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PREDICTIONS OF PERFORMANCE IN CAREER EDUCATION

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ABSTRACT

Prediction weights for educational programs in 22 vocational and technical fields are provided using ability scores from The American College Testing Program (ACT) Career Planning Profile and a Bayesian regression theory due to D. V. Lindley as developed into an operational method by Jackson, Novick, and Thayer. The criterion variable studied was first-semester grade point average. Each vocational-technical program analyzed was represented by several institutions, and the usual least-squares regression weights for each institution were replaced by Bayesian weights which used both the direct information on that institution and the collateral information present in the other institutions offering that program. Very satisfactory predictions were obtained in 18 of the 22 programs: Business and Marketing, Dental Assisting, Nursing—Registered, Nursing—Practical, Other Health, Accounting, Business Administration (4-year transfer), Computer Programming, Data Processing, Secretarial Science, Electrical Engineering Technology, Science (4-year transfer), Other Technical, Auto Mechanics, Drafting, Machine Work, Other Trades, and Police Science. Largely because of a lack of sufficient data and the heterogeneity of the programs, predictions in four fields were not judged to be satisfactory: Agriculture, Cosmetology, Social Science (4-year transfer), and Arts and Humanities (4-year transfer). A detailed discussion of the generality of the *m* group regression model is provided.

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INTRODUCTION

The prediction of performance in career education is by no means a simple problem. Each institution provides numerous diverse programs in which the enrollment in any one program is often small. An example of some typical numbers of enrolled students in several programs at a number of institutions is given in Table 1. The problem is then to predict performance in the diverse programs at many different institutions with only the minimal information available at any one institution in a particular program.

As can easily be seen from Table 1, the sample sizes for a particular program in a single institution are too small for the use of the usual least-squares procedures. Those procedures are subject to serious sampling variability in samples of such sizes.

TABLE 1

An Example of Typical Enrollments by Program and by Institution

Programs

Institution	A	B	C	D	E	F	G	H	I
1	0	16	16	0	12	0	0	6	22
2	8	26	15	0	0	7	21	42	0
3	46	38	0	53	0	38	86	0	0
4	0	0	15	0	18	0	32	13	0
5	0	0	21	0	33	12	0	0	9
6	14	28	0	15	0	0	0	31	0
7	9	0	12	0	0	18	0	23	0
8	0	15	0	27	31	0	18	0	0
9	32	16	11	0	0	0	0	0	34
10	21	0	9	18	0	0	0	24	0
11	0	47	53	0	43	51	28	0	42
12	10	0	14	0	9	0	21	0	12

It is common in 4-year colleges to pool information across all the students in a college, and because of the similarity of most freshman courses within a college, such a procedure is often successful. However, in career education, the diversity across programs within institutions is tremendous. For example, it is not feasible to combine Auto Mechanics students with those in Computer Programming. Also, even like-named programs across institutions may vary in content and level, although the diversity is commonly less than that across programs; therefore, simple pooling for a program across institutions is not practical. Consequently, a method is needed which uses the information from like-named programs at other institutions to compute predictions at a single institution while at the same time allowing for some differences in content and standards across institutions.

A procedure which allows the use both of the unique information from a program in a single institution and the *collateral information* from similar programs in other institutions is a Bayesian *m* group regression method developed by Jackson, Novick, and Thayer (1971) from a theory described by Lindley and Smith (1972). Novick, Jackson, Thayer, and Cole (1972) validated the Bayesian procedure in a group of 2-year colleges and found that the procedure yielded more efficient predictions than within-college least-squares weights in a situation in which there was enough diversity across colleges to preclude the simple pooling of data across colleges. When applied to the problem of prediction in career education, the Bayesian procedure provides for simultaneous estimation of prediction weights for like-named programs in different colleges. Thus, data such as that described in Table 1 can be used, for example, to provide predictions for students entering Institution 1 and Program B by simultaneously using the information on Program B in Institutions 2, 3, 6, 8, 9, 11. A student enrolling in Institution 1 can, therefore, be presented with a set of predictions for Programs B, C, E, H, and I; and the accuracy of these predictions will have been enhanced by experience gained at the other institutions.

The purpose of the paper is to apply this Bayesian procedure to prediction of course performance in several career education programs at a number of institutions using measures from the ACT Career Planning Program (CPP) as predictors. We examine the working details of the procedure, the quality of the predictions obtained, and the differences between various models which might be considered for prediction in career education.

Method

Conducting effective Bayesian *m* group regression analysis requires a number of steps in which the available information is summarized, examined, refined, and prepared for the final analysis. To this end, a resource person with substantive background in education, a person with substantial computer experience, and a person thoroughly acquainted with Bayesian *m* group regression is required. Of course, all of these roles may be played by the same individual, but it is essential that all these skills are present. A detailed discussion of the technical-computational problems encountered in this study is given by Jones and Novick (1972) and will, therefore, not be discussed here.

The predictors used consisted of the seven ability scales of the ACT Career Planning Profile. These are given in Table 2.

TABLE 2

CPP Scales

1. Mechanical Reasoning
2. Nonverbal Reasoning
3. Clerical Skills
4. Numerical Computation
5. Mathematical Usage
6. Space Relations
7. Reading Skills

Data were gathered in 1970 on over 10,000 entering students from over 60 institutions offering post-secondary vocational-technical educational programs. The criteria measures were collected after the completion of one term in the program. The data sources were edited to ensure complete information on each scale for each individual.

