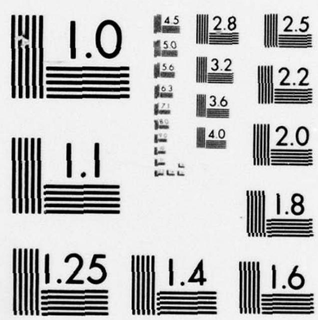
AD-A052 906 AIR FORCE MILITARY PERSONNEL CENTER RANDOLPH AFB TEX F/G 5/9
FORECASTING OFFICER LOSSES-AN EXAMINATION OF METHODS.(U)
SEP 77 T M BEATTY

UNCLASSIFIED NL

| OF |

AD
A052906

END
DATE
FILMED
5-78
DDC



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

AD A052906

(12)

FORECASTING OFFICER LOSSES-

AN EXAMINATION OF METHODS

TECHNICAL REPORT

BY

T.M. BEATTY

SEPTEMBER 1977

MODELING BRANCH
SYSTEMS DEVELOPMENT AND SUPPORT DIVISION
DIRECTORATE OF PERSONNEL DATA SYSTEMS
AIR FORCE MILITARY PERSONNEL CENTER
RANDOLPH AFB, TEXAS 78148

12

6

FORECASTING OFFICER LOSSES-
AN EXAMINATION OF METHODS.

TECHNICAL REPORT

BY

10 T.M. BEATTY

9 Technical rept.,

12 21p.

11 SEP[redacted]77

APPROVED BY:

FREDERICK S. PHILLIPS, SR., COL, USAF
DIRECTOR, PERSONNEL DATA SYSTEMS

While the contents of this report are considered to be correct, they are subject to modification upon further study. This report does not promulgate official Air Force policies or procedures. The technical conclusions are solely those of the author.

408077

ABSTRACT

Air Force Personnel Managers must be able to accurately forecast the force size. This need is explicit in meeting statutory budget limitations. Further officer losses drive accession, training, and promotion, thus the need for accuracy in forecasting losses cannot be over emphasized. To accomplish this objective loss rates have been generated using Ordinary Least Squares (OLS) stepwise regression. The objective of this paper is to expose the relative efficacies of alternative methods which could be used viz. Maximum Likelihood Estimation (MLE) and OLS standardized coefficient (Beta) predictor models.

PART I. INTRODUCTION

Background

The Directorate of Personnel Data Systems of the Air Force Military Personnel Center is the prime agency for providing officer loss rates for all personnel management actions within HQ USAF. Currently this objective is satisfied by using OLS stepwise regression and an OLS derivative technique called Odds for Effectiveness (OFE). It is presumed that readers of this paper are thoroughly familiar with; (1) The need for and various modeling/simulation applications of loss rates, and (2) The fundamentals and applications of OLS. Therefore the objective of this paper will be to compare candidate methods to produce viable loss rates, and not a tutorial on theories as to why or how loss rates may be generated.

A project was initiated late in 1976 to evaluate candidate methods for producing reliable officer loss rates. Since much has been written of late concerning MLE (See Nerlove and Press #1, Dempsey and Fast #2, Lockman & Warner #3), and these authors as well as others contend that MLE is more reliable for predicting the dichotomous dependent variable, the MLE method was the top contender to replace OLS ... MLE is theoretically more stable over time (i.e. the concomitant data shift). In search of alternative methods which may also achieve time stability, the standardized coefficient (Beta) model of OLS was also investigated. Four cases were examined:

1. Contrived data with controlled data shifts.
2. 74→75 Colonels' Retirements, Line officers.
3. 75→76 Colonels' Retirements, Line officers.
4. Fourth year group Non-Rated Line Separations 75→76.

