

4

AD-A203 835

DTIC FILE COPY

**SPECIFYING OPTIMUM EXAMINEES FOR ITEM  
PARAMETER ESTIMATION IN ITEM RESPONSE THEORY**

Martha L. Stocking

DTIC  
ELECTE  
DEC 02 1988  
S H D

This research was sponsored in part by the  
Cognitive Science Program  
Cognitive and Neural Sciences Division  
Office of Naval Research, under  
Contract No. N00014-83-K-0457

Contract Authority Identification No.  
NR 150-520

Frederic M. Lord, Principal Investigator



Educational Testing Service  
Princeton, New Jersey

October 1988

Reproduction in whole or in part is permitted  
for any purpose of the United States Government.

Approved for public release; distribution unlimited.

88 12 2 078

SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE				Form Approved OMB No. 0704-0188	
1a. REPORT SECURITY CLASSIFICATION Unclassified		1b. RESTRICTIVE MARKINGS			
2a. SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION / AVAILABILITY OF REPORT Approved for public release; distribution unlimited			
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE					
4. PERFORMING ORGANIZATION REPORT NUMBER(S) RR-88-57-ONR		5. MONITORING ORGANIZATION REPORT NUMBER(S)			
6a. NAME OF PERFORMING ORGANIZATION Educational Testing Service		6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Cognitive Science Program, Office of Naval Research (1142PT), 800 North Quincy Street		
6c. ADDRESS (City, State, and ZIP Code) Princeton, NJ 08541		7b. ADDRESS (City, State, and ZIP Code) Arlington, VA 22217-5000			
8a. NAME OF FUNDING / SPONSORING ORGANIZATION		8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER N00014-83-K-0457		
8c. ADDRESS (City, State, and ZIP Code)		10. SOURCE OF FUNDING NUMBERS			
		PROGRAM ELEMENT NO 61153N	PROJECT NO RR04204	TASK NO RR04204-01	WORK UNIT ACCESSION NO NR150-520
11. TITLE (Include Security Classification) Specifying Optimum Examinees for Item Parameter Estimation in Item Response Theory (Unclassified)					
12. PERSONAL AUTHOR(S) Martha L. Stocking					
13a. TYPE OF REPORT Technical		13b. TIME COVERED FROM _____ TO _____	14. DATE OF REPORT (Year, Month, Day) October 1988		15. PAGE COUNT 31
16. SUPPLEMENTARY NOTATION					
17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)		
FIELD 05	GROUP 10	SUB-GROUP	IRT response theory, Information functions, IRT item parameters, Optimum examinees		
19. ABSTRACT (Continue on reverse if necessary and identify by block number)					
<p>Information functions are used to find the optimum ability levels and maximum contributions to information for estimating item parameters in three commonly used logistic item response models. For the three and two parameter logistic models, examinees who contribute maximally to the estimation of item difficulty contribute little to the estimation of item discrimination. This suggests that in applications that depend heavily upon the veracity of individual item parameter estimates (e.g. adaptive testing or test construction), better item calibration results may be obtained (for fixed sample sizes) from examinee calibration samples in which ability is widely dispersed.</p>					
20. DISTRIBUTION / AVAILABILITY OF ABSTRACT <input checked="" type="checkbox"/> UNCLASSIFIED/UNLIMITED <input type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS			21. ABSTRACT SECURITY CLASSIFICATION Unclassified		
22a. NAME OF RESPONSIBLE INDIVIDUAL Dr. Charles E. Davis		22b. TELEPHONE (Include Area Code) 202-696-4046		22c. OFFICE SYMBOL ONR 1142CS	

Specifying Optimum Examinees

Specifying Optimum Examinees for Item Parameter Estimation  
in Item Response Theory

Martha L. Stocking

Educational Testing Service  
Princeton, New Jersey

October 1988

## Specifying Optimum Examinees

### Abstract

Information functions are used to find the optimum ability levels and maximum contributions to information for estimating item parameters in three commonly used logistic item response models. For the three and two parameter logistic models, examinees who contribute maximally to the estimation of item difficulty contribute little to the estimation of item discrimination. This suggests that in applications that depend heavily upon the veracity of individual item parameter estimates (e.g. adaptive testing or test construction), better item calibration results may be obtained (for fixed sample sizes) from examinee calibration samples in which ability is widely dispersed.

Keywords: Item response theory  
IRT item parameters  
Optimum examinees  
Information functions



Accession For	
NTIS GRA&I	<input checked="" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By _____	
Distribution/	
Availability Codes	
Dist	Avail and/or Special
A-1	

## Introduction

The success of applications in Item Response Theory (IRT) depends upon the accuracy with which individual item parameters can be estimated. This dependence is especially important for those applications that depend heavily upon the veracity of individual item parameter estimates in contexts perhaps unrelated to the calibration setting in which estimates were obtained. Two recent examples of such applications are adaptive testing (see, for example, Lord (1980, chap. 10); Stocking (1988)) and IRT-based test development (see, for example, van der Linden & Boekkooi-Timminga (1987)).

Typically, calibration samples are selected with an eye to convenience as random subsamples from a larger set of data (see, for example, Cook, Petersen, & Stocking (1983)). It may be possible to obtain better, i.e., more accurate, item parameter estimates if the planning for calibration sample selection explicitly includes considerations of the accuracy of the resulting item parameter estimates. This idea was suggested, based on the analogy between item parameter estimation and estimation problems in regression, 20 years ago by Lord (1968). More recently, Wingersky and Lord (1984) provide theoretical support.

One approach to issues of the accuracy of item parameter estimation considers the asymptotic expected covariance matrix. Lord (1980, p. 191) presents formulas from which this matrix can be derived for the three-parameter logistic (3PL) model in the finite sample case with known abilities. Thissen and Wainer (1982) consider the properties of the asymptotic covariance matrix for item parameters when a particular distribution of ability is assumed in the calibration example. Lord and Wingersky (1985) consider the asymptotic properties of the covariance matrix for the 3PL model when both item parameters and abilities are estimated jointly by maximum likelihood.

In this paper we explore the relationship between examinee ability and the accuracy of maximum likelihood item parameter estimation in terms of the expected (Fisher) information (Kendall & Stuart, 1979, p. 10). The advantage to this approach is that it is possible to study directly the relationship between examinee ability and contribution to information in some detail and with some surprising results. This theoretical examination depends upon the assumption that examinee abilities, as well as some item parameters, are known. However, the results can be translated into general guidelines for situations in which samples can be selected on the basis of some observed score for the purpose of obtaining accurate

parameter estimates for a collection of items whose properties are imperfectly known.

### The Theory

Suppose the probability of a correct response to an item is specified by a logistic function, either one parameter logistic (1PL), two parameter logistic (2PL) or three parameter logistic (3PL). Suppose further that estimates of the item parameters are obtained by maximum likelihood. If the model fits the data, and true abilities are known, then formulas exist for the amount of information in the sample for estimating item parameters (Lord, 1980, eqs. 12-8 through 12-13)).

Of course, the model never fits any set of real data, and true abilities are never known. Therefore, the information computed from the Lord formulas is an estimate of the maximum possible information, and will be larger than what can be realistically obtained (Mislevy & Sheehan, 1987). Nevertheless, an examination of what the theory predicts may be useful in planning a calibration sample to estimate item parameters accurately.

If the probability of a correct response by examinee  $a$  to an item is  $P_a$ , the log of the likelihood of observed responses to the item for  $N$  examinees is

$$l = \sum_{a=1}^N [u_a \ln P_a + (1 - u_a) \ln Q_a] ,$$

where  $u_a = 0$  if the response is incorrect,  $u_a = 1$  if the response is correct, and  $Q_a = 1 - P_a$ . The maximum likelihood estimates of each item parameter  $\chi$  are located at a point where the partial derivatives of the log likelihood are zero. The expected second partial derivatives of the log likelihood can be computed at this point. (The inverse of the negative of this matrix is the asymptotic variance/covariance matrix used by Thissen and Wainer (1982).) The negative of a diagonal element of the matrix of expected second partial derivatives is referred to as the information in the sample for estimating an item parameter. For any item parameter  $\chi$ , this information function has the form (Lord, 1980, equations 12-8 to 12-13)

$$I_{\chi\chi} = \sum_{a=1}^N \frac{1}{P_a Q_a} \left( \frac{\partial P_a}{\partial \chi} \right)^2 = \sum_{a=1}^N i_{\chi\chi a} .$$

The information is composed of individual additive contributions from each examinee,

$$i_{xx} = \frac{1}{PQ} \left( \frac{\partial P}{\partial x} \right)^2 \quad (1)$$

where the subscript  $a$  has been dropped for convenience. By examining the properties of an individual contribution as a function of ability, we can determine what values of ability provide the most (and least) information for estimating an item parameter, assuming other item parameters are fixed.