Prediction of grades was performed in the 2-year colleges and vocational-technical schools for 22 educational programs or clusters of programs listed in Table 3. For most programs, vocational-technical course grades were employed as the criterion measure. However, academic course grades were considered to be the relevant criterion for programs leading to transfer to 4-year academic institutions.

TABLE 3

Programs for Which Predictions Were Provided

1. Agriculture
2. Business and Marketing
3. Dental Assisting
4. Nursing—Registered
5. Nursing—Practical
6. Other Health
7. Accounting
8. Business Administration (4-year transfer)
9. Computer Programming
10. Data Processing
11. Secretarial Science
12. Electrical Engineering Technology
13. Science (4-year transfer)
14. Other Technical
15. Auto Mechanics
16. Drafting
17. Machine Work
18. Other Trades
19. Cosmetology
20. Police Science
21. Social Science (4-year transfer)
22. Arts and Humanities (4-year transfer)

Two criteria were employed in selecting these programs. First, an adequate number of institutions and students had to be available for a program. Second, where programs were combined, it was necessary that the combination represent a rational grouping of fields of study. The purpose of the grouping was to reduce heterogeneity among schools as much as possible.

Variable selection was aided by reference to *Career Planning Profile National Norms for Vocational-Technical Students beyond High School* (The American College Testing Program, 1971) in which subsets of the ability measures of the CPP which would perform best in prediction were suggested. An attempt was made to choose for each program a set of variables that would be reasonably effective for all institutions offering that program. This approach differs from the usual approach which attempts a rote maximization of a multiple correlation coefficient (R) for each institution, subject only to some limitation on the number of predictors used. For sample sizes of the magnitude encountered in the present study, reliance upon the estimated R within institution would result largely in capitalizing upon chance.

Accordingly, the field of seven predictors was reduced to combinations of one, two, or three variables at a time. Frequently, it was possible after several preliminary analyses to eliminate unsuitable variables (or unsuitable combinations of variables) from further consideration. In programs requiring some skill in Numerical Computation or Mathematical Usage, it was often possible to surmise which of these two skills would be more relevant to that program. Ordinarily, it did not prove useful to use both Numerical Computation and Mathematical Usage in the same prediction equation.

Results and Discussion

The program involving Data Processing students clearly illustrates key points of the Bayesian method; hence, the analysis for that program is discussed here in some detail. Preliminary least-squares analyses together with consultation with the resource person resulted in the selection of Numerical Computation and Reading Skills (Variables 4 and 7) as predictors for the Data Processing program. Table 4 reports the regression weights and residual variance estimates for each of the 18 institutions offering this program. The classical Model II estimates represent a rough guess at the final Bayesian solution: Inspection by the reader will reveal that they tend to be closer to the final Bayesian estimates than the least-squares estimates. These classical Model II estimates are a weighted average of the least-squares values and the generalized weight values, just as the Bayesian estimates tend to be (albeit in a slightly different and more satisfactory mathematical form). The correspondence becomes less exact when several predictors are involved, but still the relationship is a usefully descriptive one for our purposes.

The exact Bayesian weights are obtained as the solution to an elaborate system of nonlinear equations, the *Lindley equations*. The least-squares estimates provide one set of starting points for the Bayesian solution while the classical Model II estimates provide another for the Bayesian regression computer program. By using both the least-squares and classical Model II regression solutions as starting values, a check on the convergence of the solution is obtained.

A generalized weight equation

$$\hat{Y} = .025X_4 + .035X_7 - .540$$

provides the appropriate prediction for students in a Data Processing program offered by an institution on which no past records are available. These weights are provided by the full Bayesian analysis. Roughly, the individual regression weights are the average of the corresponding weights across institutions. The intercept, however, is adjusted more carefully.

Next, note how the least-squares estimates tend to be "pulled-in" toward the generalized weights. As a consequence, the three negative weights on Variable 4 (Institutions 3, 9, and 10) have been eliminated. Similarly, the negative weights on Variable 7 (Institutions 4 and 7) have disappeared. Also, the residual variance estimates move toward an average value.

The greatest variation across institutions for the Bayesian estimate occurs for the intercept. The slopes tend to cluster about the generalized weight equation value, but this does not hold for the intercept. This is probably due to two reasons. First, the average GPA probably differs from institution to

TABLE 4

Regression Weights[a] and Residual Variances for Least-Squares, Classical Model II, and Bayesian Values for the Data Processing Program

