in a data set.

Two strong positions are taken concerning the Rasch model assumption of equal item discrimination. Birnbaum (1968), Ross (1966), and Hambleton and Traub (1973) found considerable variation in item discrimination for empirical data. Nevertheless, in studies of the Rasch model, results typically show that the model is fairly robust with respect to varying item discrimination. For example, Dinero and Maertel (1977) explored simulated data in which classical item discrimination was varied up to .15 variance. They found no major reduction in fit to the Rasch model. On the other hand, studies by Hambleton and Cook (1978) and by Hambleton and Traub (1976), found the opposite result, especially when the range of variation in item parameters was large.
THE RANGE OF ITEM DISCRIMINATION CAN BE DETERMINED, TO AN EXTENT, BY EXAMINING CLASSICAL ITEM DISCRIMINATION PARAMETERS. THERE ARE NO REAL GUIDELINES AVAILABLE FOR DETERMINING AT WHAT POINT THE RANGE OF ITEM DISCRIMINATION PARAMETERS IS TOO GREAT TO FIT ASSUMPTIONS OF THE RASCH MODEL. THIS POINT IS ADDRESSED IN THE RESULTS AND CONCLUSIONS OF THIS STUDY.

UNIDIMENSIONALITY

THE ASSUMPTION THAT DATA ARE UNIDIMENSIONAL IS AN ASSUMPTION UNDERLYING NEARLY ALL OF THE POPULAR LATENT TRAIT MODELS. A SINGLE ABILITY, OR LATENT TRAIT, IS ASSUMED TO UNDERLY ITEMS IN A TEST. IN PRACTICE, FEW TESTS ARE TRULY UNIDIMENSIONAL USING A FACTOR ANALYTIC METHOD. IT IS CUSTOMARY TO FIND LESS THAN 25% OF A TEST'S TOTAL VARIANCE ACCOUNTED FOR BY A FIRST, OR GENERAL, FACTOR. HAMBLETON AND TRAUB (1976) FOUND, WITH ARTIFICIAL DATA, THAT VIOLATION OF THE ASSUMPTION OF UNIDIMENSIONALITY LED TO POOR FIT FOR DATA TO THE RASCH MODEL.

A NUMBER OF TESTS FOR UNIDIMENSIONALITY HAVE BEEN OFFERED BY VARIOUS RESEARCHERS. LUMSDEN (1961) REVIEWED FIVE METHODS FOR ASSESSING UNIDIMENSIONALITY WITHIN THE CONTEXT OF TEST DEVELOPMENT, AND CONCLUDED THAT FACTOR ANALYSIS IS THE MOST PROMISING METHOD. LATENT TRAIT RESEARCHERS HAVE USED PRINCIPAL COMPONENT ANALYSIS, MAXIMUM LIKELIHOOD FACTOR ANALYSIS, AND PRINCIPAL AXIS COMMON FACTOR ANALYSIS TO DETERMINE UNIDIMENSIONALITY IN THEIR DATA. THERE EXISTS SOME DISAGREEMENT IN THE LITERATURE CONCERNING THE CORRELATION MATRIX THAT IS MOST APPROPRIATE FOR FACTOR ANALYSIS: PHI COEFFICIENTS OR TETRACHORICS. THE LATTER REPRESENTS A MEASURE OF RELATIONSHIP BETWEEN TWO ASSUMED LATENT VARIABLES SCORED DICHOTOMOUSLY. NOT ONLY DOES THIS ASSUMPTION AGREE WITH THE PREMISES OF LATENT TRAIT THEORY, BUT ALSO, USING TETRACHORIC CORRELATIONS IMPROVES THE CHANCES FOR OBTAINING A
FACTOR ANALYTIC SOLUTION. REGARDLESS OF THE STATISTICAL TECHNIQUE USED TO DETERMINE UNIDIMENSIONALITY, ONE PERPLEXING PROBLEM REMAINS: DATA CAN BE UNIDIMENSIONAL FOR ONE SAMPLE AND NOT FOR ANOTHER. CURRENTLY, NO STATISTICAL TECHNIQUE CAN SOLVE THIS PROBLEM. BOTH THE RASCH AND THREE-PARAMETER MODELS ARE INVESTIGATED HERE WITH RESPECT TO HOW WELL THEY FIT DATA OF VARYING DIMENSIONALITY BASED ON A FACTOR ANALYTIC CRITERION.

SAMPLE SIZE AND TEST LENGTH

ONE MAJOR SOURCE OF DISAGREEMENT BETWEEN LATENT TRAIT THEORISTS CONCERNS THE MINIMUM PERSON AND ITEM SAMPLE SIZES NEEDED TO OBTAIN CONSISTENT LATENT TRAIT PARAMETER ESTIMATES. THE LOGIST COMPUTER PROGRAM MANUAL (WOOD, WINGER SKY, AND LORD, 1976) SUGGESTS MINIMUMS OF 40 ITEMS AND 1000 PERSONS. WRIGHT (1977) CONTENTS THAT SMALL SAMPLES (100 PERSONS) ARE SUFFICIENT FOR EFFECTIVE ESTIMATION. THIS STUDY EXPLORES FIT OF SMALL SAMPLE DATA (20 ITEMS, 250 PERSONS) TO THE RASCH AND THREE-PARAMETER MODELS. A CONSIDERABLY MORE EXTENSIVE STUDY OF THIS PROBLEM HAS BEEN PREPARED BY SWAMI NATHAN AND GIFFORD (1979).