#### Results

##### The 3PL Model

The 3PL item response function is

$$P = c + \frac{1 - c}{1 + e^{-Da(\theta - b)}}$$

where

$a$  is a function of the slope of the item response function in the neighborhood of the item difficulty;

$b$  characterizes the difficulty or location of the item on the ability continuum;

$c$  is the lower bound of probabilities of correct response, even from low ability examinees;

$\theta$  is examinee ability;

D is a scaling constant commonly used with the value of 1.7.

The partial derivatives of P with respect to the item parameters are given by Lord (1980, Equation 12-2). Substituting the derivative with respect to c into Equation 1 gives an examinee's contribution to the information for estimating c as

$$i_{cc} = \frac{1}{(1 - c)^2} \frac{Q}{P} \quad . \quad (2)$$

Values of ability that give local minima and maxima of Equation 2 are found where

$$\frac{\partial i_{cc}}{\partial \theta} = \frac{-Da}{(1 - c)^3} \frac{1}{P^2} Q(P - c) = 0 \quad .$$

This derivative is zero when  $Q = 0$ , in which case  $\theta = +\infty$ , and  $i_{cc}$  is zero. It is also zero when  $P = c$ , in which case  $\theta = -\infty$  and  $i_{cc} = \frac{1}{(1 - c)c}$ . This latter value forms an upper asymptote to the amount of information from all ability levels. The higher the value of c, the more examinees, even optimal examinees, are required for estimation of c.

The information for estimating  $b$  is obtained by substituting the derivative of  $P$  with respect to  $b$  into Equation 1, giving

$$i_{bb} = \frac{D^2 a^2}{(1-c)^2} (P-c)^2 \frac{Q}{P} \quad (3)$$

with partial derivative

$$\frac{\partial i_{bb}}{\partial \theta} = \frac{D^3 a^3}{(1-c)^3} \frac{Q(P-c)^2}{P^2} [-2P^2 + P + c] \quad (4)$$

A root of this derivative is found where  $Q = 0$ , in which case  $\theta = +\infty$  and  $i_{bb} = 0$ . A second root is found when  $P = c$ , where  $\theta = -\infty$  and  $i_{bb} = 0$ . Examinees with abilities far away from the item's location are useless for estimating that location. A final root of this derivative is found where  $-2P^2 + P + c = 0$ . The root of this latter quantity,  $P^*$ , where  $c \leq P^* \leq 1$ , is

$P^* = \frac{1 + \sqrt{1 + 8c}}{4}$ . The optimal ability  $\theta^*$  is then

$$\theta^* = b + \frac{1}{Da} \ln\left(\frac{P^* - c}{1 - P^*}\right) \quad (5)$$

and

$$i_{bb} = \frac{D^2 a^2}{(1 - c)^2} (P^* - c)^2 \frac{Q^*}{P^*} , \quad (6)$$

where  $Q^* = 1 - P^*$ .

The optimal ability level is at  $\theta^* = b$  when  $c = 0$ . When  $0 < c < 1$ , the optimal ability level is greater than  $b$  by an amount that depends upon both  $a$  and  $c$ . For a fixed value of  $c$ , higher values of  $a$  mean that the optimum location is closer to but still greater than  $b$ . Since  $P^*$  is a function of  $c$  alone, the maximum amount of information from an examinee for estimating  $b$ , Equation 6, depends only on  $a$  and  $c$ , and for fixed  $c$ , is proportional to the square of  $a$ .

By analogous computations, the information from each examinee (Equation 1) for estimating  $a$  for the 3PL is

$$i_{aa} = \frac{D^2}{(1 - c)^2} (\theta - b)^2 (P - c)^2 \frac{Q}{P} , \quad (7)$$

with partial derivative

$$\frac{\partial i_{aa}}{\partial \theta} = \frac{D^2}{(1-c)^2} \frac{(\theta - b)(P - c)^2 Q}{P^2} \left[ (\theta - b) \frac{Da}{(1-c)} (-2P^2 + P + c) + 2P \right] . \quad (8)$$

Three roots of Equation 8 are at  $\theta = b$ ,  $\theta = -\infty$ , and  $\theta = +\infty$ . For all three of these roots,  $i_{aa} = 0$ . Low and high ability examinees, as well as examinees whose abilities may be close to optimum for estimating  $b$  are of no use in the estimation of  $a$ . The location of optimal abilities is found from the last factor in Equation 8. This expression is zero when the optimal ability

$$\theta^{**} = b + \frac{2(1-c)P^{**}}{Da(2P^{**2} - P^{**} - c)} . \quad (9)$$

The optimal ability is not given explicitly by this expression, but values of  $\theta^{**}$  can be found by numerical methods. The top panel of Figure 1 shows  $P$  plotted as a function of  $\theta - b$ , from Equation 9. When  $P = c$ ,  $\theta - b = -\frac{1}{Da}$ , and when  $P = 1$ ,  $\theta - b = \frac{2}{Da}$ . The plot suggests that these values form upper and lower bounds respectively for two regions in which the optimal ability might be found:

$$\theta < b - \frac{1}{Da} \text{ and } \theta > b + \frac{2}{Da} .$$

-----  
Insert Figure 1 about here  
-----

#### Numerical Examples

Equations 2, 3, and 7 are plotted as functions of ability in the top panel of Figure 2 for an item with  $a = 1$ ,  $b = 0$ , and  $c = .2$ . Additive contributions to information for estimating  $a$  or  $b$  from examinees at various ability levels must be read from the right-hand scale; those for estimating  $c$  must be read from the left-hand scale. Figure 2 demonstrates graphically what we have learned analytically: 1) the contribution of examinees to the information available for estimating item difficulty is asymmetric around  $b$ , with higher ability examinees contributing more information; 2) examinees who are most informative in the estimation of item difficulty are of little use in estimating item discrimination; 3) examinees who do contribute to the estimation of discrimination are asymmetrically distributed around the item difficulty; and 4) only low ability examinees contribute much information for the estimation of  $c$ , and there is a limit to this contribution.

-----  
Insert Figure 2 about here  
-----

The effects of different values of  $a$ , for fixed  $b$  and  $c$ , on the additive contribution of examinees to information for estimating  $a$  are shown in the top left panel of Figure 3. Each examinee contributes substantially more information to the estimation of  $a$  if the value of  $a$  is low rather than high. More lower ability examinees than higher ability examinees are required to obtain a given amount of information for the estimation of  $a$ , regardless of the value of  $a$ , since lower ability examinees contribute less information than higher ability examinees.

-----  
Insert Figure 3 about here  
-----

The middle left panel of Figure 3 shows the effects of different values of  $b$ , for fixed  $a$  and  $c$ , on the additive contribution of examinees to information for estimating  $b$ . Changing  $b$  shifts the location of optimal examinees, but not the maximum contribution. The effects of different  $c$ 's on the additive contribution for estimating  $c$ , for fixed  $a$  and  $b$ , are shown in the bottom left panel of Figure 3. For lower ability levels, the higher the guessing parameter, the less the additive contribution for each examinee; more examinees are required to obtain a given amount of information about  $c$ . Regardless of the value of  $c$ , higher ability examinees do

not contribute much. However, they contribute more if  $c$  is higher than if  $c$  is lower.

Numerical values of optimal abilities and maximal contributions to information (in parentheses) are presented for typical values of  $a$  and  $b$  for  $c = .2$  in Table 1. Optimal abilities and maximal contributions for  $b$  come directly from Equations 5 and 6. Those for  $a$  come from the application of numerical methods to Equations 9 and 7.

-----  
 Insert Table 1 about here  
 -----

#### The 2PL and 1PL Models

The 2PL item response function can be considered as a special case of the 3PL with  $c = 0$ . In this case,

$$P = \frac{1}{1 + e^{-Da(\theta - b)}}$$

The 1PL item response function is also a special case of the 3PL with  $c = 0$  and constant  $a$ . The expression for  $P$  is identical to that for the 2PL immediately above, but the item discrimination is constant for all items.