Institution	N	Least-Squares Values $\hat{\beta}_0$	$\hat{\beta}_4$	$\hat{\beta}_7$	$\hat{\phi}$	Classical Model II Values $\hat{\hat{\beta}}_0$	$\hat{\hat{\beta}}_4$	$\hat{\hat{\beta}}_7$	$\hat{\hat{\phi}}$	Bayesian Values $\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{\phi}$	R
1	12	-1.825	.041	.052	.8000	-1.203	.034	.047	.2015	- .382	.028	.034	.4715	.5082
2	12	-3.024	.096	.039	.5620	- .335	.032	.041	.5443	.006	.029	.032	.4788	.5015
3	14	2.698	-.012	.014	.3101	1.176	.008	.024	.3932	.495	.019	.025	.4760	.5016
4	18	1.774	.019	-.003	.5991	.212	.022	.022	.5701	.072	.020	.027	.4801	.4977
5	12	- .694	.024	.042	.2660	- .699	.025	.042	.3718	- .528	.027	.036	.4735	.5081
6	15	1.020	.005	.034	.6349	-1.126	.022	.038	.5857	- .151	.027	.032	.4788	.5028
7	19	2.558	.013	-.005	.5528	.445	.020	.024	.5429	.040	.022	.028	.4794	.4979
8	10	-2.332	.020	.056	.3885	-1.990	.023	.046	.4579	-1.144	.018	.041	.4765	.5054
9	10	-1.072	-.061	.014	.3493	- .845	.003	.063	.4360	- .699	.023	.039	.4787	.5034
10	10	- .677	-.004	.067	.2146	- .812	.010	.054	.3486	- .696	.022	.039	.4747	.5066
11	30	-2.215	.052	.042	.1039	-1.262	.034	.042	.8663	- .881	.031	.038	.4963	.4860
12	35	-1.465	.049	.035	.4520	-1.214	.042	.038	.4687	- .857	.035	.037	.4757	.5107
13	28	-1.173	.042	.027	.8188	-1.127	.033	.035	.7231	- .873	.028	.036	.4875	.4966
14	50	-1.312	.017	.058	.6559	-1.179	.020	.052	.6308	-1.004	.026	.043	.4872	.5009
15	12	-2.760	.075	.026	.4087	-1.414	.040	.036	.4627	- .757	.028	.036	.4766	.5044
16	17	- .009	.008	.034	.5936	- .952	.021	.039	.5659	- .661	.020	.035	.4784	.5024
17	37	-1.275	.016	.058	.7797	-1.059	.019	.050	.7132	- .790	.023	.041	.4898	.4935
18	17	-2.544	.042	.047	.4738	-1.914	.033	.044	.4941	- .908	.025	.037	.4767	.5045

[a] β_0 Intercept
β_4 Weight for Variable 4 (Numerical Computation)
β_7 Weight for Variable 7 (Reading Skills)
ϕ Residual Variance

institution according to local grading practices. Second, the fact that the predictor variables have an approximate mean of 50 and a standard deviation of 10 will imply that the y-intercept will vary substantially despite only small changes in the slopes.

In addition, Table 4 reports the multiple correlation coefficient (R) for the Bayesian regression estimates. Calculations we made used the formula

$$R^2 = 1 - \frac{\phi}{\phi_0}$$

where ϕ = Bayesian estimate of the residual variance using all predictors and ϕ_0 = Bayesian estimate of the residual variance using no predictors. It is important to emphasize that both the estimates ϕ and ϕ_0 depend upon the same set of institutions. Since these estimates are regressed for each institution within the program, the estimates of multiple Rs tend to be similar within the program. It should be noted that the above estimate of R^2 is not a true Bayesian estimate but only a crude classical approximation and, hence, subject to the usual aberrations of classical estimation in Model II (a negative estimate is possible).

The most important statistics for each of the 22 vocational-technical programs are contained in Tables 5-26. In these tables, the institution sizes, regression weights, residual-variance estimates, and multiple Rs are given. Table 5 reports the generalized weight equations by program and Table 6 lists the predictor variables used for each program. Tables 7-28 contained in the Appendix give the specific Bayesian weights for each school on a program-by-program basis.

TABLE 5

Generalized Regression Coefficients for CPP Predictions of GPA by Vocational-Technical Program

Program	Number of Institutions	Total No. Students	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_2$	$\tilde{\beta}_3$	$\tilde{\beta}_4$	$\tilde{\beta}_5$	$\tilde{\beta}_6$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	13	328	1.300	—	—	—	—	—	—	.027	.1726	.4339
2	12	199	-.782	—	—	—	.026	—	—	.038	.6580	.3298
3	12	307	.021	—	—	—	.019	—	—	.033	.5775	.3185
4	18	583	.656	—	—	—	.009	—	—	.025	.3483	.4480
5	19	475	.611	—	—	—	.012	—	—	.034	.5126	.2918
6	16	529	.213	—	—	—	.016	—	—	.031	.5002	.3774
7	14	291	.147	—	—	—	.021	—	—	.027	.5216	.3989
8	12	306	.468	—	—	—	.016	—	—	.020	.3268	.4077
9	12	258	-.401	—	—	.020	—	.035	—	—	.4472	.5414
10	18	358	-.540	—	—	—	.025	—	—	.035	.5019	.4797
11	26	914	.148	—	—	—	.020	—	—	.029	.4646	.4853
12	27	824	-.484	.013	—	—	—	.031	—	.012	.4463	.6060
13	10	235	.526	—	—	—	—	.022	—	.011	.4525	.4493
14	19	369	.966	—	—	—	—	.031	—	—	.3738	.4449
15	20	764	.503	.014	—	—	.013	—	—	.014	.4165	.4360
16	17	428	-.341	.025	—	—	.017	—	—	.012	.4470	.5124
17	10	163	-.336	.020	—	—	.037	—	—	—	.5930	.3820
18	24	1398	.779	.016	—	—	.009	—	—	.010	.3764	.4896
19	9	163	1.519	—	—	—	—	—	—	.026	.4551	.2034
20	8	209	.736	.013	—	—	—	—	—	.023	.4250	.4674
21	11*	419	1.430	—	—	—	—	—	—	.020	.1421	.5490
22	6*	326	1.430	—	—	—	—	—	—	.020	.1421	.5490

*Programs 21 and 22 were combined to calculate the generalized regression coefficients.