GOODNESS-OF-FIT

MANY DEFINITIONS FOR GOODNESS-OF-FIT APPEAR IN THE LATENT TRAIT LITERATURE (HAMBLETON, 1979). NOT ONLY DO DEFINITIONS OF FIT VARY FROM AUTHOR TO AUTHOR, BUT METHODS FOR TESTING FIT OF MODELS TO DATA VARY FROM MODEL TO MODEL. MANY OF THE STATISTICAL MEASURES EMPLOYED FOR TESTING GOODNESS-OF-FIT ARE CONSIDERED UNSOUND (BIRNBAUM, 1968). THE CHI SQUARE TEST IS OFTEN UTILIZED FOR GOODNESS-OF-FIT, THOUGH, GIVEN A SUFFICIENT SAMPLE SIZE, MOST DATA WILL BE REJECTED BY THIS MEASURE. NEVERTHELESS, THIS AUTHOR HAS CHOSEN TO EMPLOY CHI SQUARE TEST
STATISTICS IN THIS STUDY. SINCE THE STUDY IS COMPARATIVE IN NATURE, ONLY RELATIVE FIT NEED BE ASSESSED. IN ADDITION, A METHOD WAS NEEDED THAT WOULD BE APPROPRIATE TO BOTH MODELS UNDER STUDY. THE CHI SQUARE STATISTIC MEETS THESE CRITERIA.

METHODOLOGY

DESCRIPTION AND PROCESSING OF TEST DATA

FIVE DATA SETS WERE SELECTED FOR THIS STUDY:

1. CALIFORNIA TEST OF BASIC SKILLS - VOCABULARY SUBTEST, GRADE 10;
2. CALIFORNIA TEST OF BASIC SKILLS - MATH COMPREHENSION SUBTEST, GRADE 10;
3. SCHOLASTIC APTITUDE TEST - VERBAL, GRADE 12;
4. STANFORD ACHIEVEMENT TEST - VOCABULARY SUBTEST, GRADE 5;
5. STANFORD ACHIEVEMENT TEST - SCIENCE SUBTEST, GRADE 5.

TESTS WERE SELECTED TO COVER A RANGE OF BOTH CONTENT AND GRADE LEVELS. TWO LIMITATIONS WERE PLACED ON DATA SELECTION. FIRST, A MINIMUM SAMPLE SIZE OF 1000 WAS REQUIRED (AT A SINGLE GRADE LEVEL). SECONDLY, THE MINIMUM NUMBER OF ITEMS IN A TEST OR SUBTEST WAS FORTY. EACH OF THE TESTS SELECTED FOR STUDY WAS FOUND TO BE RELATIVELY UNIDIMENSIONAL. IN PILOT ANALYSES, IT WAS FOUND THAT PARAMETER ESTIMATION FOR DATA WHICH IS NOT UNIDIMENSIONAL OFTEN DOES NOT REACH CONVERGENCE WITHIN A REASONABLE TIME LIMIT (400 COMPUTER SECONDS). ANALYSIS OF DATA SETS THAT DO NOT HAVE A DOMINANT SINGLE FACTOR IS PLANNED IN THE NEAR FUTURE.

A FLOW CHART DEPICTING THE DESIGN OF THIS STUDY IS PRESENTED IN FIGURE 1. FOR EACH DATA SET, THE FOLLOWING STEPS
WERE EXECUTED. EACH TEST OR SUBTEST WAS SCORED BY A FORTRAN PROGRAM. THE TETRAHORIC CORRELATION MATRIX WAS OBTAINED AND FACTOR ANALYZED USING A PRINCIPAL COMPONENTS SOLUTION. RESULTS OF THE FACTOR ANALYSIS ARE USED TO CHARACTERIZE DATA IN TERMS OF DIMENSIONALITY. FOLLOWING THE FACTOR ANALYSIS, A RANDOM SAMPLE OF 1000 CASES WAS DRAWN FROM THE TOTAL SAMPLE. THIS SAMPLE WAS RETAINED FOR FURTHER ANALYSIS. CLASSICAL ITEM ANALYSIS WAS PERFORMED TO CHARACTERIZE TESTS IN TERMS OF STANDARD TESTING METHODOLOGY AND TO COMPARE CLASSICAL WITH LATENT TRAIT PARAMETER ESTIMATES. FOR EACH TEST THE AVERAGE, RANGE, AND CONFIDENCE BAND FOR ITEM-TOTAL CORRELATIONS WERE CALCULATED TO EXAMINE THE ASSUMPTION OF EQUAL ITEM DISCRIMINATION. IN ADITION, CLASSICAL ITEM DIFFICULTIES FOR THE LOWEST DECADE OF EXAMINEES WERE COMPUTED AS AN INDICATOR OF GUESSING ON DIFFICULT ITEMS.

---INSERT FIGURE 1 AROUND HERE-----


SINCE THE INPUT PARAMETER SET FOR EACH LOGIST EXECUTION VARYED GREATLY (OVER 50 PARAMETERS CAN BE SPECIFIED), AN INTERACTIVE TIME-SHARING FORTRAN PROGRAM, LOGPREP, WAS DESIGNED TO CREATE INPUT FILES. FOR MOST THREE-PARAMETER MODEL RUNS THE DEFAULT OPTIONS OF LOGIST WERE USED. THE ONE-PARAMETER MODEL IS ESTIMATED BY FIXING GUESSING AT ZERO AND ITEM DISCRIMINATION AT ONE. OUTPUTS FROM LOGIST ALONG
With the raw data were input into a FORTRAN program, THEITM, to obtain raw and expected raw scores utilizing the appropriate one or three-parameter item characteristic functions. The raw score is defined as:

\[(2.1)\]

Where \( u = 1 \) if the item is answered correctly and \( u = 0 \), otherwise. The expected raw score based on latent trait theory is:

\[(2.2)\]

Where \( p(\theta) \) is the probability of a correct response on item \( g \) by persons with ability level \( \theta \). To compare observed and expected raw scores (under each model) it was necessary to round expected raw scores to the closest integer. Finally, expected and observed raw scores and grouped raw score frequencies were obtained using SPSS. An interactive FORTRAN program, CHISQ, was used to perform chi square tests for each model-sample-test length combination. The chi square is defined as:

\[(2.3)\]

\( O \) stands for the observed frequency and \( E \) indicates expected frequency.