CASE 1: CONTRIVED DATA WITH CONTROLLED SHIFTS

Three primary objectives were sought in this case; (1) Known and controlled data, (2) A small case, and (3) Controlled data shifts. To meet these objectives the following test was built:

N=50

Dependent Variable:	Off (Ø)	70%
	On (1)	30%

Variable #1 was distributed as below in the sample test file and the two x-validation files:

ON/OBS*	TEST FILE VALUE	X-VAL FILE #1 VALUE	X-VAL FILE #2 VALUE
1/10	1	0	0
2/10	8	9	5
3/10	27	22	22
4/10	64	72	60
5/10	125	150	110

Variables 2 and 3 were held constant in all three files as below:

		VAR 2: 0	VAR 2: 1
VAR 3	0	0/12	7/13
	1	7/13	1/12

Variable four was distributed as follows in the three files:

ON/OBS	TEST FILE VALUE	X-VAL FILE #1 VALUE	X-VAL FILE #2 VALUE
1/10	1	3	0
3/10	2	5	1
7/10	3	6	2
3/10	4	7	2
1/10	5	9	3

CASE 2: COLONELS' RETIREMENT 74→75, LINE OFFICERS

This case used historical data from the Air Force Military Personnel System with an objective of building a "weak" predictor model. The following six attributes were chosen from the '74 data to meet this objective:

*Ten observations have a value of 1 in the sample test file. One of these observations is "ON".

1. Total Active Federal Commissioned Service (TAFCS)
2. Age (years)
3. Officer Effectiveness Report, Weighted Mean
4. Officer Effectiveness Report, Current
5. Number Permanent Passovers
6. Below the Zone Selection to Colonel (1/0)

CASE 3: COLONELS' RETIREMENT 75→76, LINE OFFICERS

A more comprehensive analysis was done in this case to produce a "strong" predictor model. Historical data were analyzed for colonels' retirements in 1973, 1974 and 1975 to select the attributes and attribute values which would be used. In this analysis three conditions were imposed: (1) Consistency, (2) Discrimination, and (3) Representative incumbency. Use of these constraints provided 13 attributes which were then transformed to provide yet a "stronger" model, or at least one with a higher r-squared. Stepwise regression results subsequently reduced the number of attributes used to six:

1. Total Active Federal Commissioned Service (TAFCS)
2. Number of Dependents
3. Source of Commission
4. Permanent Grade
5. Duty Air Force Specialty Code
6. Officer Effectiveness Report, Weighted Mean

CASE 4: FOURTH YEAR GROUP NON-RATED LINE SEPARATIONS 75→76

Statistical phenomena which occur at or near .50 should be more difficult to model. Intuitively one expects the potential discriminators also to be distributed at or near a fifty-fifty split just as the dependent variable. Fourth year separations approach fifty percent for non-rated line officers as this point is the end of obligated service for all except Air Force Academy accessions. Just as in the colonels' cases the constraints of discrimination and representative incumbency were applied...consistency over time was not. Transforming the data and applying stepwise regression reduced the predictor attributes to the following nine:

1. Permanent Grade
2. Source of Commission
3. Officer Effectiveness Report, Current
4. Service Component
5. DOB (year)
6. Major Air Command Assigned
7. Officer Effectiveness Report, Weighted Mean
8. Race
9. Academic Specialty

METHOD

In each of the four cases prediction equations were developed using the three methods to be evaluated; MLE, OLS Simple B, and OLS standardized (Beta). Then these equations were applied to the sample test file to compute the probability of attrition for each observation in the following manner: $P(A) = \Sigma$coefficient*F(observed value). In this application the function of the observed value concept was used because of the diversity of the three models, in which the B model uses raw values, the Beta model uses standardized variates and the MLE model uses deviation from the mean.

A cut score was determined which correctly identified the observed number of attriters in the sample test file. For example in the Beta Model the observations which have a computed probability of greater than .64 might account for the known number of observations which were attriters. This cut score would be used to predict the 1/0 (attrit/non-attrit) status of the observations in the cross validation file.

The predictor equations were then applied to the cross validation files. In each of the three live data cases, these files were the next years population which is analogous to the real-world problem of predicting into the future year. However, historical data were employed for cross validation purposes and actual attrition results were known and used for analysis of prediction efficiency. Likewise in the contrived data case, the results of the "future" were known and used to measure predictive strength of the various models.

In all cases the data is displayed not only as the number of predicted attriters but also in the classical hits/false-positive/false-negative format commonly used in screening applications. Additionally the expected value concept was examined. Expected value might be employed in a stochastic model wherein the probability of attrition is computed and compared to a uniform random number to make the 1/0 determination. For this reason, the expected value of a cross validation run (the sum of all the computed probabilities) is a pertinent index of predictive strength in the arena of officer loss rates.