TABLE 6

List of Variables Used by Vocational-Technical Program

1. Agriculture:
   Reading Skills
2. Business and Marketing:
   Numerical Computation, Reading Skills
3. Dental Assisting:
   Numerical Computation, Reading Skills
4. Nursing—Registered:
   Numerical Computation, Reading Skills
5. Nursing—Practical:
   Numerical Computation, Reading Skills
6. Other Health:
   Numerical Computation, Reading Skills
7. Accounting:
   Numerical Computation, Reading Skills
8. Business Administration (4-year transfer):
   Numerical Computation, Reading Skills
9. Computer Programming:
   Clerical Skills, Mathematical Usage
10. Data Processing:
    Numerical Computation, Reading Skills
11. Secretarial Science:
    Numerical Computation, Reading Skills
12. Electrical Engineering Technology:
    Mechanical Reasoning, Mathematical Usage, Reading Skills
13. Science (4-year transfer):
    Mathematical Usage, Reading Skills
14. Other Technical:
    Mathematical Usage
15. Auto Mechanics:
    Mechanical Reasoning, Numerical Computation, Reading Skills
16. Drafting:
    Mechanical Reasoning, Numerical Computation, Reading Skills
17. Machine Work:
    Mechanical Reasoning, Numerical Computation
18. Other Trades:
    Mechanical Reasoning, Numerical Computation, Reading Skills
19. Cosmetology:
    Reading Skills
20. Police Science:
    Mechanical Reasoning, Reading Skills
21. Social Science (4-year transfer):
    Reading Skills
22. Arts and Humanities (4-year transfer):
    Reading Skills

The Generality of the Bayesian *m* Group Model

A full discussion of the theory of *m* group regression is given by Lindley and Smith (1972) and of the method by Jackson, Novick, and Thayer (1971) and, therefore, this will not be repeated here. However, it might be useful to discuss certain features of the model in greater depth than in previous papers; in particular, the assumptions underlying the model and how the model, in its generality, subsumes special cases considered by classical statistics.

First, an assumption of exchangeability is required for the analysis and must be emphasized here. The theory demands that our prior information be such that we not have (substantial) information to distinguish one course from another. This seems reasonable if all of our groups consist of students in Data Processing courses in various institutions, but it would not be reasonable if we also included in the analysis some Auto Mechanics groups. This does not imply that we believe, apriori, that all of the groups are the same, only that they are similar and that we do not have substantial prior information to differentiate them. One way of helping to justify the exchangeability assumption is to restrict the analysis to a single sex for some programs. For example, in the Nursing—Registered program, we used data only from female students. Prior experience suggests that somewhat different predictions are required for males; and thus, to the extent that some groups might have a higher percentage of males, they would not be exchangeable with the other groups. The effectiveness of this restriction to a single sex was demonstrated in the Novick, Jackson, Thayer, and Cole (1972) cross-validation.

When confronted with a problem of *m* group regression and, for the moment, putting aside the Bayesian solution, one is generally faced with the problem of selecting one of several possible models each requiring a restrictive assumption with regard to the data. Let us consider four such possible models and their relative attractiveness.

Pooled Data within Institution

It has been common in higher education to pool all data within an institution for prediction of college performance. In traditional 4-year colleges, such pooling is reasonable because of the similarity of courses taken by all freshman students. However, in career education, there is much greater diversity in the courses included in different programs. Thus, pooling data from very dissimilar programs is not a feasible approach in career education, and such pooling would result in very poor predictions. Even if such pooling within institution were reasonable, it should be noted that within-institution pooling is a special case of a Bayesian *m* group regression on programs within institution. When the variance of regression coefficients across programs in such an analysis is very small, this Bayesian procedure reduces to the pooled-data within-institution model.

Within-Program Group Least Squares

Each program within an institution may be considered separately; and within-program, within-institution least-squares regression lines may be computed. In the present situation, this is probably the model that schools working their own would need to use because they would not have information on other schools. However, the samples are usually so small as to make within-group least squares infeasible. Even if information from other institutions were available to them, this would be the appropriate model for use if the various programs were, in fact, very dissimilar. It turns out that this model, also, is a special case of the Bayesian *m* group model; and results comparable to within-group least squares will be given by *m* group Bayesian regression when the data, in their entirety, support the assumption of a very large variance of the various regression coefficients between schools.

Pooled Data for Programs across Institutions

The third possible model goes to the other extreme and assumes there are no differences of the various like-named programs at different institutions and, thus, all of the data for a program are pooled and a single regression line is computed. It seems clear to us from the data in Table 4 and the other similar tables generated in this study together with general knowledge about the field of career education and the results obtained by Novick, Jackson, Thayer, and Cole (1972) that this model cannot be taken seriously in this application. However, we note that the pooled program data model is a special case of the Bayesian *m* group regression model, and corresponding estimates will be generated in the (unlikely) event that the variances across groups of *all* the regression coefficients are zero.

Equal-Slopes Unequal-Intercepts

If one is forced into a prior commitment to a simple model, this is probably the most realistic one of the four we discuss. We do not believe that the same slopes should be used for all schools, but we probably will do reasonably well as long as we allow the intercepts to vary. The weakness of this model is that it does least well when we have a school for which we have much data and the data indicate that this school, in fact, requires a different slope. Again, the Bayesian *m* group regression model includes this model as a special case, but if the data suggest that one or more schools have different slopes, the Bayesian solution will move in that direction for those schools.