To assess the influence of sample size on estimating item parameters, an additional logist run was executed under the assumptions of each model. These runs used ability estimates (\( \theta \)) from the 1000-person sample and recomputed item parameters on a small sample of 250 persons. Analysis of item parameters was then accomplished using the ADAPT interactive statistical package (A TIME-SHARING, APL-BASED STATISTICAL ANALYSIS PACKAGE). Analysis included Pearson and
SPEARMAN CORRELATIONS BETWEEN SMALL AND LARGE SAMPLE PARAMETERS UNDER THE TWO MODELS, AND IN ADDITION, THE AVERAGE ABSOLUTE DIFFERENCE BETWEEN SMALL AND LARGE SAMPLE PARAMETERS UNDER THE TWO MODELS WAS OBTAINED. A SIMILAR PROCEDURE WAS UTILIZED TO ANALYZE ABILITY ESTIMATES FROM SHORT AND LONG TESTS. IN THIS CASE, ITEM PARAMETERS FOR 20 ITEMS (FROM THE OVERALL "TOTAL" TEST LENGTH ANALYSIS) WERE USED, AND ABILITY ESTIMATES WERE RECOMPUTED FOR THE SHORT TEST UNDER THE ONE AND THREE-PARAMETER MODEL ASSUMPTIONS. THE RESULTING PARAMETER ESTIMATES WERE ANALYZED, AS ABOVE, WITH THE ADAPT STATISTICAL SYSTEM.

FOR EACH LOGIST COMPUTER ESTIMATION COST WAS TALLIED. THE TWO MODELS ARE EXPLORED IN TERMS OF THEIR COMPUTER COSTS. COSTS ARE PRESENTED FOR EACH TEST AND FOR VARIOUS ITEM AND PERSON SAMPLE SIZES.

BECAUSE A NUMBER OF THE RESULTS OF THIS STUDY CONFLICTED WITH THE PREDICTIONS DERIVED FROM THE THEORY OF LATENT TRAITS, ADDITIONAL ANALYSES WERE MADE TO CHECK THE RESULTS. FOUR ADDITIONAL LOGIST ESTIMATIONS WERE EXECUTED ON THE SCHOLASTIC APTITUDE VERBAL SUBTEST. IN EACH CASE A TWENTY (20) ITEM SUBSET OF DATA WAS USED. ONE SUBSET WAS DESIGNED SUCH THAT THE ITEM DISCRIMINATION PARAMETERS WERE EQUAL (A .03 RANGE AROUND THE MEAN POINT-BISERIAL). A SECOND SUBTEST WAS DESIGNED SO THAT THERE RESULTED UNUSUAL ITEM DISCRIMINATIONS (OUTSIDE OF A .1 RANGE ABOUT THE MEAN POINT-BISERIAL). ANALYSES WERE THEN PERFORMED ON THESE DATA TO COMPARE THE ONE AND THREE-PARAMETER MODELS.

RESULTS

FIT OF THE ONE AND THREE-PARAMETER LOGISTIC MODELS
For each of the five data sets, the expected raw score distribution fit the observed raw score distribution better for the one-parameter model than for the three-parameter model. Chi square statistics, averaged across five tests, are presented in Table 2. Chi square statistics for each individual test are presented in Table 3. The chi square statistics for smaller sample sizes are less in magnitude, as one would expect, although there were some conflicting results in the data. For the one-parameter model, the short tests yielded better fits. The opposite result holds for the three-parameter model. The difference in magnitudes for the chi squares in Table 3 might be attributed to the way in which the scores were grouped, especially for the long test which contained a varying total number of items. Scores were usually grouped into six categories, but in some instances the lowest raw score group had frequencies too low for computing the chi square statistic. In this case, the lowest two score groups were combined. On 20-item tests, the first category included scores 1 through 4, whereas all other categories contained 3 scores. On longer tests, five or more raw scores composed each grouping, with the exception of the lowest and highest score groups. These contained from six to twelve raw scores. On any given test the groupings were constant.

------------INSERT TABLES 2 AND 3 AROUND HERE---------

The very high chi square statistics can almost always be attributed to lack of fit in the lowest score grouping. This effect was especially noticeable for the three-parameter model data. Even with this score category omitted, better fit was found for the one-parameter model. An exception to this trend was found for the science subtest of the Stanford Achievement Test. Here, the fit to both models was equal. It should also be noted that the criterion for fit in this study, the raw
SCORE, IS A SUFFICIENT STATISTIC FOR THE RASCH MODEL, BUT NOT FOR THE THREE-PARAMETER MODEL. THE RESULTS NEED TO BE CONSIDERED IN VIEW OF THIS FACT.