PART II. RESULTS

CASE 1 - CONTRIVED DATA

Correlation matrices are revealing tools in the analysis of data and are, in fact, the "guts" of OLS. As can be seen in the table below the correlation matrix for the sample test file does not protend for a strong predictor model and the resulting R-Squared of 0.19 supported this conclusion.

Intercorrelation Matrix for Case 1

	Y	X_1	X_2	X_3	X_4
Y	1.00	.29	.04	.04	0
X_1	.29	1.00	-.57	-.20	.43
X_2	.04	-.57	1.00	-.04	-.37
X_3	.04	-.20	-.04	1.00	-.85
X_4	0	.43	-.37	-.85	1.00

Stepwise regression produced the following results:

Variable	B Coefficient	Beta Coefficient	F
X_1	.00517	.51460	9.14191
X_2	.45993	.50182	5.00405
X_3	.46047	.50241	1.92134
X_4	.12701	.39195	1.01117
Constant	-.77401		

Multiple R = 0.44001
R-Squared = 0.19360
Standard Error = 0.43377

Albeit that the last two variables are not signigicant at .05 by application of the F statistics, the four variable model was used because the Beta Coefficients indicated significant influence. Application of the B model to the sample test file produced a cutting score of 0.33, i.e. classifying all observations with a computed probability of 0.33 as "1" or "on" resulted in the correct (observed) number of "ons". As indicated above the prediction equation and cutting score were then applied to the cross-validation files. Cross-validation file #1 was designed to test the models under extreme positive data shifts. To meet this objective the mean of X_1 was increased from 45 to 51, and the mean of X_4 was increased from 3 to 6, while X_2 and X_3 were left unchanged. Using the cut score produced 49 observations identified as "on" and one observation labeled "off". The expected number of "ons" was 36. Displayed below is the hits/false-positive/false-negative results of this prediction:

		Predicted on	Predicted off
Actual	on	15	0
	off	34	1

Since the number of observed records which were "on" was 15, the tentative conclusion can be drawn that the OLS B model is not reliable with strong positive data shift. Next the negative data shift in cross-validation #2 was processed with the B model.

In this case the mean of X_1 was shifted from 45 to 39, X_4 from 3 to 1.6, and X_2 and X_3 remained unchanged. Use of the cut score predicted 5 observations to be "on". The expected number of "ons" was 6.7. Below are displayed the hits/false-positive/false-negative data:

		Predicted on	Predicted off
Actual	on	5	10
	off	0	35

Again the conclusion can be drawn that the B model is not viable under extreme data shifts.

Beta model results are shown below:

<u>Cross-validation #1 - Positive Data Shift</u>

		Predicted on	Predicted off
Actual	on	10	5
	off	7	28

Cut score prediction = 17
Expected value = 15

Cross-validation #2 - Negative Data Shift

		Predicted on	Predicted off
Actual	on	9	6
	off	7	28

Cuts score prediction = 16
Expected value = 15

MLE results follow:

Cross-validation #1 - Positive Data Shift

		Predicted on	Predicted off
Actual	on	10	5
	off	7	28

Cut score prediction = 17
Expected value = 16

Cross-validation #2 - Negative Data Shift

		Predicted on	Predicted off
Actual	on	9	6
	off	2	33

Cut score prediction = 11
Expected value = 14

Case 1 summary is shown below for the three models evaluated:

Cross-validation #1 - Positive Data Shift

	B	BETA	MLE
% Hits	32	76	76
% "Ons" = on	30	59	59
% "Offs" = off	100	85	85
% False-positive	68	14	14
% False-negative	0	10	10
Cut score prediction	49	17	17
Expected value	36	15	16
Observed "on"	15		

Cross-validation #2 - Negative Data Shift

	B	BETA	MLE
% Hits	80	74	84
% "Ons" = on	100	[illegible]2	85
% "Offs" = off	78	56	82
% False-positive	0	14	4
% False-Negative	20	12	12
Cut score prediction	5	16	11
Expected value	6.7	15	14
Observed "on"	15		

CASE 2 - LINE COLONELS' RETIREMENTS, '75 FROM '74

In this case a "weak" predictor model was designed as is indicated by the validity vector below and the resultant R-Squared of .16:

Validity Vector for Case 2

Variable	
Tenure (TAFCS)	0.37613
Age:	0.29107
Old OER Mean:	-0.17088
No. permanent passovers:	0.11924
Last OER:	-0.07066
Below Zone Selection:	-0.11534

Stepwise regression produced the following results:

Variable	B Coefficient	Beta Coefficient	F
Tenure (TAFCS)	.04861	.32330	215.559
# Permanent Pass	.05433	.07597	20.004
Age	.00728	.05772	6.892
Old OER Mean	-.00453	-.02754	1.954
Last OER	-.00955	-.01005	.317
Below Zone Selection	.00429	.00330	.037
Constant	-.94884		

Multiple R = .39049
R-Squared = .15248
Standard Error = .39870

Using the B model and Beta model on the cross-validation file, the 1975 Line Colonels, produced prediction results as follows:

OLS Predicted 1975 Line Colonels' Retirements

B Model

		Predicted 1*	Predicted 0
Actual	1	377	409
	0	211	2422

Beta Model

		Predicted 1	Predicted 0
Actual	1	434	352
	0	340	2293

	B Model	Beta Model
Cut score prediction	= 588	774
Expected value	= 697	857
Observed	= 786	

* 1 = Retire, 0 = Stay

The MLE results are shown below:

MLE Predicted 1975 Line Colonels' Retirements

		Predicted 1	Predicted 0
Actual	1	446	340
	0	361	2272

Cut score prediction = 807
Expected value = 859
Observed = 786

Case 2 summary results are as follows:

Cross-validation - 1975 Line Colonels' Retirements

	B	BETA	MLE
% Hits	82	79	79
% "Retirees" that retired	64	56	55
% "Stayers" that stayed	86	87	87
% False-positive	6	10	11
% False-negative	12	10	10
Cut score prediction	588	774	807
Expected value	697	857	859
Observed Retirees	786		

CASE 3 - LINE COLONELS' RETIREMENT, '76 FROM '75

As outlined earlier, extensive analysis and data transformation were undertaken to build a "strong" predictor model. The resultant validity vector is shown below. An R-Squared of 0.26 was achieved.

Validity Vector for Case 3

Tenure (TAFCS):	.49036
No. of Dependents:	.20485
Source of Commission:	.22527
Permanent Grade:	.27404
DAFSC (first two):	.08344
Old OER Mean:	.19063

Stepwise regression results are displayed below:

Variable	B Coefficient	Beta Coefficient	F
Tenure (TAFCS)	.00952	.46560	566.528
No. Of Dependents	.00349	.07148	21.129
Source of Commission	.00290	.06529	16.294
Permanent Grade	-.00206	-.05677	8.950
DAFSC (first two)	.00518	.04323	8.468
Old OER Mean	.00226	.04306	7.701

Application of the B model and the Beta model to the 1976 Colonels file produced the following prediction results:

OLS Predicted 1976 Line Colonels' Retirements

B Model

		Predicted 1	Predicted 0
Actual	1	276	397
	0	231	2528

Beta Model

		Predicted 1	Predicted 0
Actual	1	341	332
	0	337	2422

	B Model	Beta Model
Cut score prediction	= 501	678
Expected value	= 623	690
Observed	= 673	

The MLE prediction, consistent with case one and two, varies only slightly from the Beta prediction.

MLE Predicted 1976 Line Colonels' Retirements

		Predicted 1	Predicted 0
Actual	1	343	342
	0	333	2414

Cut score prediction = 676
Expected value = 691
Observed = 673

Case 3 summary results are as follows:

Cross-validation - 1976 Line Colonels' Retirements

	B	BETA	MLE
% Hits	82	81	80
% "Retirees" that retired	55	50	51
% "Stayers" That stayed	86	88	88
% False-positive	7	10	10
% False-negative	12	10	10
Cut score prediction	501	678	676
Expected value	623	690	691
Observed Retirees	673		

In the interest of brevity, only the detail and summary results will be displayed for Case 4. The methodology followed has been sufficiently detailed in Cases 1 thru 3.