It is possible to consider other more restrictive models, but this is no longer necessary. In fact, the Bayesian model incorporates a wide range of restrictive models as special cases and moves in the direction of one of these models as the data suggest the relevance of the particular model.

The price one pays for the generality of the Bayesian model is its complexity, the relative computational difficulty of getting out numerical solutions, and the care that is required in specifying some prior parameters. We feel, however, that the success of the method justifies the energy that has been spent developing and implementing it, and that those who are prepared to devote a substantial investment of time to the study of the method will have mastered a powerful tool. On the other hand, the computational difficulties involved in its application will probably restrict its usefulness to large-scale studies such as the one reported herein.

In the case of career education, the data presented here strongly suggest that the general Bayesian *m* group regression model will provide more efficient predictions of performance than possible with a simpler more restrictive model. This is not to say that one should routinely use the Bayesian *m* group regression or that it will be advantageous in all situations. If there is strong prior belief that a simpler model will be satisfactory in a situation, that model should certainly be used, subject to the understanding that if the data contradict the model, the model will be abandoned. However, for the prediction of performance in multiple diverse career-education programs at many institutions with only small numbers available in any one program within a single institution, the complexities of the Bayesian system appear to be necessary to provide satisfactory prediction.

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APPENDIX

Tables 7-28 contain the specific Bayesian prediction weights for the various institutions providing data for the remaining 21 programs. The same numbers in the various tables do not generally signify the same institutions. The second column (n) gives the within-school sample size. The next column ($\tilde{\beta}_0$) gives the Bayesian estimate of the intercepts. The next one, two, or three columns give the Bayesian estimates of the regression coefficients for the variables used in prediction. For example, in Table 8, the Variables 4 (Numerical Computation) and 7 (Reading Skills) are used. The next column, headed $\tilde{R}$, gives an estimate of the true correlation between the predictor composite and criterion, and the final column gives an estimate of the residual variance.

TABLE 7

Regression Coefficients and Residual Variances for CPP Predictions of GPA for Institutions by Vocational-Technical Program

Agriculture

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	37	1.980	.022	.0989	.4457
2	10	1.242	.028	.1811	.4314
3	18	1.995	.026	.2037	.4257
4	13	1.329	.027	.1905	.4287
5	17	1.889	.027	.1802	.4326
6	13	.576	.029	.1568	.4370
7	22	1.460	.028	.1777	.4332
8	16	.977	.029	.1902	.4289
9	115	.238	.032	.0911	.4553
10	14	1.171	.027	.1734	.4324
11	13	1.568	.027	.1846	.4311
12	27	1.091	.028	.1805	.4313
13	13	1.388	.028	.1889	.4297

TABLE 8

Business and Marketing

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	36	.334	.017	.027	.6410	.3436
2	10	- .630	.026	.030	.6592	.3275
3	11	-1.416	.031	.036	.6585	.3302
4	16	-1.684	.029	.063	.6674	.3269
5	18	-1.238	.027	.048	.6631	.3253
6	11	.843	.021	.021	.6552	.3326
7	18	- .814	.025	.040	.6560	.3300
8	21	- .865	.027	.037	.6593	.3272
9	10	-1.222	.029	.043	.6596	.3281
10	11	- .954	.029	.038	.6588	.3294
11	20	-1.431	.030	.046	.6612	.3268
12	17	- .308	.025	.023	.6556	.3303

TABLE 9

Dental Assisting

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	19	.620	.005	.033	.5605	.3155
2	33	-1.520	.027	.036	.5008	.3198
3	21	.314	.016	.032	.5388	.3316
4	14	- .561	.033	.033	.5602	.3181
5	33	.150	.021	.032	.5638	.3131
6	11	1.356	.007	.030	.5556	.3190
7	45	- .837	.019	.039	.5616	.3164
8	15	.862	.003	.032	.5552	.3189
9	16	- .199	.024	.032	.5546	.3192
10	40	- .120	.021	.034	.5670	.3128
11	42	.523	.031	.027	.5546	.3215
12	18	- .332	.021	.033	.5603	.3162

TABLE 10

Nursing—Registered

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	17	.460	.008	.031	.3386	.4550
2	55	-.521	.009	.043	.3465	.4544
3	13	.732	.009	.025	.3538	.4446
4	20	.881	.011	.021	.3349	.4558
5	62	.567	.007	.025	.3371	.4537
6	13	.518	.009	.026	.3563	.4434
7	53	.109	.006	.037	.3508	.4519
8	26	.384	.010	.028	.3542	.4447
9	24	1.048	.007	.020	.3556	.4413
10	41	1.218	.007	.017	.3512	.4429
11	50	.834	.009	.019	.3508	.4447
12	17	.765	.009	.022	.3331	.4560
13	19	.562	.007	.025	.3266	.4599
14	21	.599	.009	.028	.3611	.4411
15	53	.690	.013	.024	.3536	.4463
16	26	.976	.009	.018	.3562	.4412
17	48	1.488	.009	.020	.3584	.4389
18	25	.489	.009	.024	.3423	.4505