The information for estimating  $b$  for the 2PL is algebraically the same as for the 1PL:

$$i_{bb} = D^2 a^2 PQ \quad , \quad (10)$$

with derivative with respect to ability

$$\frac{\partial i_{bb}}{\partial \theta} = D^3 a^3 PQ(1 - 2P) \quad .$$

These are obtained from Equations 3 and 4 for the 3PL by setting  $c = 0$ . Examinees with abilities of  $\pm\infty$  contribute nothing to the estimation of  $b$  in these models. Examinees with  $\theta^* = b$  ( $P^* = .5$ ) contribute the maximum amount of information,  $.25D^2 a^2$ . The additive contribution from each examinee depends upon the square of the discrimination of the item.

For the 2PL model, the information for estimating  $a$  is

$$i_{aa} = D^2 (\theta - b)^2 PQ \quad (11)$$

with derivative

$$\frac{\partial i_{aa}}{\partial \theta} = D^2(\theta - b)PQ[Da(\theta - b)(1 - 2P) + 2] ,$$

again obtained from the 3PL results (Equations 7 and 8) by setting  $c = 0$ . As with the 3PL, examinees with low and high abilities, as well as examinees whose abilities are optimal for estimating  $b$  are useless for estimating  $a$ . The location of optimal abilities is found by setting  $Da(\theta - b)(1 - 2P) + 2 = 0$  in which case the optimal ability  $\theta^{**}$  is

$$\theta^{**} = b + \frac{2}{Da(2P - 1)} . \quad (12)$$

The bottom panel of Figure 1 shows  $P$  plotted as a function of  $\theta - b$  for the 2PL in Equation 12. When  $P = 0$ ,  $\theta - b = -\frac{2}{Da}$ , and when  $P = 1$ ,  $\theta - b = \frac{2}{Da}$ . As with the 3PL, there are two regions in which  $\theta^{**}$  might be found:  $\theta < b - \frac{2}{Da}$  and  $\theta > b + \frac{2}{Da}$ . In contrast to the 3PL, these regions are symmetric around  $\theta - b = 0$ .

The additive contribution to estimating  $a$  for optimal examinees is

$$i_{aa} = .25D^2(\theta^{**} - b)^2 - \frac{1}{a^2} . \quad (13)$$

Both terms in Equation 13 decrease for higher values of  $a$  since the optimal  $\theta$  is closer to the difficulty for increased  $a$ , given fixed  $b$ . In contrast with the 3PL, the contributions of examinees whose true abilities are symmetric around the item difficulty are identical.

#### Numerical Examples

Equation 10 for the 2PL and 1PL and Equation 11 for the 2PL are plotted as functions of ability in the bottom panel of Figure 2 for an item with  $a = 1$  and  $b = 0$ . Additive contributions to information for estimating  $a$  (for fixed  $b$ ) or  $b$  (for fixed  $a$ ) are higher in models that do not contain a guessing parameter. This is seen by comparing the two panels in Figure 2.

The effects of different  $a$  values (with fixed  $b$ ) on the additive contributions for estimating  $a$  in the 2PL (Equation 11) are shown in the top right panel of Figure 3. Examinees symmetrically located around the item difficulty contribute equally to information. As in the 3PL (top left panel), each examinee contributes more to information for estimating  $a$  when  $a$  is low. In contrast to the 3PL, examinee's additive contributions are higher when the model does not contain a guessing parameter (compare the two top panels of Figure 3). Equation 10 for the 2PL with fixed  $a$  or the 1PL is plotted for different values of  $b$  in the middle right

panel of Figure 3. As with the 3PL (middle left panel), changing values of  $b$  shifts the location of optimal examinees but not the maximum contribution to information for estimating item difficulty.

Numerical values of optimal abilities and maximum contributions to information (in parentheses) are presented for typical values of  $a$  and  $b$  for the 2PL and 1PL in Table 2. Optimal abilities and maximum contributions for estimating  $b$  come directly from Equation 10 and its consequences. Comparable data for information for estimating  $a$  for the 2PL comes from the application of numerical methods to Equation 12 and Equation 13.

-----

Insert Table 2 about here

-----

#### Discussion

The focus of this paper has been to explore the contribution of examinees with different true abilities to the expected information available for estimating item parameters. This is not the same as an exploration of the accuracy with which item parameters may be estimated, but has the advantage of directly suggesting strategies of calibration sample selection. In terms of making statements about the accuracy with which item parameters are estimated, the analyses presented here are immediately relevant to the problem of

estimating a single item parameter, conditional on other item parameters being fixed at their true values. However, statements about the accuracy of item parameter estimates are usually made in a broader context in which all three item parameters must be estimated and a particular distribution of true ability may be assumed. Such considerations then take into account the covariances among the item parameters, and depend upon the assumed distribution of ability. The results need not hold for different ability distributions.

As an example, the results presented here show that in both the 2PL and 3PL, optimal examinees contribute more information for estimating item discrimination when that discrimination is low. This cannot be interpreted to mean that low  $a$ 's are necessarily more accurately estimated than high  $a$ 's, for a fixed sample size or a fixed distribution of ability. Thissen and Wainer (1982), using the expected asymptotic variance/covariance matrix and assuming a normal distribution of ability, show that, for fixed  $b$ , the asymptotic standard error of  $a$  decreases with  $a$  for the 2PL. However, for fixed  $b$  in the 3PL model, the asymptotic error of  $a$  is larger for both small and large values of  $a$  than it is for more moderate values of  $a$ . These results depend on the assumed distribution of ability as well as the covariances among the item parameters.

As an illustration of this phenomenon, Figure 4 shows the Thissen and Wainer asymptotic standard error of  $b$  plotted against  $b$  for the 3PL (solid curve). This is a partial reproduction of Thissen and Wainer's Figure 1, with  $a = 1.5$ ,  $c = 0.$ , and a standard normal calibration sample of  $N = 2500$ . The results presented here suggest that a calibration sample with a larger spread of abilities will improve the accuracy of the estimation of high and low difficulties. Figure 4 shows the same information for the same item when a calibration sample of the same size is drawn from a normal distribution of ability with a variance of 4 (dashed line). Although the sample size is the same, the accuracy of estimation is much improved for the more extreme difficulties.

-----

Insert Figure 4 about here

-----

Given the knowledge of the location of optimal examinees for estimating the parameters for a single item in three different item response models presented here, what suggestions can we make for calibration sample selection that would aid practitioners who must jointly estimate the item parameters for many items simultaneously? If the practitioner chooses the 1PL as the appropriate model, then examinees whose true ability is equal to item difficulty are most

informative. If a collection of items to be calibrated is thought to have a broad spread of difficulties, based perhaps on the conventional proportions correct, then the distribution of true abilities in the calibration sample should also be broad. Such a sample could possibly be selected based on some available observed auxiliary information. If the range of abilities is too small, the sample will provide information only for middle difficulty items; little information will be provided to estimate the difficulty for easy and hard items.

If the 2PL is the appropriate model, estimation of both  $a$  and  $b$  requires a wider range of true abilities than for the 1PL. This is so because only examinees with ability not equal to  $b$  are informative in the estimation of  $a$ . If the range of abilities is too small, information for the estimation of difficulties for middle level items may be provided, but information for estimating their discrimination may not be. Information for the estimation of discriminations for easy and hard items may be provided, but information for estimating their difficulties may not be.

If the 3PL is the most appropriate model, only abilities well below the item difficulty are informative about  $c$ . Abilities below and above the difficulty are most informative about  $a$  and abilities slightly above the difficulty are most informative about  $b$ . Even if

all items are of equal difficulty, a normal distribution of abilities centered slightly above the item difficulty may not provide much information for the estimation of all parameters simultaneously. If the items have a spread of difficulties, better results may be obtained by sampling all ability levels equally. Wingersky and Lord (1984) show that when item and ability parameters are estimated simultaneously, a sample of abilities drawn from a uniform distribution produces standard errors nearly as small as a sample of abilities four times as large drawn from a bell-shaped distribution.

Calibration samples, particularly for the more complex models, typically consist of several thousand examinees. Depending upon the nature of the collection of items to be calibrated, which can be roughly assessed through the use of conventional item statistics, such samples, although large, may not prove useful for estimating the parameters of all items. If the success of a particular application of IRT depends heavily on the veracity of item level data, it seems worthwhile to consider selecting more informative samples.