ITEM DISCRIMINATION, GUESSING, AND UNIDIMENSIONALITY

IT IS IMPOSSIBLE TO OBTAIN A RAW SCORE OF ZERO WITH THE THREE-PARAMETER MODEL IF ANY GUESSING OCCURS. ALTHOUGH LOGIST WAS FAIRLY ACCURATE IN ESTIMATING GUESSING FOR ITEMS FALLING AT THE EXTREMES (NO GUESSING OR MUCH GUESSING), GENERALLY THE GUESSING PARAMETERS WERE UNESTIMABLE. THE ESTIMATION PROCEDURE SETS THE GUESSING PARAMETER TO THE QUANTITY \( \left( \frac{1}{NCH} \right) - 0.05 \) AT THE OUTSET OF ESTIMATION, WHERE \( NCH \) IS THE NUMBER OF MULTIPLE CHOICE ALTERNATIVES. IF ESTIMATION OF OTHER PARAMETERS IS STABLE, GUESSING IS ALLOWED TO VARY. THIS WAS NOT USUALLY THE CASE FOR THIS DATA. THE FOLLOWING ARE APPROXIMATE LOWER BOUNDS FOR EXPECTED RAW SCORES UNDER THE THREE-PARAMETER MODEL FOR EACH OF THE FIVE TESTS:

- SCHOLASTIC APTITUDE VERBAL = 12.75
- CALIFORNIA MATH COMPREHENSION = 7.2
- CALIFORNIA VOCABULARY = 8.0
- STANFORD VOCABULARY = 10.0
- STANFORD SCIENCE = 12.0

(THese lower bounds are computed using the number of items and number of choices). ALTHOUGH SOME OF THE POOR FIT FOR THE THREE-PARAMETER MODEL CAN BE ATTRIBUTED TO THE LOWEST SCORE GROUP, THE RESULTS WERE STILL RATHER SURPRISING. TWO POSSIBLE EXPLANATIONS EXIST. ONE POSTULATE IS THAT THE DATA CHOSEN FOR STUDY ARE ALL ONE-PARAMETER DATA. A SECOND EXPLANATION IS THAT THERE MAY BE SOME DIFFICULTY IN ESTIMATING PARAMETERS FOR THE THREE-PARAMETER MODEL BECAUSE OF THE ADDITIONAL NUMBER OF UNKNOWN QUANTITIES THAT NEED TO BE ESTIMATED. THE RESULTS ARE MOST LIKELY A COMBINATION OF THESE TWO EXPLANATIONS.
Both guessing and item discrimination were further investigated to determine whether they had been properly estimated. Table 4 presents some results concerning the guessing parameter. The extent of guessing on each test was determined by calculating classical item difficulties for the 25% most difficult items for the lowest decile of examinees based on the sample (raw score criterion). On this criterion, each test was rated for the percent of guessing behavior displayed on hard items by low ability examinees. Latent trait guessing estimates were compared to these values. The last column of Table 5 indicates how often latent trait and classical parameters were in concordance, which was defined as the number of times that high latent trait guessing estimates matched high guessing estimates using classical test theory indicators. With the exception of the California vocabulary subtest (which was the shortest and most difficult test), Logist was quite accurate in pinpointing items at either extreme (minimal or maximum guessing). Generally though, the guessing parameter was overestimated. Although this overestimation clearly affected the lowest score group, in general, the effects of this overestimation were not found across the ability distribution. Thus, the less adequate fit of the data to the three-parameter model can not be attributed solely to overestimation of the guessing parameter.

-------------------------INSERT TABLE 4 ARROUND-------------------------

Tables 5 and 6 present results concerning the item discrimination parameter. These results are based on 20-item tests constructed to have very different or very similar item discriminations (by classical item indicators). In Table 5 chi square statistics are computed for six score groups. In this table we find that when the item discrimination

--- INSERT TABLES 5 AND 6 AROUND HERE ---

IT WAS IMPOSSIBLE TO DETERMINE THE INTERRELATIONSHIP BETWEEN GUESSING, ITEM DISCRIMINATION, AND MODEL FIT FOR SPECIFIC DATA SETS IN THIS STUDY. THE TWO SUBTESTS ON WHICH EXAMINEES SHOWED THE MOST GUESSING, ALSO HAD THE NARROWEST RANGE OF ITEM DISCRIMINATIONS. ONE OF THESE, THE STANFORD VOCABULARY, SHOWED CLOSE FIT TO THE RASCH MODEL, AND GOOD FIT TO THE THREE-PARAMETER MODEL AS WELL. THE OTHER, STANFORD SCIENCE, WAS THE SINGLE TEST THAT FIT THE THREE-PARAMETER MODEL AS WELL AS THE RASCH MODEL.

AN EXPLANATION OF MODEL FIT IN TERMS OF UNIDIMENSIONALITY IN THIS STUDY IS CONTAMINATED BY THE FACT THAT TESTS DIFFERED IN BOTH LENGTH AND DIFFICULTY. IT CAN BE SAID, HOWEVER, THAT THE
STANFORD VOCABULARY SUBTEST FIT BOTH MODELS BETTER THAN THE OTHER TESTS, ALTHOUGH THIS TEST WAS NOT THE MOST UNIDIMENSIONAL. TABLE 6 CHARACTERIZES DIMENSIONALITY OF TESTS IN TERMS OF THE FIRST LATENT ROOT FROM THE PRINCIPAL COMPONENT ANALYSIS, AND SHOWS THE VARIANCE ACCOUNTED FOR BY THE FIRST FACTOR. BY THESE CRITERIA, THE TEST WHICH BEST MEETS THE ASSUMPTION OF UNIDIMENSIONALITY IS THE CALIFORNIA MATH TEST. THIS TEST IS ALSO THE EASIEST TEST IN TERMS OF AVERAGE CLASSICAL ITEM DIFFICULTIES. THE RESULTS SHOW THAT THIS TEST FIT BOTH MODELS QUITE WELL. THE CHI SQUARE STATISTIC FOR RASCH MODEL FIT WAS 1.02, THE SECOND BEST FIT FOUND IN THE STUDY.