OLS Predicted 1976 4th Year Group Non-rated Line Separations

B Model

		Predicted 1	Predicted 0
Actual	1	1193	364
	0	212	2020

Beta Model

		Predicted 1	Predicted 0
Actual	1	1230	327
	0	317	1915

	B Model	Beta Model
Cut score prediction	= 1405	1547
Expected value	= 1437	1674
Observed	= 1557	

MLE Predicted 1964 4th Year Group Non-rated Line Separations

		Predicted 1	Predicted 0
Actual	1	1207	350
	0	301	1931

Cut score prediction = 1508
Expected value = 1730
Observed = 1557

Cross-validation - 1976 4th Year Group Non-rated Line Separations

	B	BETA	MLE
% Hits	85	83	83
% "Separatees" that separated	85	80	80
% "Stayers" that stayed	85	85	85
% False-positive	6	8	8
% False-negative	10	9	9
Cut score prediction	1405	1547	1508
Expected value	1437	1674	1730
Observed Separations	1557		

PART III. SUMMARY

Based on the empirical data presented, the conclusion must be drawn that the usual B model application of OLS is not a viable solution to the loss rate prediction problem. (And by this is meant the prediction of the correct number without regard to the correct classification). However, either the OLS Beta model or MLE model provide highly reliable predictions of the correct count. To reinforce this point the predicted count for the three models is shown below for the five cross-validation cases.

Cut Score Predictions

	Observed	B	Beta	MLE
Case 1 - Positive data shift	15	49	17	17
Case 1 - Negative data shift	15	5	16	11
Case 2 - 1975 Colonels' Retirement	786	588	774	807
Case 3 - 1976 Colonels' Retirement	673	501	678	676
Case 4 - 1976 4th Yr Gp Separation	1557	1405	1547	1508

Expected Value Predictions

	Observed	B	Beta	MLE
Case 1 - Positive data shift	15	35	15	16
Case 2 - Negative data shift	15	7	15	14
Case 2 - 1975 Colonels' Retirement	786	697	857	859
Case 3 - 1976 Colonels' Retirement	673	623	690	691
Case 4 - 1976 4th Yr Gp Separation	1557	1437	1674	1730

Further examination of the data shown above leads to the conclusion that the cut score predictions of the Beta and MLE models are consistently more reliable than the expected value predictions. This suggests that it is more difficult to correctly map the individual probabilities into the future than it is to map a 1/0 criterion such as is done with a cut score applied to the estimates of the probabilities.

Significance tests at .05 were applied to Cases 2 and 3, the Line Colonel Retirement data. The conclusion was drawn that the B model predictions were not equivalent to the observed values while both the Beta and MLE predictions were equivalent to the observed values. Further the predictions of the Beta and MLE models were found to be equivalent at .05. Thus the selection of a model reduces to one of economics.

Lockman and Warner (# 3) noted that MLE will require more resources than OLS. In this study, the MLE program employed required from 2.3 to 5 times the computer processor time required by OLS. It should be further noted that the cases analyzed were small, compared to typical real-world problems, and that MLE tends toward exponentially increasing resource consumption with increase in the number of independent variables. Thus the analyst is left on the horns of a dilemma....MLE is theoretically more accurate but at the same time may be significantly more costly to use. The OLS Beta model will always cost less than MLE but may not be reliably accurate over the spectrum of problems which must be solved.

PART IV. CONCLUSION

Loss rate generation can be dichotomized into two classes... first, the problem of predicting the correct number for applications such as force structure modeling, and second the problem of classification which finds application in screening for selective admission. The empirical evidence presented for a diversity of data in this study supports the use of the Beta model for the prediction of the number of losses. Cut score predictions for the Beta model in all cases were equally as good as the MLE predictions. In addition the Beta model can be used with only marginal increase in costs over the B model (Beta requires the Mean and Standard Deviation of the independent data in the observations to be predicted) while the MLE model incurs greater resource costs. There is, however, one serious shortcoming of the Beta model, also shared by the MLE model. Neither of the techniques consistently provided reasonable Expected Value predictions. Thus, until further research unravels the Expected Value anomalies, the recommendation is made that the Beta model using cut score for the 1/0 criterion be used for forecasting loss rates.

PART V. ET CETERA

Several loose ends, questions, and conjectures are left which did not appropriately fit in the above discussion. This section will present those remaining elements for deliberation and possible resolution.