## References

- Cook, L. L., Petersen, N. J., & Stocking, M. L. (1983). IRT versus conventional equating methods: A comparative study of scale stability. Journal of Educational Statistics, 8, 136-156.
- Kendall, M., & Stuart, A. (1979). The advanced theory of statistics. Volume 2. Inference and Relationship. New York: Macmillan.
- Lord, F. M. (1968). An analysis of the Verbal Scholastic Aptitude Test using Birnbaum's three-parameter logistic model. Educational and Psychological Measurement, 28, 989-1020.
- Lord, F. M. (1980). Applications of item response theory to practical testing problems. Hillsdale, NJ: Erlbaum.
- Lord, F. M. (1983). Statistical bias in maximum likelihood estimators of item parameters. Psychometrika, 48, 425-435.
- Lord, F. M., & Wingersky, M. S. (1985). Sampling variances and covariances of parameter estimates in item response theory. In D. J. Weiss (Ed.), Proceedings of the 1982 IRT/CAT Conference (pp. 69-88). Minneapolis, MN: CAT Laboratory, Department of Psychology, University of Minnesota.
- Mislevy, R. J., & Sheehan, K. M. (1988). The information matrix in latent variable model. Research Report 88-24. Princeton, NJ: Educational Testing Service.

- Stocking, M. L. (1988). Scale drift in on-line calibration. Report 88-24. Princeton, NJ: Educational Testing Service.
- Thissen, D., & Wainer, H. (1982). Some standard errors in item response theory. Psychometrika, 47, 397-412.
- Wingersky, M. S., & Lord, F. M. (1984). An investigation of methods for reducing sampling error in certain IRT procedures. Applied Psychological Measurement, 8, 347-364.
- van der Linden, W. J., & Boekkooi-Timminga, E. (1987). A maximum model for test design with practical constraints. Research Report 87-10. Princeton, NJ: Educational Testing Service.

Acknowledgment

This work was supported by Contract No. N00014-83-C-0457, project designation NR 150-520, from Cognitive Science Program, Cognitive and Neural Sciences Division, Office of Naval Research and Educational Testing Service through the Program Research Planning Council. Reproduction in whole or in part is permitted for any purpose of the United States Government. The author wishes to acknowledge the invaluable assistance of Maxine B. Kingston in carrying out this study, and to thank Dr. Charles Lewis for his many insightful comments on earlier drafts of this paper.

Table 1

Optimum Abilities and Maximum Contributions (in Parentheses)  
to Information for Estimating a or b Assuming Fixed Values  
for the Other Parameters for the 3PL Model with  $c = .2$

a	b	lower optimal $\theta$ for a	upper optimal $\theta$ for a	optimal $\theta$ for b
.5 ( $i_{aa} = .58, 1.38$ ) ( $i_{bb} = .12$ )	-2	-3.96	.86	-1.69
	-1	-2.96	1.86	-.69
	0	-1.96	2.86	.31
	1	-.96	3.86	1.31
	2	.04	4.86	2.31
1.0 ( $i_{aa} = .14, .35$ ) ( $i_{bb} = .49$ )	-2	-2.98	-.57	-1.84
	-1	-1.98	.43	-.84
	0	-.98	1.43	.16
	1	.02	2.43	1.16
	2	1.02	3.43	2.16
1.5 ( $i_{aa} = .06, .15$ ) ( $i_{bb} = 1.11$ )	-2	-2.65	-1.05	-1.90
	-1	-1.65	-.05	-.90
	0	-.65	.95	.10
	1	.35	1.95	1.10
	2	1.35	2.95	2.10
2.0 ( $i_{aa} = .04, .09$ ) ( $i_{bb} = 1.97$ )	-2	-2.49	-1.28	-1.92
	-1	-1.49	-.28	-.92
	0	-.49	.72	.08
	1	.51	1.72	1.08
	2	1.51	2.72	2.08
2.5 ( $i_{aa} = .02, .06$ ) ( $i_{bb} = 3.08$ )	-2	-2.39	-1.43	-1.94
	-1	-1.39	-.43	-.94
	0	-.39	.57	.06
	1	.61	1.57	1.06
	2	1.61	2.57	2.06

Table 2

Optimum Abilities and Maximum Contributions (in Parentheses) to Information for Estimating a or b Assuming Fixed Values for the Other Parameters for the 2PL and 1PL Models with  $c = 0$

a	b	lower optimal $\theta$ for a	upper optimal $\theta$ for a	optimal $\theta$ for b
.5 ( $i_{aa} = 1.76, 1.76$ ) ( $i_{bb} = .18$ )	-2	-4.82	.82	-2.00
	-1	-3.82	1.82	-1.00
	0	-2.82	2.82	.00
	1	-1.82	3.82	1.00
	2	-.82	4.82	2.00
1.0 ( $i_{aa} = .44, .44$ ) ( $i_{bb} = .72$ )	-2	-3.41	-.59	-2.00
	-1	-2.41	.41	-1.00
	0	-1.41	1.41	.00
	1	-.41	2.41	1.00
	2	.59	3.41	2.00
1.5 ( $i_{aa} = .20, .20$ ) ( $i_{bb} = 1.63$ )	-2	-2.94	-1.06	-2.00
	-1	-1.94	-.06	-1.00
	0	-.94	.94	.00
	1	.06	1.94	1.00
	2	1.06	2.94	2.00
2.0 ( $i_{aa} = .11, .11$ ) ( $i_{bb} = 2.90$ )	-2	-2.70	-1.30	-2.00
	-1	-1.70	-.30	-1.00
	0	-.70	.70	.00
	1	.30	1.70	1.00
	2	1.30	2.70	2.00
2.5 ( $i_{aa} = .07, .07$ ) ( $i_{bb} = 4.53$ )	-2	-2.56	-1.44	-2.00
	-1	-1.56	-.44	-1.00
	0	-.56	.56	.00
	1	.44	1.56	1.00
	2	1.44	2.56	2.00

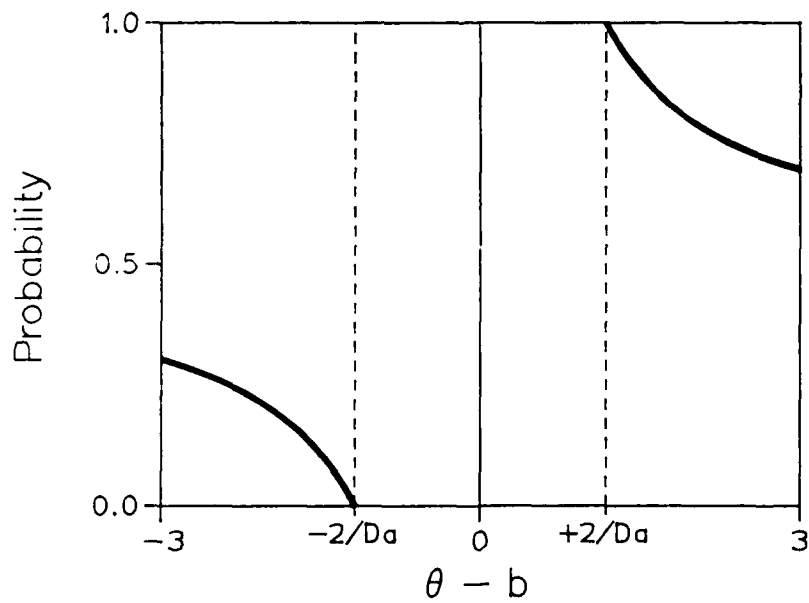
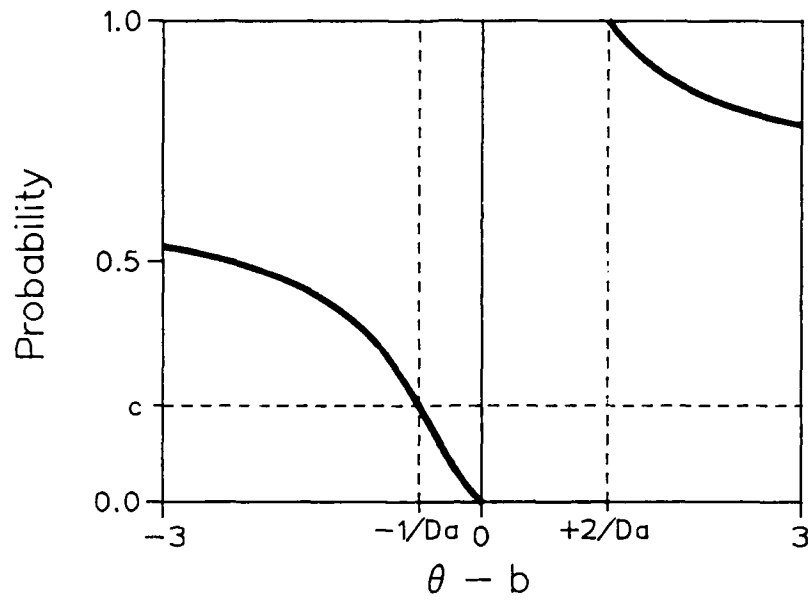


Figure 1. The top panel shows  $P$  as a function of  $\theta - b$  from Equation 9 for the 3PL (solid curves). The bottom panel shows  $P$  as a function of  $\theta - b$  from Equation 12 for the 2PL (solid curves).