TABLE 11

Nursing—Practical

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	12	1.486	.010	.033	.5169	.2891
2	11	.617	.013	.034	.5157	.2901
3	28	.533	.012	.034	.5037	.2965
4	22	.332	.015	.033	.5035	.2968
5	14	.582	.012	.035	.5119	.2929
6	51	.339	.013	.034	.5224	.2864
7	15	.652	.012	.032	.4942	.3011
8	33	.593	.011	.033	.5150	.2894
9	10	.535	.012	.033	.5105	.2925
10	23	.831	.011	.034	.5101	.2931
11	57	.361	.013	.031	.5109	.2915
12	11	.408	.013	.034	.5117	.2923
13	15	.548	.012	.033	.5152	.2900
14	19	.349	.014	.035	.5085	.2956
15	37	.649	.015	.035	.5186	.2905
16	16	1.068	.011	.034	.5114	.2925
17	59	.546	.011	.033	.5228	.2855
18	16	.409	.014	.034	.5162	.2902
19	26	.777	.013	.034	.5189	.2887

TABLE 12

Other Health

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	11	-1.613	.036	.041	.5000	.3845
2	23	.191	.018	.031	.5081	.3728
3	89	.202	.013	.031	.4864	.3850
4	62	1.331	.000	.028	.5008	.3737
5	10	.070	.019	.032	.5012	.3770
6	10	.467	.013	.031	.4975	.3787
7	90	.756	.013	.026	.4957	.3763
8	21	.718	.014	.029	.5038	.3747
9	21	1.551	.008	.023	.5003	.3764
10	33	-1.694	.029	.043	.5012	.3802
11	15	-1.064	.028	.038	.5073	.3737
12	16	.913	.011	.027	.5006	.3763
13	51	1.052	.005	.027	.5000	.3738
14	10	- .204	.021	.033	.5000	.3779
15	14	1.570	.007	.024	.5035	.3732
16	53	- .832	.023	.039	.4964	.3846

TABLE 13

Accounting

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	10	.236	.022	.023	.5190	.4011
2	17	- .282	.021	.035	.5223	.3984
3	10	.250	.021	.027	.5231	.3968
4	32	- .599	.024	.039	.5281	.3970
5	21	.502	.019	.021	.5203	.3968
6	20	- .608	.024	.041	.5279	.3973
7	20	.578	.020	.021	.5138	.4069
8	24	1.189	.018	.012	.5199	.3982
9	36	- .339	.022	.028	.5128	.4070
10	10	- .090	.021	.031	.5222	.3971
11	30	- .226	.022	.035	.5239	.3971
12	14	.145	.020	.028	.5226	.3968
13	33	.800	.020	.021	.5217	.3965
14	14	.507	.019	.022	.5221	.3973

TABLE 14

Business Administration (4-year transfer)

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	53	.418	.016	.018	.2679	.4308
2	30	.279	.018	.021	.3352	.4047
3	26	.394	.017	.024	.3397	.4042
4	15	.602	.014	.020	.3322	.4046
5	15	.586	.012	.019	.3232	.4080
6	11	.437	.016	.022	.3339	.4050
7	66	.921	.016	.016	.3026	.4160
8	19	.421	.015	.020	.3322	.4049
9	12	.422	.016	.021	.3405	.4017
10	11	.335	.016	.022	.3293	.4070
11	16	.339	.017	.022	.3400	.4026
12	32	.461	.016	.020	.3327	.4049

TABLE 15

Computer Programming

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_3$	$\tilde{\beta}_5$	$\tilde{R}$	$\tilde{\phi}$
1	10	- .138	.020	.034	.4498	.5378
2	13	- .360	.020	.033	.4377	.5496
3	10	- .491	.020	.034	.4411	.5454
4	37	.377	.016	.033	.4494	.5351
5	23	- .330	.020	.035	.4477	.5417
6	12	-1.193	.023	.039	.4432	.5527
7	55	- .758	.023	.036	.4504	.5326
8	20	- .685	.021	.036	.4460	.5448
9	16	.564	.015	.034	.4519	.5344
10	12	- .376	.018	.037	.4483	.5408
11	40	- .825	.021	.036	.4469	.5417
12	10	- .599	.020	.035	.4455	.5409

TABLE 16

Data Processing

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	12	- .382	.028	.034	.5082	.4715
2	12	.006	.029	.032	.5015	.4788
3	14	.495	.019	.025	.5016	.4760
4	18	.072	.020	.027	.4977	.4801
5	12	- .528	.027	.036	.5081	.4735
6	15	- .151	.027	.032	.5028	.4788
7	19	.040	.022	.028	.4979	.4794
8	10	-1.144	.018	.041	.5054	.4765
9	10	- .699	.023	.039	.5034	.4787
10	10	- .696	.022	.039	.5066	.4747
11	30	- .881	.031	.038	.4860	.4963
12	35	- .857	.035	.037	.5107	.4757
13	28	.873	.028	.036	.4966	.4875
14	50	-1.004	.026	.043	.5009	.4872
15	12	- .757	.028	.036	.5044	.4766
16	17	- .661	.020	.035	.5024	.4784
17	37	- .790	.023	.041	.4935	.4898
18	17	- .908	.025	.037	.5045	.4767