SAMPLE SIZE

TABLE 7 PROVIDES DATA ON THE ACCURACY OF PARAMETER ESTIMATION FOR SMALL SAMPLES (N=250). THE RESULTS ARE AVERAGED ACROSS THE FIVE TESTS. PEARSON PRODUCT MOMENT CORRELATIONS, SPEARMAN RANK ORDER CORRELATIONS, AND AVERAGE ABSOLUTE DIFFERENCES BETWEEN PARAMETERS ESTIMATED WITH THE 1000 PERSON AND 250 PERSON SAMPLES ARE GIVEN. ALL ESTIMATES WERE FIRST STANDARDIZED TO MEAN ZERO TO OBTAIN THESE RESULTS. ESTIMATES FOR DIFFICULTY ARE QUITE ACCURATE IN THE SMALL SAMPLE FOR BOTH MODELS. THE SMALL SAMPLE ESTIMATE FOR GUESING, ALTHOUGH CLOSE IN MAGNITUDE TO THE LARGE SAMPLE ESTIMATE, HAD A LOW CORRELATION WITH THE LARGER SAMPLE ESTIMATE. IT IS APPARENT FROM THIS DATA THAT 250 PERSONS MAY NOT BE A SUFFICIENT SAMPLE SIZE UPON WHICH TO ESTIMATE GUESING. IN FACT, EVEN IN THE 1000-PERSON SAMPLE, THE MAJORITY OF GUESING PARAMETERS FOR THIS DATA REMAINED UNESTIMATED BY THE MAXIMUM LIKELIHOOD METHOD. ESTIMATION OF ITEM DISCRIMINATION IN THE 250 PERSON SAMPLE IS RELATIVELY CONSISTENT WITH 1000 PERSON ESTIMATE. BUT, BY THE AVERAGE ABSOLUTE DEVIATION CRITERION, THIS SMALL SAMPLE ESTIMATE
FAIRED LESS WELL THAN EITHER GUESSING OR DIFFICULTY. IT
APPEARS THAT WHEN DISCRIMINATION IS POORLY ESTIMATED, ALL
OTHER ESTIMATES ARE EFFECTED. THEREFORE, THE DIFFICULTY
PARAMETERS IN THE THREE-PARAMETER CASE DO NOT APPEAR TO BE
ESTIMATED AS EFFECTIVELY WITH SMALL SAMPLES AS IN THE
ONE-PARAMETER CASE.

---------INSERT TABLE 7 AROUND HERE----------

TEST LENGTH

TEST LENGTH WAS EXAMINED TO DETERMINE WHETHER LATENT
TRAIT THEORY CAN BE APPLIED TO SHORT TESTS (23 ITEMS). TABLE
8 PRESENTS THE RESULTS OF THIS ANALYSIS IN TERMS OF PEARSON
AND SPEARMAN CORRELATIONS, AND AVERAGE ABSOLUTE DIFFERENCES
BETWEEN SHORT AND LONG TESTS, AVERAGED ACROSS FIVE DATA SETS.
FOR BOTH MODELS, ESTIMATES OF ABILITY FROM THE SHORT TEST HERE
REASONABLY CONSISTENT WITH ESTIMATES DERIVED FROM THE LONGER
TESTS. HERE, AS BEFORE, MORE CONSISTENCY WAS FOUND FOR THE
ONE-PARAMETER MODEL.

---------INSERT TABLE 8 AROUND HERE-------

COSTS

IN ADDITION TO FINDING IMPROVEMENT IN FIT FOR THE
ONE-PARAMETER MODEL BY STATISTICAL CRITERIA, THE DATA IN TABLE
9 DEMONSTRATE THAT THE COSTS OF ESTIMATING RASCH PARAMETER
VALUES ARE CONSIDERABLY LESS THAN THOSE FOR THE
THREE-PARAMETER MODEL. THE COSTS SHOWN IN TABLE 9 ARE
AVERAGED ACROSS FIVE TESTS. THIS TABLE ALSO SHOWS THE
RELATIONSHIP BETWEEN COMPUTER COSTS FOR LATENT TRAIT ESTIMATES
AND THE NUMBER OF PERSONS AND ITEMS ESTIMATED. THESE COSTS
ARE BASED ON A CHARGE OF $400 PER HOUR. THEY DO NOT REFLECT
AUXILIARY COSTS (DISC STORAGE, MAGNETIC TAPES, DATA PREPARATION, ETC.). ALL OF THE FIGURES IN TABLE 9 ARE BASED ON EXECUTIONS OF LOGIST IN WHICH PERSON AND ITEMS ARE ESTIMATED SIMULTANEOUSLY. TABLES 10 AND 11 SHED DIFFERENT LIGHT ON THE COSTS OF THE ONE AND THREE-PARAMETER MODELS. TABLE 10 INDICATES COMPUTER COSTS AVERAGED OVER FIVE 20-ITEM TESTS WHEN ITEM PARAMETERS ARE KNOWN. THERE IS ESSENTIALLY NO DIFFERENCE BETWEEN THE COSTS OF ESTIMATING ABILITY FOR THE ONE AND THREE-PARAMETER MODELS. SINCE THIS IS THE USUAL MANNER IN WHICH LATENT TRAIT THEORY IS APPLIED, THIS EQUIVALENCE OF COSTS SHOULD BE NOTED BY PRACTITIONERS PLANNING TO USE THESE MODELS. TABLE 10 GIVES COMPUTER COSTS FOR LOGIST RUNS AVERAGED ACROSS FIVE TESTS FOR ESTIMATING ITEM PARAMETERS ON SAMPLES OF 250 PERSONS WHEN ABILITY IS KNOWN. THE COSTS GIVEN FOR THIS STUDY CAN ONLY BE GENERALIZED TO THE LOGIST COMPUTER PROGRAM AND DO NOT APPLY TO COMPARISONS WITH OTHER ESTIMATION ROUTINES. IF THE ONE-PARAMETER ESTIMATION HAD BEEN EXECUTED ON THE BICAL COMPUTER PROGRAM (WRIGHT AND MEAD, 1976), THE COMPUTER COSTS FOR THE ONE-PARAMETER MODEL WOULD HAVE BEEN CONSIDERABLY LESS. IN THE BICAL PROCEDURE ONE EQUATION IS NEEDED FOR EACH RAW SCORE CATEGORY, WHEREAS IN THE MAXIMUM LIKELIHOOD METHOD, SEPARATE EQUATIONS ARE NEEDED FOR EACH EXAMINEE.