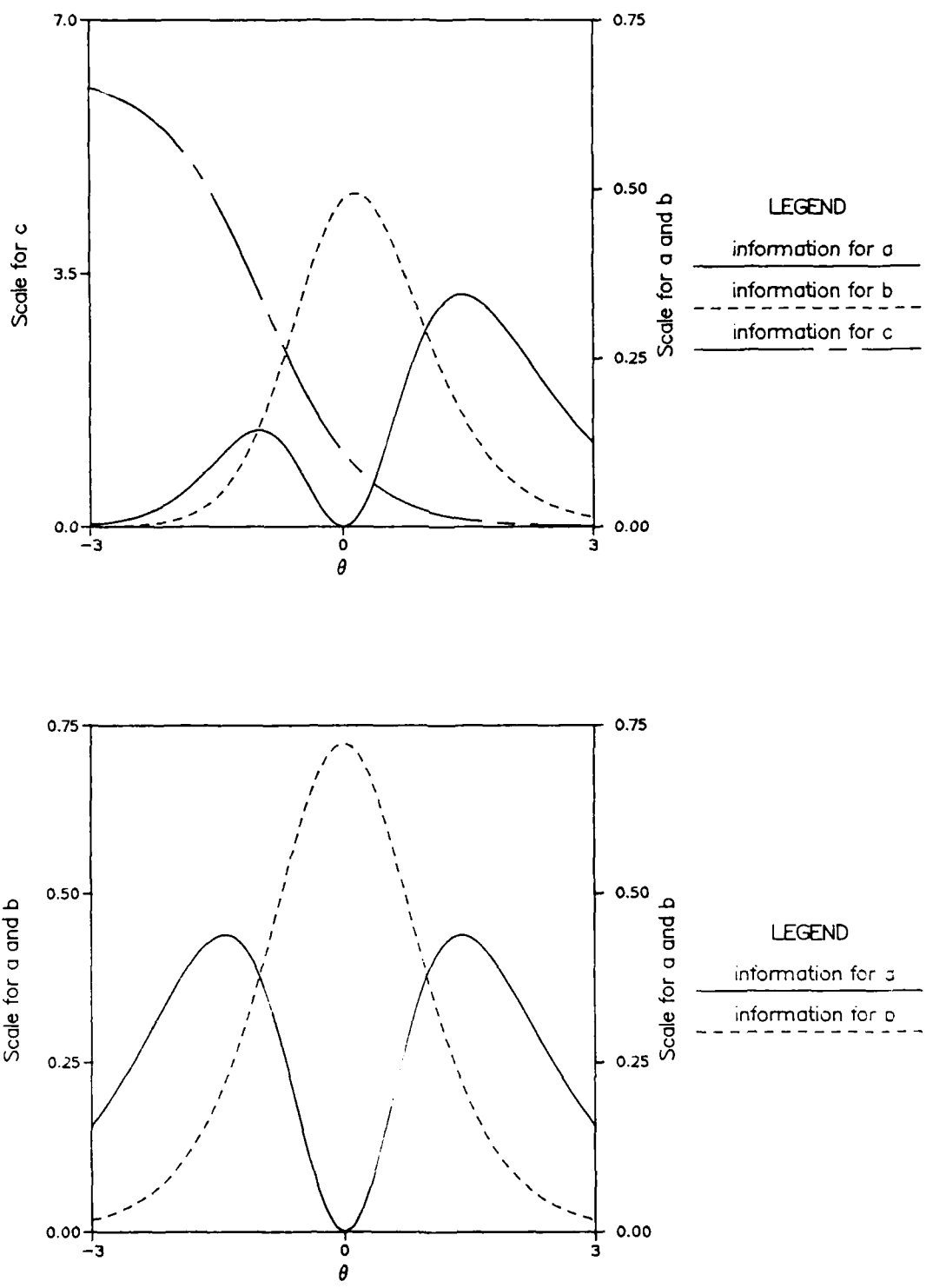


Figure 2. Contributions to information for estimating item parameters as functions of ability for the 3PL (top;  $a=1, b=0, c=.2$ ), the 2PL and 1PL (bottom;  $a=1, b=0$ ).

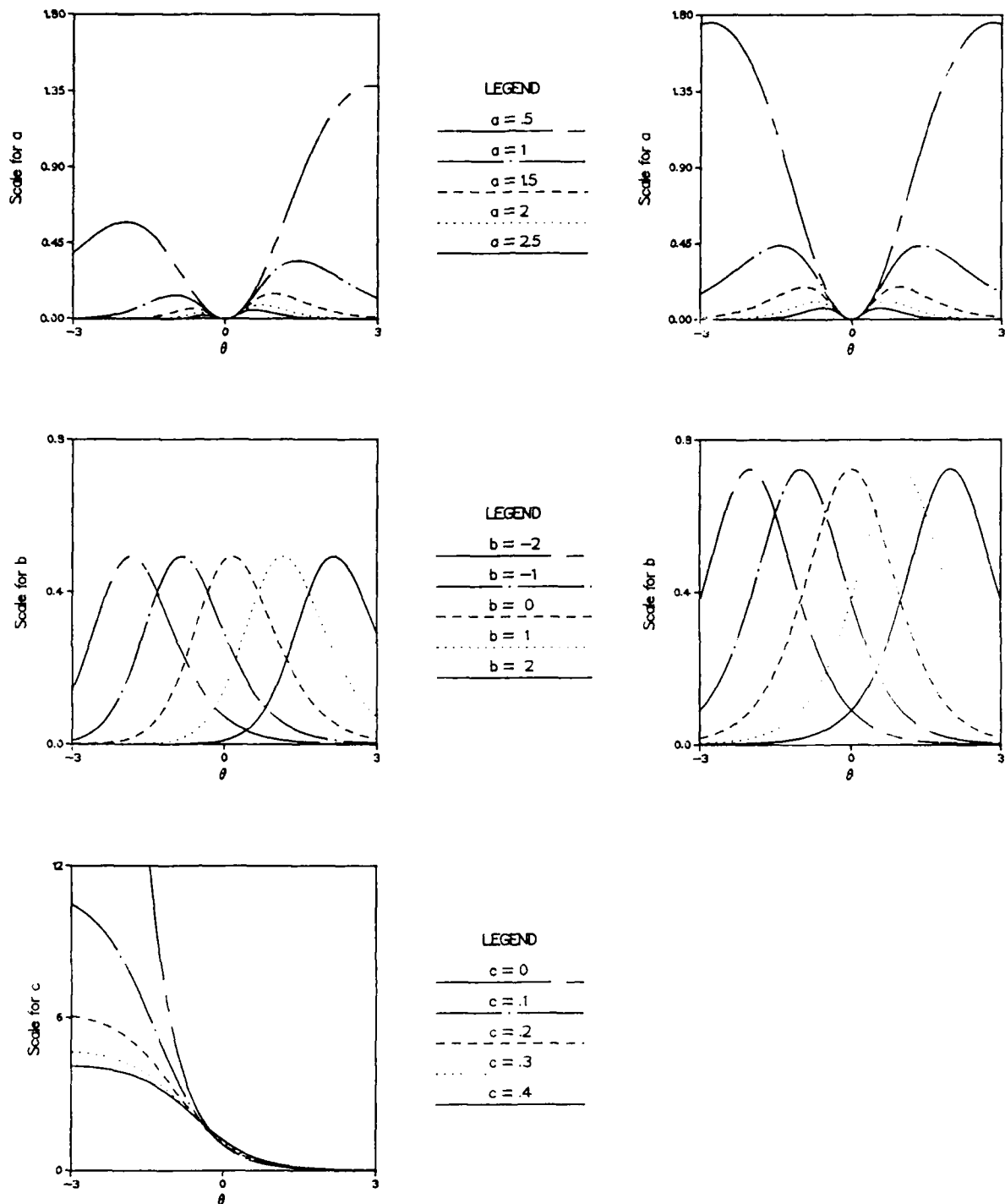


Figure 3. Contributions to information for estimating item parameters for the 3PL (left) and 2PL and 1PL (right). The effects of varying  $a$  conditional on fixed  $b=0$  (and  $c=.2$  for the 3PL) are shown in the top row. The effects of varying  $b$  for fixed  $a=1$  (and  $c=.2$  for the 3PL) are shown in the middle row. The effects of varying  $c$  for the 3PL conditional on  $a=1$  and  $b=0$  are shown in the bottom row.