TABLE 17

Secretarial Science

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	22	.618	.020	.031	.4678	.4798
2	44	.085	.018	.029	.4648	.4831
3	49	-.134	.019	.029	.4691	.4814
4	40	.319	.020	.031	.4622	.4877
5	27	.004	.017	.026	.4602	.4868
6	48	.162	.018	.029	.4621	.4849
7	64	.089	.023	.032	.4768	.4786
8	33	.128	.020	.030	.4662	.4839
9	23	.176	.020	.029	.4567	.4921
10	34	.084	.017	.027	.4586	.4873
11	24	.207	.019	.028	.4636	.4836
12	25	.142	.020	.030	.4609	.4898
13	23	.121	.019	.029	.4654	.4824
14	31	.059	.020	.029	.5215	.4770
15	30	.121	.019	.028	.4585	.4910
16	40	.161	.019	.031	.4549	.4977
17	21	.445	.020	.030	.4664	.4816
18	32	-.030	.021	.029	.4602	.4928
19	36	-.101	.021	.031	.4768	.4799
20	51	.151	.020	.029	.4693	.4807
21	32	.063	.019	.027	.4517	.4959
22	33	.323	.018	.027	.4545	.4898
23	35	.248	.022	.033	.4716	.4840
24	42	.100	.020	.029	.4764	.4776
25	46	.271	.019	.030	.4616	.4879
26	29	.036	.020	.030	.4698	.4819

TABLE 18

Electrical Engineering Technology

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_5$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	17	- .337	.012	.031	.011	.4535	.5977
2	25	- .308	.013	.031	.010	.4511	.6016
3	21	- .457	.012	.031	.012	.4371	.6130
4	57	.174	.011	.029	.010	.4491	.5890
5	16	- .541	.012	.032	.012	.4451	.6052
6	39	-1.065	.018	.033	.013	.4550	.6032
7	28	- .429	.012	.031	.011	.4484	.5984
8	18	-1.257	.018	.034	.013	.4362	.6289
9	15	- .430	.013	.031	.011	.4489	.6018
10	28	- .707	.013	.032	.013	.4328	.6284
11	45	- .679	.015	.031	.013	.4475	.6094
12	15	- .487	.013	.031	.011	.4506	.5995
13	15	- .338	.011	.031	.011	.4501	.5991
14	34	- .796	.012	.033	.013	.4412	.6151
15	17	- .884	.014	.032	.012	.4432	.6086
16	17	- .098	.011	.030	.011	.4483	.5990
17	17	- .501	.014	.031	.011	.4513	.5987
18	65	- .483	.014	.031	.012	.4648	.5824
19	15	.328	.009	.029	.010	.4476	.6011
20	72	.037	.009	.029	.010	.4577	.5820
21	26	.184	.009	.028	.010	.4462	.5976
22	18	- .271	.010	.030	.010	.4354	.6115
23	29	.112	.010	.029	.010	.4354	.6209
24	59	-1.421	.019	.034	.015	.4456	.6254
25	25	-1.001	.013	.033	.013	.4304	.6293
26	70	- .622	.013	.032	.012	.4388	.6129
27	21	- .785	.014	.032	.012	.4409	.6096

TABLE 19

Science (4-year transfer)

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_5$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	40	.281	.023	.011	.4414	.4588
2	16	-.283	.031	.014	.4549	.4496
3	14	.681	.017	.020	.4569	.4462
4	11	.425	.026	.005	.4534	.4486
5	15	.281	.024	.012	.4544	.4474
6	58	2.054	.009	.000	.4400	.4557
7	24	-.101	.030	.011	.4563	.4475
8	12	.515	.026	.001	.4522	.4494
9	13	.751	.019	.015	.4551	.4474
10	32	.658	.019	.017	.4586	.4430

TABLE 20

Other Technical

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_5$	$\tilde{R}$	$\tilde{\phi}$
1	10	.825	.030	.3626	.4513
2	13	.922	.031	.3754	.4437
3	20	.759	.033	.3776	.4432
4	20	1.496	.029	.3794	.4401
5	14	1.722	.029	.3778	.4422
6	12	.434	.033	.3724	.4460
7	11	.913	.031	.3754	.4431
8	12	.677	.033	.3722	.4470
9	41	.976	.031	.3728	.4456
10	15	1.006	.030	.3700	.4461
11	23	.931	.031	.3728	.4442
12	16	.755	.033	.3706	.4489
13	17	.433	.033	.3705	.4477
14	10	1.195	.031	.3736	.4453
15	19	.768	.031	.3765	.4421
16	33	1.651	.029	.3700	.4466
17	35	.590	.034	.3774	.4447
18	25	1.502	.029	.3807	.4396
19	23	.805	.032	.3718	.4470

TABLE 21

Auto Mechanics

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	18	.159	.015	.013	.018	.4160	.4369
2	16	.261	.015	.014	.016	.4211	.4336
3	15	-.159	.015	.013	.021	.4196	.4340
4	28	1.475	.013	.012	.001	.4170	.4353
5	38	.926	.013	.013	.007	.3935	.4504
6	64	.125	.016	.013	.016	.4260	.4300
7	41	1.208	.013	.010	.005	.4167	.4320
8	15	.166	.012	.012	.019	.4066	.4413
9	19	1.602	.013	.011	.001	.4184	.4345
10	34	.571	.014	.012	.013	.4114	.4384
11	38	.155	.018	.015	.015	.4259	.4339
12	39	.389	.014	.013	.016	.4283	.4268
13	174	.249	.011	.015	.018	.4471	.4129
14	23	.944	.014	.012	.009	.4242	.4297
15	16	.570	.014	.012	.013	.4219	.4311
16	37	-.107	.015	.012	.022	.3911	.4553
17	16	.227	.015	.013	.017	.4068	.4445
18	20	-.263	.015	.013	.023	.4205	.4342
19	96	.165	.018	.012	.015	.3981	.4505
20	17	1.401	.013	.012	.002	.4123	.4382