TABLE 14 HIGHLIGHTS COSTS FOR EACH SUBTEST. THERE IS A RELATIONSHIP BETWEEN THE NUMBER OF ITEMS IN A TEST AND ITS COST, BUT THE HIGHER COSTS FOR SOME SUBTESTS CAN ALSO BE ATTRIBUTED TO A LOWER DEGREE OF UNIDIMENSIONALITY.

---------INSERT TABLES 9, 10, 11 AND 12 AROUND HERE.--------

SUMMARY AND CONCLUSIONS

THE RESULTS OF THIS STUDY INDICATE THAT FOR DATA HAVING
ITEMS EQUAL IN DISCRIMINATION, THE RASCH MODEL PROVIDES BETTER FIT TO EMPIRICAL DATA THAN THE THREE-PARAMETER LOGISTIC MODEL. A PRACTICAL METHOD FOR DETERMINING EQUALITY OF ITEM DISCRIMINATION, USING CLASSICAL POINT-BISERIALS, was SUGGESTED. IT WAS ALSO NOTED THAT THE MAXIMUM LIKELIHOOD Estimate of the discrimination parameter may be inadequate at THIS TIME. AS IMPROVEMENTS ARE MADE IN THE THREE-PARAMETER ESTIMATION METHODS, A MORE SENSITIVE ESTIMATE OF THIS PARAMETER MAY BE FOUND.

ALTHOUGH THE DATA USED IN THIS STUDY WERE MULTIPLE CHOICE IN NATURE, VIOLATION OF THE "NO GUESSING" ASSUMPTION OF THE RASCH MODEL DID NOT APPEAR TO EFFECT FIT OF THE ONE-PARAMETER MODEL TO DATA. THE MAXIMUM LIKELIHOOD PROCEDURE TENDED TO OVERESTIMATE GUESSING FOR THIS DATA. THIS CAUSED REDUCED MODEL-DATA FIT OF THE THREE-PARAMETER MODEL ESPECIALLY IN THE LOWER ABILITY RANGE. GENERALLY, GUESSING WAS UNESTIMABLE FOR THIS DATA. UNFORTUNATELY, NO ALTERNATIVE CRITERIA COULD BE FOUND FOR ESTIMATING THE TRUE AMOUNT OF GUESSING. BECAUSE GUESSING AND DISCRIMINATION WERE CONFOUNDED IN THE DATA, IT WAS IMPOSSIBLE TO DETERMINE WHETHER THE GUESSING PARAMETER MIGHT HAVE IMPROVED FIT IN THE THREE-PARAMETER CASE.

EMPIRICAL DATA, SUCH AS OPEN-ENDED TEST QUESTIONS, IN WHICH GUESSING IS IMPOSSIBLE, IS NEEDED TO COMPARE FIT OF THE ONE AND THREE-PARAMETER MODELS. RESEARCH INTO THIS AREA MIGHT BEST BE CONDUCTED THROUGH STUDIES USING SIMULATED DATA, WITH ARTIFICIAL DATA, FACTORS, SUCH AS THOSE CONFOUNDED THE CURRENT RESEARCH, COULD BE CONTROLLED. BETTER ESTIMATES ARE NEEDED FOR BOTH ITEM DISCRIMINATION AND GUESSING IF THE THREE-PARAMETER MODEL IS TO BE USED EFFECTIVELY.

USING A FACTOR ANALYTIC CRITERION, THE DATA USED IN THIS STUDY WERE ALL FOUND TO HAVE ONE GENERAL FACTOR WHICH, IN ALL CASES, ACCOUNTED FOR MORE THAN 20 PERCENT OF THE TEST VARIANCE. THE DATA INDICATE THAT THE MORE A DATA SET MEETS THIS ASSUMPTION, THE LESS TIME IT TAKES TO CONVERGE TO A
SOLUTION BY THE LOGIST PROGRAM. THERE ALSO APPEARED TO BE SOME IMPROVEMENT OF FIT IN BOTH MODELS FOR DATA THAT SHOWED EXTREMELY STRONG FIRST FACTOR VARIANCE. MORE RESEARCH IN THIS AREA IS NEEDED WITH DATA SETS THAT CLEARLY VIOLATE THE ASSUMPTION OF UNIDIMENSIONALITY. IN ADDITION, CRITERIA, OTHER THAN FACTOR ANALYSIS, ARE NEEDED FOR DETERMINING THE EXTENT OF DIMENSIONALITY IN DATA.