First and foremost is the contention in the literature that the OLS B Model and Beta Model are mathematically equivalent. They are, indeed, equivalent when applied to the sample test file and when applied in the typical manner of cross-validation (see discussion below). However, the cases examined in this study clearly indicate that the two models are not equivalent when applied to real-world, or controlled data, problems. As is suggested by Fast and Dempsey (#4), the OLS B model perishes under the influence of data shifts. The Beta model does not. Therefore the two models are not equivalent in application, or when cross-validated in the loss forecasting arena.

Cross-validation as documented, taught, and practiced has no relevance to loss forecasting. Typically the researcher will randomnly divide a data file into two statistically equivalent halves, build a predictor model with one half, and cross-validated into the other half. In practice, this technique will always cross-validate if the researcher is successful in producing statistically equivalent files. The additional step of constructing independent predictor models in each file and cross-validating into the other file contributes nothing to loss forecasting. It is also the incorrect approach. In loss forecasting, the objective is to build a predictor model with an historical population which predicts the losses for a population in the future which usually will not be statistically equivalent to the historical population due to data shifts. To accomplish this, the researcher should employ an analog of the process to be modeled by using two previous years of data. One to build the predictor model and the subsequent year to cross-validate the predictor model. Only in this way can any conclusions be drawn regarding the efficiency of models for predicting losses.

Predicting losses over time leads to the concomitant shift of data over time. Any model nominated for this task must be able to accommodate shifts in data values. Consideration of this requirement resulted in the conjecture that the three models evaluated are equal if there is no shift of data in the cross-validation file, as is the case with statistically equivalent files.

Is the Beta model equivalent to the MLE model? Or even more accurate? Isolating the question to the five cases presented would result in a strong affirmative to the first question and a "perhaps" to the second. However, such is not the case. Without a doubt, cases could be contrived, particularly bivariate cases, in which the Beta model would be inferior to the MLE model. This is an important consideration because loss rates will usually present a multivariate problem. With this type of problem, and more particularly with data which provide low R-Squares, it is conjectured that the sigmoid curve produced by MLE will be essentially flat and thus the equivalent of the Beta model.

Finally, the classification question. In officer loss rate generation, correct classification is not germane; however, the serendipity which is evident should not be ignored, for the Air Force personnel managers are responsible for accession actions in which classification is essential. Reference to the summary data shown on pages 7-12, above, reveals that the Beta and MLE model classify with approximately the same accuracy. One other form of the Beta model was investigated as a result of informal correspondence with Dr. Joe Ward at the Air Force Human Resources Laboratory. Ward suggested that a more accurate Beta model could be derived by using the validity vector from the sample test file and the correlation matrix from the cross-validation file. This is in the form of $[\beta] = [R_2]^{-1} [V_1]$. Such a prediction equation was built and tested in Case 4, the 4th Year Group Non-rated Line Separations. For comparison purposes the summary table is presented.

Cross-validation #4 - 4th Year Group 1976 Non-rated Line Sep

	B	Beta	MLE	WARD
% Hits	85	83	83	85
% "Separatees" that separated	85	80	80	86
% "Stayers" that stayed	85	85	85	85
% False-positive	6	8	8	5
% False-negative	10	9	9	9
Cut score prediction	1405	1547	1508	1396
Expected value	1437	1674	1673	1673
Observed Separations	1557			

Although the Ward method resulted in the worst cut score prediction (90% of actual separations), the accuracy on classification is the best of the four methods. This suggests an area for further research for those who have an interest in screening tools.

REFERENCES

1. Nerlove, Marc and S. James Press. Univariate And Multivariate Log-Linear And Logistic Models (Santa Monica, California: Rand Corporation, 1973)

2. Dempsey, Jack R. and Jonathan C. Fast. A Method To Simultaneously Reduce Involuntary Discharges And Increase The Available Manpower Pool (Professional paper presented at the OSD/ONR First Term Enlisted Attrition Conference, Leesburg, Virginia, 4-7 April 1977)

3. Lockman, Robert F. and John T. Warner. Predicting Attrition: A Test of Alternative Approached (Professional paper presented at the OSD/ONR First Term Enlisted Attrition Conference, Leesburg, Virginia, 4-7 April 1977)

4. Dempsey, Jack R. and Jonathan C. Fast. Motivational Attrition Prediction Model (Informal paper presented at the Air Force Military Personnel Center, Randolph AFB, Texas, 21 Jan 1976)