7

GMAT SCORES AND PERFORMANCE: SELECTING STUDENTS INTO A GRADUATE MANAGEMENT SCHOOL

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Abstract:

Research shows that scores on the Graduate Management Admission Test (GMAT) are positively correlated with academic performance at graduate management schools. This study replicates this finding on Australian data and extends the analysis to cover performance at the individual course level as well as for aggregate grade point average. This traditional treatment of the data while directed at the admission decision is in fact structured to explain variance in performance. A novel analysis is presented in parallel which investigates the trade-off between Type I errors (rejecting a student who would pass) and Type II errors (accepting a student who fails). This reveals that, while GMAT may be a good predictor of performance, it is an inefficient discriminator for selection purposes.

Keywords:

ACADEMIC PERFORMANCE; GRADUATE MANAGEMENT ADMISSION TEST; SELECTION ERRORS; STUDENT ADMISSION

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1. *INTRODUCTION*

Selecting students for admission to academic institutions has traditionally been a matter of clinical judgement. The admissions committee evaluates the applicant's ability to express his or her reasons for applying, academic record, choice of referees and their comments, oral skills and appearance if interviewed, and any other aspects of the applicant's history thought relevant by the committee. However, at least four developments have militated against this approach: increasing numbers of applicants, the increasing costs to the institution of accepting students who subsequently fail, the development of standardised predictors such as the Graduate Management Admission Test (GMAT), and advances in statistical integration of predictive information.

While the first three developments are specific to the admissions decision, the fourth is more general and has received considerable attention in the literature. The consensus is that linear models equal or outperform clinical judgement on the prediction of numerical outcomes, including academic performance, from numerical predictors, such as GMAT scores, prior academic performance, and referees' ratings [Dawes (1971), (1980)]. However, regression and most other forms of linear analysis minimise predictive errors equally across the observed range of the dependent variable. Moreover, measures of comparative performance across decision schemes typically also weight such errors equally. In contrast, the student admission decision is sensitive to errors over a very restricted range. The decision required is simply to partition the applicants into two groups: those who are predicted to satisfy the minimum performance standards in the programme, and those who are not. It is not concerned with predicting differential performance amongst those accepted, and therefore the use of linear models may be less appropriate than elsewhere.

Whatever the method, the resultant errors of exclusion and inclusion have very different consequences for the applicants and the graduate management school. The personal cost to an applicant who is erroneously rejected is very evident to the applicant, but usually of little concern to the academic institution, which bears no direct cost for such mistakes. Nevertheless the increasing costs to the institutions of erroneous acceptances have apparently motivated them to look more closely at the selection decision.

Now, most alternatives to clinical judgement require standardised predictors which provide common yardsticks for consideration of applicants of widely varying backgrounds. Recently one of these, namely GMAT, has come to dominate all other similar indices within graduate management schools and is endorsed by the Graduate Management Admissions Council as:

> "(..Scores on the GMAT) are dependable predictors of certain mental abilities that have been found to be important in the study of management at the graduate level. In repeated studies of the effectiveness of the GMAT, it has been consistently found that the test scores are good, although imperfect, predictors of academic success in graduate schools of management."

The Council warn, however, that

> "..in making admissions decisions, schools of management have been cautioned to use GMAT scores as <u>only one measure of an applicant's ability to succeed in graduate work</u>." (original emphasis) [ETS (1979)]

Their claim and subsequent qualification highlight two separate issues which although closely related are conceptually distinct. One is the value of the GMAT Total score and its constituent Quantitative and Verbal scores as numerical predictors of the applicant's academic performance in a master's programme, both overall and in individual courses.[1] The other is the value of using GMAT scores as cut-off points in trading off erroneous acceptances against erroneous rejections. The former concerns our ability to explain variance in student performance. The latter focuses on selection errors.

Most research although directed towards the selection decision is in fact structured to explain performance variance. Investigating GMAT as a predictor of Graduate Grade Point Average (GGPA), Deckro and Woundenberg (1977) analysed the performance of 62 full time and 95 part time students at Kent State University. They found that 14.5% of the variance in GGPA could be explained by a linear combination of GMAT Total score, Undergraduate Grade Point Average (UGPA), Junior/Senior (High School) GPA and Sex. Work experience, age, minority status and the student's part time/full time status explained additional variance. While noting the confounding from multi-collinearity, they concluded that GMAT Total score was the most significant <u>single</u> criterion for admission. It is interesting to note that the admission "hurdle" of UGPA > 2.5 and GMAT Total > 480 (although not stressed in the paper) provided approximately 20% Type II errors: cases of students who were admitted and who subsequently failed to meet the minimum performance requirements of the Kent State programme. On this evidence, GMAT is an "imperfect predictor of academic success"; but is it also a "good" one, as the Council claim?

Similarly, Daft (1978) found that 23% of the variation in the first year GGPA of 70 Queens University MBA students who enrolled in the second year of the programme could be explained by variations in GMAT Total score. Furthermore, when the difference between Verbal and Quantitative scores (V - Q) was added to the predictor variable set along with Marital Status, UGPA, and "Potential to Communicate," the explained variance rose to 42%. This suggests that GMAT in conjunction with other criteria is a good predictor. However, this large incremental gain in explained variance from additional criteria variables is not the typical finding. Indeed, Daft's results may be an artefact of his research strategy.[2]

Similar research on the Graduate Record Exam (GRE) as a predictor of GGPA suggests that GRE is also an imperfect predictor of academic success and probably a weaker predictor than is GMAT. Studying a highly homogeneous population of 167 students from NASA, the USAF, and their subcontractors in the Cape Canaveral area, Gayle and Jones (1973) found that only 16% of the variance in GGPA could be explained by age and GRE scores, with the latter providing the greater part of the variance. Gayle and Jones also found that, when GRE and UGPA were both included as independent variables, UGPA did not account for any additional variance.