ALTHOUGH THE ABILITY ESTIMATES FROM SHORT TESTS WERE REASONABLY GOOD, ITEM ESTIMATES FROM SMALL SAMPLES OF PERSONS TENDED NOT TO BE SO GOOD. THIS RESULT WAS ESPECIALLY APPARENT IN ESTIMATING ITEM DISCRIMINATION FROM SMALL SAMPLES.

WHEN THE LOGIST PROGRAM IS USED WITH KNOWN ITEM PARAMETERS, THE COST OF ESTIMATION IN THE ONE AND THREE-PARAMETER CASES IS EQUIVALENT. IN ESTIMATING ITEM PARAMETERS SIMULTANEOUSLY WITH ABILITY, THE SAVINGS FOUND BY USING THE ONE-PARAMETER MODEL ARE CONSIDERABLE. IT IS DIFFICULT TO COMMENT ON THIS COST DIFFERENTIAL UNTIL IT IS DETERMINED WHETHER THERE ARE OTHER SUBSTANTIAL GAINS TO BE FOUND WITH THE THREE-PARAMETER MODEL.

IN SUMMARY, USING COSTS AND FIT TO TEST SCORE DISTRIBUTIONS AS CRITERIA, THE RASCH MODEL WAS CLEARLY SUPERIOR IN FIT TO EMPIRICAL DATA THAN THE THREE-PARAMETER LOGISTIC MODEL. IT IS IMPORTANT TO POINT OUT THAT OTHER CRITERIA FOR FIT MIGHT HAVE BEEN SELECTED WHICH WOULD HAVE SHOWN BETTER FIT FOR THE THREE-PARAMETER MODEL. FOR EXAMPLE, IF A WEIGHTED RAW SCORE HAD BEEN UTILIZED, RATHER THAN THE SIMPLE RAW SCORE, IMPROVEMENT OF FIT FOR THE THREE-PARAMETER MODEL MIGHT HAVE BEEN SEEN. THE RESULTS ALSO SHOW THAT IN THE CASE WHEN ITEM DISCRIMINATIONS ARE QUITE DISSIMILAR, THE THREE-PARAMETER MODEL DEMONSTRATED SUPERIOR FIT TO THE RASCH MODEL. RESEARCH IS NEEDED TO DETERMINE HOW UNEQUAL ITEM DISCRIMINATION NEED TO BE FOR THE THREE-PARAMETER MODEL TO BECOME MORE EFFECTIVE. HERE AGAIN A SIMULATED-DATA STUDY.
SIMILAR TO THE ONE PROJECTED ABOVE FOR GUESSING, IS NEEDED IN CONJUNCTION WITH REFINING THE ESTIMATION PROCEDURES.

FINALLY, IT IS IMPORTANT TO POINT OUT THAT THE CONCLUSIONS DRAWN IN THIS PAPER ARE TENTATIVE. THE PROJECT IS IN MIDSTREAM: ONLY HALF OF THE PROJECTED DATA SETS HAVE BEEN ANALYZED TO DATE.
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CHICAGO: STATISTICAL LABORATORY, DEPARTMENT OF EDUCATION,
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WRIGHT, B.D., AND PANCHAPAKESAN, N. A PROCEDURE FOR
SAMPLE-FREE ITEM ANALYSIS. EDUCATIONAL AND PSYCHOLOGICAL
### Table 1
**Description of Tests**

<table>
<thead>
<tr>
<th>TEST</th>
<th>ITEMS</th>
<th>MEAN</th>
<th>ST. DEV.</th>
<th>ITEM DIFF.</th>
<th>AVEF.</th>
<th>CHIEF</th>
<th>CHOICES</th>
<th>PEOPLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT VERBAL</td>
<td>85</td>
<td>48.111</td>
<td>17.174</td>
<td>.566</td>
<td>.912</td>
<td>5</td>
<td>3000</td>
<td></td>
</tr>
<tr>
<td>CTES MATH</td>
<td>48</td>
<td>30.045</td>
<td>11.614</td>
<td>.525</td>
<td>.944</td>
<td>5</td>
<td>1112</td>
<td></td>
</tr>
<tr>
<td>CTES VOCAB</td>
<td>40</td>
<td>21.572</td>
<td>9.061</td>
<td>.473</td>
<td>.927</td>
<td>4</td>
<td>1112</td>
<td></td>
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<tr>
<td>SIGN VOCAB</td>
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<td>37.814</td>
<td>9.605</td>
<td>.556</td>
<td>.903</td>
<td>4</td>
<td>4160</td>
<td></td>
</tr>
<tr>
<td>STN SCI</td>
<td>60</td>
<td>39.626</td>
<td>12.187</td>
<td>.510</td>
<td>.921</td>
<td>4</td>
<td>4160</td>
<td></td>
</tr>
</tbody>
</table>

### Table 2
**Average Chi Squares Across Tests by Model, Sample Size: Test Length**

<table>
<thead>
<tr>
<th></th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>TEST LENGTH:</td>
<td>LONG</td>
<td>SHORT</td>
</tr>
<tr>
<td>SAMPLE SIZE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1000</td>
<td>7.95</td>
<td>8.51</td>
</tr>
<tr>
<td>250</td>
<td>4.07</td>
<td>4.94</td>
</tr>
<tr>
<td>AVG. BY MODEL</td>
<td>6.34</td>
<td>4.48</td>
</tr>
</tbody>
</table>
### Table 3