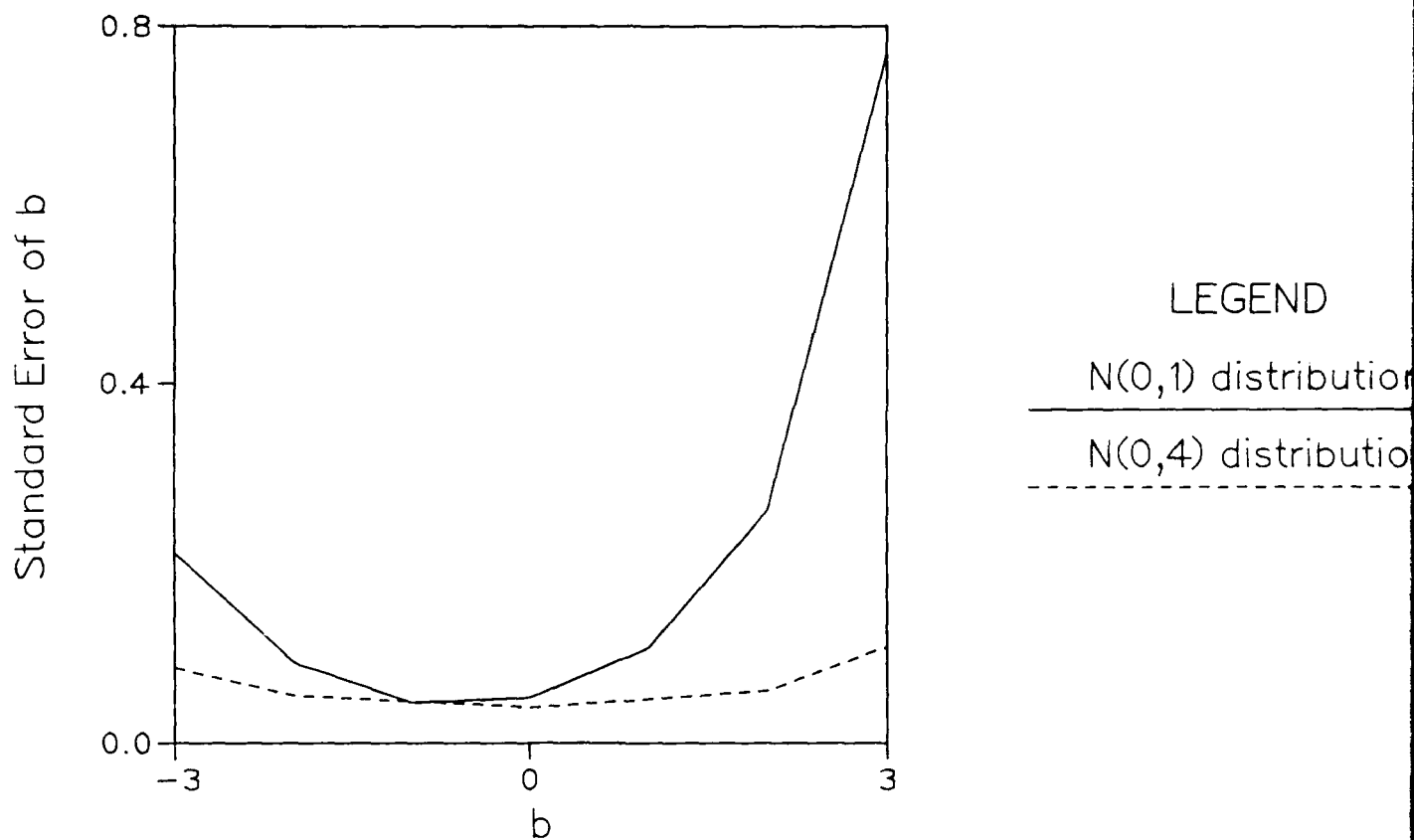


Figure 4. Standard errors of estimated item difficulties for the 3PL model,  $a=1.5$ ,  $c=0$ . A calibration sample of  $N=2,500$  is drawn from an  $N(0,1)$  distribution (solid) and from an  $N(0,4)$  distribution (dotted).

## Educational Testing Service/Stocking

Dr. Terry Ackerman  
American College Testing Programs  
P.O. Box 168  
Iowa City, IA 52243

Dr. Robert Ahlers  
Code N711  
Human Factors Laboratory  
Naval Training Systems Center  
Orlando, FL 32813

Dr. James Algina  
1403 Norman Hall  
University of Florida  
Gainesville, FL 32605

Dr. Erling B. Andersen  
Department of Statistics  
Studivestraede 6  
1455 Copenhagen  
DENMARK

Dr. Eva L. Baker  
UCLA Center for the Study  
of Evaluation  
145 Moore Hall  
University of California  
Los Angeles, CA 90024

Dr. Isaac Bejar  
Mail Stop: 10-R  
Educational Testing Service  
Rosedale Road  
Princeton, NJ 08541

Dr. Menucha Birenbaum  
School of Education  
Tel Aviv University  
Ramat Aviv 69978  
ISRAEL

Dr. Arthur S. Blaiwes  
Code N712  
Naval Training Systems Center  
Orlando, FL 32813-7100

Dr. Bruce Bloxom  
Defense Manpower Data Center  
550 Camino El Estero,  
Suite 200  
Monterey, CA 93943-3231

Dr. R. Darrell Bock  
University of Chicago  
NORC  
6030 South Ellis  
Chicago, IL 60637

Cdt. Arnold Bohrer  
Sectie Psychologisch Onderzoek  
Rekruterings-En Selectiecentrum  
Kwartier Koningen Astrid  
Bruijnstraat  
1120 Brussels, BELGIUM

Dr. Robert Breaux  
Code 7B  
Naval Training Systems Center  
Orlando, FL 32813-7100

Dr. Robert Brennan  
American College Testing  
Programs  
P. O. Box 168  
Iowa City, IA 52243

Dr. James Carlson  
American College Testing  
Program  
P.O. Box 168  
Iowa City, IA 52243

Dr. John B. Carroll  
409 Elliott Rd., North  
Chapel Hill, NC 27514

Dr. Robert M. Carroll  
Chief of Naval Operations  
OP-01B2  
Washington, DC 20350

Dr. Raymond E. Christal  
UES LAMP Science Advisor  
AFHRL/MOEL  
Brooks AFB, TX 78235

Dr. Norman Cliff  
Department of Psychology  
Univ. of So. California  
Los Angeles, CA 90089-1061

## Educational Testing Service/Stocking

Director,  
 Manpower Support and  
 Readiness Program  
 Center for Naval Analysis  
 2000 North Beauregard Street  
 Alexandria, VA 22311

Dr. Stanley Collyer  
 Office of Naval Technology  
 Code 222  
 800 N. Quincy Street  
 Arlington, VA 22217-5000

Dr. Hans F. Crombag  
 Faculty of Law  
 University of Limburg  
 P.O. Box 616  
 Maastricht  
 The NETHERLANDS 6200 MD

Dr. Timothy Davey  
 Educational Testing Service  
 Princeton, NJ 08541

Dr. C. M. Dayton  
 Department of Measurement  
 Statistics & Evaluation  
 College of Education  
 University of Maryland  
 College Park, MD 20742

Dr. Ralph J. DeAyala  
 Measurement, Statistics,  
 and Evaluation  
 Benjamin Bldg., Rm. 4112  
 University of Maryland  
 College Park, MD 20742

Dr. Dattprasad Divgi  
 Center for Naval Analysis  
 4401 Ford Avenue  
 P.O. Box 16268  
 Alexandria, VA 22302-0268

Dr. Hei-Ki Dong  
 Bell Communications Research  
 6 Corporate Place  
 PYA-1K226  
 Piscataway, NJ 08854