TABLE 22

Drafting

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	68	-.655	.026	.024	.009	.4468	.5158
2	10	-.274	.025	.015	.015	.4497	.5104
3	30	.331	.023	.018	.009	.4584	.5024
4	10	-.279	.025	.018	.013	.4481	.5104
5	26	-.173	.025	.014	.012	.4528	.5058
6	25	-.392	.024	.016	.013	.4463	.5115
7	11	-.668	.026	.013	.016	.4432	.5175
8	10	-.389	.025	.016	.014	.4504	.5068
9	11	-.758	.025	.018	.016	.4521	.5077
10	15	-.475	.024	.017	.013	.4380	.5195
11	17	-.027	.023	.019	.004	.4378	.5197
12	62	-.514	.023	.023	.013	.4591	.4987
13	12	-.528	.026	.020	.011	.4410	.5199
14	10	-.763	.027	.015	.018	.4396	.5225
15	11	.157	.025	.016	.008	.4491	.5095
16	74	-.594	.026	.016	.019	.4430	.5188
17	26	.202	.022	.017	.000	.4398	.5158

TABLE 23

Machine Work

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_4$	$\tilde{R}$	$\tilde{\phi}$
1	12	- .173	.024	.035	.5900	.3855
2	14	.613	.005	.039	.5931	.3822
3	24	.139	.004	.038	.5925	.3793
4	10	- .573	.032	.036	.5964	.3810
5	12	- .703	.021	.038	.5941	.3803
6	17	- .886	.033	.035	.5954	.3785
7	27	- .089	.021	.033	.5906	.3817
8	19	-1.444	.043	.033	.5931	.3823
9	11	- .307	.010	.040	.5920	.3835
10	17	.067	.006	.039	.5891	.3862

TABLE 24

Other Trades

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_4$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	90	1.283	.012	.006	.007	.3794	.4783
2	34	.595	.017	.009	.013	.4154	.4854
3	29	.599	.015	.011	.012	.3916	.4782
4	67	1.052	.019	.008	.007	.3828	.4844
5	40	.713	.013	.010	.011	.3774	.4882
6	49	1.279	.016	.006	.006	.3798	.4839
7	54	.688	.018	.010	.010	.3830	.4871
8	28	.845	.015	.009	.010	.3926	.4885
9	31	.487	.018	.011	.012	.3624	.5040
10	58	.615	.016	.011	.011	.3605	.5022
11	27	.682	.016	.009	.011	.3840	.4845
12	21	1.227	.018	.005	.006	.3753	.4894
13	25	.789	.016	.009	.010	.3556	.5045
14	20	.507	.016	.012	.012	.3810	.4883
15	138	.900	.014	.008	.010	.3820	.4764
16	194	.571	.013	.010	.014	.4023	.4696
17	39	1.061	.019	.007	.007	.3823	.4867
18	47	.703	.018	.009	.011	.3742	.4918
19	37	1.035	.018	.008	.008	.3750	.4899
20	34	.692	.018	.009	.011	.3863	.4827
21	51	.462	.017	.011	.013	.3733	.4942
22	60	.799	.016	.009	.010	.3773	.4894
23	167	.340	.016	.013	.014	.3408	.5264
24	58	.767	.011	.009	.012	.3556	.5017

TABLE 25

Cosmetology

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	15	1.716	.032	.5365	.1002
2	33	1.473	.030	.4466	.6277
3	17	1.419	.016	.3111	.1373
4	15	1.702	.034	.5830	.1505
5	18	1.463	.023	.2391	.6039
6	15	1.490	.023	.0000	.9227
7	12	1.359	.016	.4441	.0932
8	16	1.506	.026	.3319	.2867
9	22	1.541	.033	.5046	.5539

TABLE 26

Police Science

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	51	.462	.015	.025	.4221	.4716
2	18	.561	.013	.025	.4290	.4642
3	36	1.312	.009	.018	.4171	.4721
4	26	.732	.015	.021	.4211	.4702
5	18	.609	.014	.022	.4242	.4670
6	24	.821	.013	.023	.4280	.4647
7	21	1.621	.007	.020	.4261	.4666
8	15	-.226	.018	.028	.4317	.4634

TABLE 27

Social Science (4-year transfer)

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_7$	$\tilde{R}$	$\tilde{\phi}$
1	69	.910	.026	.0000	.5724
2	31	1.286	.021	.1555	.5449
3	20	1.409	.020	.1652	.5420
4	18	1.647	.018	.1545	.5447
5	152	2.296	.010	.1462	.5456
6	30	.867	.026	.1732	.5405
7	37	.825	.027	.1212	.5570
8	17	1.173	.023	.1700	.5412
9	16	1.441	.020	.1584	.5448
10	19	1.650	.018	.1714	.5397
11	10	1.475	.020	.1596	.5431

TABLE 28

Arts and Humanities (4-year transfer)

Institution	N	$\tilde{\beta}_0$	$\tilde{\beta}_1$	$\tilde{R}$	$\tilde{\phi}$
1	25	1.730	.015	.0900	.5577
2	17	1.889	.015	.1352	.5497
3	236	2.067	.011	.0000	.5760
4	15	1.289	.022	.1685	.5416
5	22	1.492	.019	.1545	.5454
6	11	.873	.026	.1371	.5501

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