**Chi Squares by Test, Model, Sample Size, and Test Length**

<table>
<thead>
<tr>
<th>Test</th>
<th>Sample Size</th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Test Length</strong></td>
<td>Long</td>
<td>Short</td>
<td>Long</td>
</tr>
<tr>
<td>SAT Verbal</td>
<td>1000</td>
<td>17.78</td>
<td>6.36</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>7.81</td>
<td>3.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8.81</td>
<td></td>
</tr>
<tr>
<td>CTBS Math</td>
<td>1000</td>
<td>2.63</td>
<td>3.50</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>5.50</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.24</td>
<td></td>
</tr>
<tr>
<td>CTBS Vocab</td>
<td>1000</td>
<td>5.08</td>
<td>23.74</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>1.37</td>
<td>12.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10.63</td>
<td></td>
</tr>
<tr>
<td>STAN Vocab</td>
<td>1000</td>
<td>3.24</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>.46</td>
<td>3.44</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.08</td>
<td></td>
</tr>
<tr>
<td>STAN SCI</td>
<td>1000</td>
<td>10.53</td>
<td>7.75</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>5.21</td>
<td>4.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6.96</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4

**Investigation of Guessing by Test**

<table>
<thead>
<tr>
<th>Test</th>
<th>Items</th>
<th>25% of Items</th>
<th>% of Guessing on Hard Items</th>
<th>% of Good Estimates by Latent Trait Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT Verbal</td>
<td>105</td>
<td>21</td>
<td>43%</td>
<td>76%</td>
</tr>
<tr>
<td>CTBS Math</td>
<td>48</td>
<td>12</td>
<td>60%</td>
<td>83%</td>
</tr>
<tr>
<td>CTBS Vocab</td>
<td>40</td>
<td>10</td>
<td>70%</td>
<td>50%</td>
</tr>
<tr>
<td>STAN Vocab</td>
<td>50</td>
<td>13</td>
<td>75%</td>
<td>27%</td>
</tr>
<tr>
<td>STAN SCI</td>
<td>60</td>
<td>14</td>
<td>71%</td>
<td>86%</td>
</tr>
</tbody>
</table>

### Table 5

**Chi Squares - A Study Groups**

<table>
<thead>
<tr>
<th>SAT Verbal</th>
<th>20 Item Test</th>
<th>Equal vs. Unequal Item Discrimination</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equal</td>
<td>Unequal</td>
</tr>
<tr>
<td></td>
<td>3-Parameter Model</td>
<td>1-Parameter Model</td>
</tr>
<tr>
<td></td>
<td>Equal</td>
<td>Unequal</td>
</tr>
<tr>
<td></td>
<td>41.17</td>
<td>7.05</td>
</tr>
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</table>
### Table 7

Influence of Sample Size on Item Parameter Estimation by Model (250 versus 1000 People)

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.833</td>
<td>0.974</td>
</tr>
<tr>
<td>B</td>
<td>0.930</td>
<td>0.975</td>
</tr>
<tr>
<td>C</td>
<td>0.407</td>
<td>0.153</td>
</tr>
<tr>
<td>Diff.</td>
<td>0.030</td>
<td>0.122</td>
</tr>
</tbody>
</table>

### Table 8

Influence of Test Length on Ability Estimation by Model (20 versus Total Items)

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson Corr.</td>
<td>0.866</td>
<td>0.923</td>
</tr>
<tr>
<td>Spearman Corr.</td>
<td>0.918</td>
<td>0.926</td>
</tr>
<tr>
<td>Avg. Abs. Diff.</td>
<td>0.372</td>
<td>0.300</td>
</tr>
</tbody>
</table>

### Table 9

Computer Costs by Model

<table>
<thead>
<tr>
<th>Model</th>
<th>Long</th>
<th>Short</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-Parameter</td>
<td>$44.40</td>
<td>$15.73</td>
</tr>
<tr>
<td>1-Parameter</td>
<td>$13.45</td>
<td>$6.04</td>
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</tbody>
</table>

### Table 10

Computer Costs (20 Item Test) When Item Parameters are Known

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>$3.28</td>
<td>$3.24</td>
</tr>
</tbody>
</table>

### Table 11

Computer Costs (200 People) When Ability Scores are Known

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>3-Parameter Model</th>
<th>1-Parameter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>$3.46</td>
<td>$3.27</td>
</tr>
</tbody>
</table>

### Table 12

Computer Costs by Test (N=1000 Persons)

<table>
<thead>
<tr>
<th>Test</th>
<th>3-Parameter Model Long</th>
<th>3-Parameter Model Short</th>
<th>1-Parameter Model Long</th>
<th>1-Parameter Model Short</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT Verbal</td>
<td>$44.96</td>
<td>$26.38</td>
<td>$5.94</td>
<td>$2.55</td>
</tr>
<tr>
<td>CTIS Math</td>
<td>$31.56</td>
<td>$17.10</td>
<td>$13.46</td>
<td>$5.82</td>
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<tr>
<td>CTIS Verbal</td>
<td>$30.46</td>
<td>$25.18</td>
<td>$10.62</td>
<td>$6.23</td>
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<tr>
<td>SHAP Verbal</td>
<td>$44.37</td>
<td>$18.39</td>
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<td>$5.79</td>
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</tbody>
</table>

* # Not Requested