Dr. Fritz Drasgow  
 University of Illinois  
 Department of Psychology  
 603 E. Daniel St.  
 Champaign, IL 61820

Defense Technical  
 Information Center  
 Cameron Station, Bldg 5  
 Alexandria, VA 22314  
 Attn: TC  
 (12 Copies)

Dr. Stephen Dunbar  
 224B Lindquist Center  
 for Measurement  
 University of Iowa  
 Iowa City, IA 52242

Dr. James A. Earles  
 Air Force Human Resources Lab.  
 Brooks AFB, TX 78235

Dr. Kent Eaton  
 Army Research Institute  
 5001 Eisenhower Avenue  
 Alexandria, VA 22333

Dr. John M. Eddins  
 University of Illinois  
 252 Engineering Research  
 Laboratory  
 103 South Mathews Street  
 Urbana, IL 61801

Dr. Susan Embretson  
 University of Kansas  
 Psychology Department  
 426 Fraser  
 Lawrence, KS 66045

Dr. George Englehard, Jr.  
 Division of Educational Studies  
 Emory University  
 210 Fishburne Bldg.  
 Atlanta, GA 30322

Dr. Benjamin A. Fairbank  
 Performance Metrics, Inc.  
 5825 Callaghan  
 Suite 225  
 San Antonio, TX 78228

## Educational Testing Service/Stocking

Dr. P-A. Federico  
Code 51  
NPRDC  
San Diego, CA 92152-6800

Dr. Leonard Feldt  
Lindquist Center  
for Measurement  
University of Iowa  
Iowa City, IA 52242

Dr. Richard L. Ferguson  
American College Testing  
P.O. Box 168  
Iowa City, IA 52243

Dr. Gerhard Fischer  
Liebiggasse 5/3  
A 1010 Vienna  
AUSTRIA

Dr. Myron Fischl  
U.S. Army Headquarters  
DAPE-MER  
The Pentagon  
Washington, DC 20310-0300

Prof. Donald Fitzgerald  
University of New England  
Department of Psychology  
Armidale, New South Wales 2351  
AUSTRALIA

Mr. Paul Foley  
Navy Personnel R&D Center  
San Diego, CA 92152-6800

Dr. Alfred R. Fregly  
AFOSR/NL, Bldg. 410  
Bolling AFB, DC 20332-6448

Dr. Robert D. Gibbons  
Illinois State Psychiatric Inst.  
Rm 529W  
1601 W. Taylor Street  
Chicago, IL 60612

Dr. Janice Gifford  
University of Massachusetts  
School of Education  
Amherst, MA 01003

Dr. Robert Glaser  
Learning Research  
& Development Center  
University of Pittsburgh  
3939 O'Hara Street  
Pittsburgh, PA 15260

Dr. Bert Green  
Johns Hopkins University  
Department of Psychology  
Charles & 34th Street  
Baltimore, MD 21218

DORNIER GMBH  
P.O. Box 1420  
D-7990 Friedrichshafen 1  
WEST GERMANY

Dr. Ronald K. Hambleton  
University of Massachusetts  
Laboratory of Psychometric  
and Evaluative Research  
Hills South, Room 152  
Amherst, MA 01003

Dr. Delwyn Harnisch  
University of Illinois  
51 Gerty Drive  
Champaign, IL 61820

Dr. Grant Henning  
Senior Research Scientist  
Division of Measurement  
Research and Services  
Educational Testing Service  
Princeton, NJ 08541

Ms. Rebecca Hetter  
Navy Personnel R&D Center  
Code 63  
San Diego, CA 92152-6800

Dr. Paul W. Holland  
Educational Testing Service, 21-T  
Rosedale Road  
Princeton, NJ 08541

Prof. Lutz F. Horntke  
Institut für Psychologie  
RWTH Aachen  
Jaegerstrasse 17/19  
D-5100 Aachen  
WEST GERMANY

## Educational Testing Service/Stocking

Dr. Paul Horst  
677 G Street, #184  
Chula Vista, CA 92010

Mr. Dick Hoshaw  
QP-135  
Arlington Annex  
Room 2834  
Washington, DC 20350

Dr. Lloyd Humphreys  
University of Illinois  
Department of Psychology  
603 East Daniel Street  
Champaign, IL 61820

Dr. Steven Hunka  
3-104 Educ. N.  
University of Alberta  
Edmonton, Alberta  
CANADA T6G 2G5

Dr. Huvnh Huvnh  
College of Education  
Univ. of South Carolina  
Columbia, SC 29208

Dr. Robert Jannarone  
Elec. and Computer Eng. Dept.  
University of South Carolina  
Columbia, SC 29208

Dr. Douglas H. Jones  
Thatcher Jones Associates  
P.O. Box 6640  
10 Trafalgar Court  
Lawrenceville, NJ 08648

Dr. Milton S. Katz  
European Science Coordination  
Office  
U.S. Army Research Institute  
Box 65  
FPO New York 09510-1500

Prof. John A. Keats  
Department of Psychology  
University of Newcastle  
N.S.W. 2308  
AUSTRALIA

Dr. G. Gage Kingsbury  
Portland Public Schools  
Research and Evaluation Department  
501 North Dixon Street  
P. O. Box 3107  
Portland, OR 97209-3107

Dr. William Koch  
Box 7246, Meas. and Eval. Ctr.  
University of Texas-Austin  
Austin, TX 78703

Dr. James Kraatz  
Computer-based Education  
Research Laboratory  
University of Illinois  
Urbana, IL 61801

Dr. Leonard Kroeker  
Navy Personnel R&D Center  
Code 62  
San Diego, CA 92152-6800

Dr. Jerry Lehnus  
Defense Manpower Data Center  
Suite 400  
1600 Wilson Blvd  
Rosslyn, VA 22209

Dr. Thomas Leonard  
University of Wisconsin  
Department of Statistics  
1210 West Dayton Street  
Madison, WI 53705

Dr. Michael Levine  
Educational Psychology  
210 Education Bldg.  
University of Illinois  
Champaign, IL 61801

Dr. Charles Lewis  
Educational Testing Service  
Princeton, NJ 08541-0001

Dr. Robert L. Linn  
Campus Box 249  
University of Colorado  
Boulder, CO 80309-0249

## Educational Testing Service/Stocking

Dr. Robert Lockman  
Center for Naval Analysis  
4401 Ford Avenue  
P.O. Box 16268  
Alexandria, VA 22302-0268

Dr. Frederic M. Lord  
Educational Testing Service  
Princeton, NJ 08541

Dr. George B. Macready  
Department of Measurement  
Statistics & Evaluation  
College of Education  
University of Maryland  
College Park, MD 20742

Dr. Gary Marco  
Stop 31-E  
Educational Testing Service  
Princeton, NJ 08451

Dr. James R. McBride  
The Psychological Corporation  
1250 Sixth Avenue  
San Diego, CA 92101

Dr. Clarence C. McCormick  
HQ, USMEPCOM/MEPCT  
2500 Green Bay Road  
North Chicago, IL 60064

Dr. Robert McKinley  
Educational Testing Service  
16-T  
Princeton, NJ 08541

Dr. James McMichael  
Technical Director  
Navy Personnel R&D Center  
San Diego, CA 92152-6800

Dr. Barbara Means  
SRI International  
333 Ravenswood Avenue  
Menlo Park, CA 94025

Dr. Robert Mislevy  
Educational Testing Service  
Princeton, NJ 08541

Dr. William Montague  
NPRDC Code 13  
San Diego, CA 92152-6800

Ms. Kathleen Moreno  
Navy Personnel R&D Center  
Code 62  
San Diego, CA 92152-6800

Headquarters Marine Corps  
Code MPI-20  
Washington, DC 20380

Dr. W. Alan Nicewander  
University of Oklahoma  
Department of Psychology  
Norman, OK 73071

Deputy Technical Director  
NPRDC Code 01A  
San Diego, CA 92152-6800

Director, Training Laboratory,  
NPRDC (Code 05)  
San Diego, CA 92152-6800

Director, Manpower and Personnel  
Laboratory,  
NPRDC (Code 06)  
San Diego, CA 92152-6800

Director, Human Factors  
& Organizational Systems Lab,  
NPRDC (Code 07)  
San Diego, CA 92152-6800

Library, NPRDC  
Code F201L  
San Diego, CA 92152-6800

Commanding Officer,  
Naval Research Laboratory  
Code 2627  
Washington, DC 20390

Dr. Harold F. O'Neil, Jr.  
School of Education - WPH 801  
Department of Educational  
Psychology & Technology  
University of Southern California  
Los Angeles, CA 90089-0031

## Educational Testing Service/Stocking

Dr. James B. Olsen  
WICAT Systems  
1875 South State Street  
Orem, UT 84058

Office of Naval Research,  
Code 1142CS  
800 N. Quincey Street  
Arlington, VA 22217-5000  
(6 Copies)

Office of Naval Research,  
Code 12F  
800 N. Quincey Street  
Arlington, VA 22217-5000

Assistant for MPE Research,  
Development and Studies  
OP 01B7  
Washington, DC 20370

Dr. Judith Orasanu  
Basic Research Office  
Army Research Institute  
5001 Eisenhower Avenue  
Alexandria, VA 22333

Dr. Jesse Orlansky  
Institute for Defense Analyses  
1801 N. Beauregard St.  
Alexandria, VA 22311

Dr. Randolph Park  
Army Research Institute  
5001 Eisenhower Blvd.  
Alexandria, VA 22333

Wayne M. Patience  
American Council on Education  
GED Testing Service, Suite 20  
One Dupont Circle, NW  
Washington, DC 20036

Dr. James Paulson  
Department of Psychology  
Portland State University  
P.O. Box 751  
Portland, OR 97207

Dept. of Administrative Sciences  
Code 54  
Naval Postgraduate School  
Monterey, CA 93943-5026

Department of Operations Research,  
Naval Postgraduate School  
Monterey, CA 93940

Dr. Mark D. Reckase  
ACT  
P. O. Box 168  
Iowa City, IA 52243

Dr. Malcolm Ree  
AFHRL/MQA  
Brooks AFB, TX 78235

Dr. Barry Riegelhaupt  
HumRRD  
1100 South Washington Street  
Alexandria, VA 22314

Dr. Carl Ross  
CNLT-PDCD  
Building 90  
Great Lakes NTC, IL 60085

Dr. J. Ryan  
Department of Education  
University of South Carolina  
Columbia, SC 29208

Dr. Fumiko Samejima  
Department of Psychology  
University of Tennessee  
310B Austin Peay Bldg.  
Knoxville, TN 37916-0900

Mr. Drew Sands  
NPRDC Code 62  
San Diego, CA 92152-6800

Lowell Schoer  
Psychological & Quantitative  
Foundations  
College of Education  
University of Iowa  
Iowa City, IA 52242

Dr. Mary Schratz  
Navy Personnel R&D Center  
San Diego, CA 92152-6800

Dr. Dan Segall  
Navy Personnel R&D Center  
San Diego, CA 92152

## Educational Testing Service/Stocking

Dr. W. Steve Sellman  
DASQ (MRA&L)  
2B269 The Pentagon  
Washington, DC 20301

Dr. Kazuo Shigemasu  
7-9-24 Kugenuma-Kaigan  
Fujisawa 251  
JAPAN

Dr. William Sims  
Center for Naval Analysis  
4401 Ford Avenue  
P.O. Box 16268  
Alexandria, VA 22302-0268

Dr. H. Wallace Sinaiko  
Manpower Research  
and Advisory Services  
Smithsonian Institution  
801 North Pitt Street, Suite 120  
Alexandria, VA 22314-1713

Dr. Richard E. Snow  
School of Education  
Stanford University  
Stanford, CA 94305

Dr. Richard C. Sorensen  
Navy Personnel R&D Center  
San Diego, CA 92152-6800

Dr. Paul Speckman  
University of Missouri  
Department of Statistics  
Columbia, MO 65201

Dr. Judy Sprav  
ACT  
P.O. Box 166  
Iowa City, IA 52243

Dr. Martha Stocking  
Educational Testing Service  
Princeton, NJ 08541

Dr. William Stout  
University of Illinois  
Department of Statistics  
101 Illini Hall  
725 South Wright St.  
Champaign, IL 61820

Dr. Hariharan Swaminathan  
Laboratory of Psychometric and  
Evaluation Research  
School of Education  
University of Massachusetts  
Amherst, MA 01003

Mr. Brad Sympson  
Navy Personnel R&D Center  
Code-62  
San Diego, CA 92152-6800

Dr. John Tangney  
AFOSR/NL, Bldg. 410  
Bolling AFB, DC 20332-6448

Dr. Kikumi Tatsuoka  
CERL  
252 Engineering Research  
Laboratory  
103 S. Mathews Avenue  
Urbana, IL 61801

Dr. Maurice Tatsuoka  
220 Education Bldg  
1310 S. Sixth St.  
Champaign, IL 61820

Dr. David Thissen  
Department of Psychology  
University of Kansas  
Lawrence, KS 66044

Mr. Gary Thomasson  
University of Illinois  
Educational Psychology  
Champaign, IL 61820

Dr. Robert Tsutakawa  
University of Missouri  
Department of Statistics  
222 Math. Sciences Bldg.  
Columbia, MO 65211

Dr. Ledyard Tucker  
University of Illinois  
Department of Psychology  
603 E. Daniel Street  
Champaign, IL 61820

## Educational Testing Service/Stocking

Dr. Vern W. Urry  
 Personnel R&D Center  
 Office of Personnel Management  
 1900 E. Street, NW  
 Washington, DC 20415

Dr. David Vale  
 Assessment Systems Corp.  
 2233 University Avenue  
 S.u.t. 440  
 St. Paul, MN 55114

Dr. Frank L. Vicino  
 Navy Personnel R&D Center  
 San Diego, CA 92152-6800

Dr. Howard Wainer  
 Educational Testing Service  
 Princeton, NJ 08541

Dr. Ming-Mei Wang  
 Lindquist Center  
 for Measurement  
 University of Iowa  
 Iowa City, IA 52242

Dr. Thomas A. Warm  
 Coast Guard Institute  
 P. O. Substation 18  
 Oklahoma City, OK 73169

Dr. Brian Waters  
 HumPRO  
 12908 Argyle Circle  
 Alexandria, VA 22314

Dr. David J. Weiss  
 N650 Elliott Hall  
 University of Minnesota  
 75 E. River Road  
 Minneapolis, MN 55455-0344

Dr. Ronald A. Weitzman  
 Box 146  
 Carmel, CA 93921

Major John Welsh  
 AFHPL/MOAN  
 Brooks AFB, TX 78223

Dr. Douglas Wetzel  
 Code 51  
 Navy Personnel R&D Center  
 San Diego, CA 92152-6800

Dr. Rand R. Wilcox  
 University of Southern  
 California  
 Department of Psychology  
 Los Angeles, CA 90089-1061

German Military Representative  
 ATIN: Wolfgang Wildgrube  
 Streitkrafteamt  
 D-5300 Bonn 2  
 4000 Brandywine Street, NW  
 Washington, DC 20016

Dr. Bruce Williams  
 Department of Educational  
 Psychology  
 University of Illinois  
 Urbana, IL 61801

Dr. Hilda Wing  
 NRC MH-176  
 2101 Constitution Ave.  
 Washington, DC 20418

Dr. Martin F. Wiskoff  
 Defense Manpower Data Center  
 550 Camino El Estero  
 Suite 200  
 Monterey, CA 93943-3231

Mr. John H. Wolfe  
 Navy Personnel R&D Center  
 San Diego, CA 92152-6800

Dr. George Wong  
 Biostatistics Laboratory  
 Memorial Sloan-Kettering  
 Cancer Center  
 1275 York Avenue  
 New York, NY 10021

Dr. Wallace Wulfeck, III  
 Navy Personnel R&D Center  
 Code 51  
 San Diego, CA 92152-6800

Educational Testing Service/Stocking

Dr. Kentaro Yamamoto  
03-T  
Educational Testing Service  
RoseJale Road  
Princeton, NJ 08541

Dr. Wendy Yen  
CTB/McGraw Hill  
Del Monte Research Park  
Monterey, CA 93940

Dr. Joseph L. Young  
National Science Foundation  
Room 320  
1800 G Street, N.W.  
Washington, DC 20550

Mr. Anthony R. Zara  
National Council of State  
Boards of Nursing, Inc.  
625 North Michigan Avenue  
Suite 1544  
Chicago, IL 60611

Dr. Peter Stoloff  
Center for Naval Analysis  
4401 Ford Avenue  
P.O. Box 16268  
Alexandria, VA 22302-0268