The typical research study and the majority of North American graduate school selection systems use GMAT Total scores, or their equivalent, rather than their constituent Verbal and Quantitative elements, or other dimensions. Against this, Page and West (1969) point out that a number of studies have shown that Admission Test for Graduate Study in Business (as GMAT was then known) scores were more useful when separated into their Verbal and Quantitative components. In particular, they conclude that Quantitative scores appear more closely related to

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[1]To avoid confusion with the psychological usage of the word "subject," we use instead the word "course" throughout; a "programme" is the portfolio of individual courses undertaken by the student for his or her degree.

[2]Daft used the variable (V - Q) because for his population it was uncorrelated with GMAT Total. But there is evidence that the distribution of Verbal scores is left-skewed while the distribution of Quantitative scores is right-skewed, which would lead to a negative correlation between (V - Q) and programme performance.

academic performance than do Verbal scores. However, using a quantitative intelligence score to predict performance in a multi-disciplinary school would raise a number of validity problems as well as ideological issues.

Finally, the above findings refer only to students who had been accepted for and subsequently attended a graduate management school. Now, all the schools involved applied minimum GMAT entry requirements. When Deckro and Woundenberg studied the Kent State programme, the cut-off was GMAT Total > 480. The research findings may be limited to a restricted range on the main criterion variable. This effect of population curtailment on the correlation between predictor and criterion variables is discussed by Hills (1977), Nord, Connelly, and Daignault (1974), and Srinivasan and Weinstein (1973). The performance of excluded students cannot be evaluated and thus there can be no measure of the rate of Type I errors: cases of students who were not admitted but who would have satisfied the minimum performance requirements of the programme, had they been so admitted. Srinivasan and Weinstein suggest procedures to correct for curtailment errors by assuming that the regression equations derived from the student population also apply to the applicant population, and that errors in prediction are homoscedastic across all values of the predictor variables. These are very strong assumptions. What is needed is an experiment where a school accepts students with a wider range of GMAT scores.[3]

In this study, we replicate some of the above research in the Australian context. The target organisation admits students with a wider range of GMAT scores than do the North American schools represented in the existing research literature, permitting us some comment on the attenuation issue. However, unlike these schools, the target organisation's own evaluation system is not based on grade point averages or other aggregate measures, but on individual course performance. Failure in two required or "core" courses constitutes grounds for cancelling a student's registration. This suggests a probability analysis which addresses directly the frequency of selection errors, rather than a linear model which predicts student performance. As noted earlier, the former is not commonly found in the literature. For completeness, both forms of analysis are reported here.

2. *METHODOLOGY*

In order to investigate the relationships among predictor and criterion variables, student performance and GMAT data have been edited to exclude: students for whom GMAT scores were unknown; courses taken outside the target institution; courses in which results awarded were "pass" or "fail" only; students who were not enrolled in the master's programmes; results where students failed to sit for the final exam; and results which had not been determined at the time of this analysis. This restricts the subjects for this investigation to 111 students taking 56 courses. The unedited data comprise data for 143 students taking 88 courses. (The reduction in the number of courses stems from courses taken outside the target institution.)

Performance criteria are considered in terms of five different procedures for calculating GGPA: GGPA defined as a unit weighted average across all courses; GGPA restricted to "core" courses, "verbal electives" and "quantitative electives"; and performance in individual "core" courses. "Core" courses are those which all students must complete to satisfactory standard in order to qualify for the MBA and MPA degrees, while "verbal electives" and "quantitative electives" are courses the student chooses to take and in which, a priori, verbal

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[3]Two econometric papers dealing with "truncated data" have recently appeared [Heckman (1979), Olsen (1980)]. It may be that the approximations outlined therein would allow consideration of population curtailment.

or quantitative skills might be expected to dominate.

Three predictor variables are examined, namely GMAT Verbal, Quantitative, and Total Scores.

Two basic sets of analysis are undertaken. In one, simple linear regressions of performance on GMAT variables are presented. The other analysis reports estimates of the Type I and Type II errors for different GMAT Total cut-off points in the selection process, given three levels of minimum acceptable GGPA: 55%, 60% and 65%.[4]

3. *RESULTS*

3.1 *Linear Models*

Figure 1 supports the claim by the Graduate Management Admissions Council that GGPA and GMAT Total are positively correlated (r = 0.61). However, the variance reduction achieved by using GGPA rather than individual course scores is evident from a comparison of Figures 1 and 2. Where the student's survival is dependent on GGPA or similar construct, the variance reduction is both appropriate and desirable. As the use of GGPA is the norm in North American graduate schools of management, it is not surprising that the existing research literature is almost universally restricted to analysis at this level of aggregation. In contrast, in the target organisation the survival of the student is a function of performance in individual courses, and, in particular, of performance in core courses. As such, the variance reduction from Figure 2 to Figure 1 is of some concern as it is the outliers forming the lower boundary in Figure 2 which are the critical performance indicators.

Table 1 reports the linear relationships among the different performance and criterion variables. There is no evidence that factoring out Verbal and Quantitative GMAT scores increases predictive power over and above that obtained from GMAT Total. This appears to endorse the use of the Total GMAT score by management schools in their selection process. Note that the low correlation between GMAT Quantitative and performance in quantitative electives is a function of curtailment: students with low quantitative scores tend to avoid these courses.

With the exception of quantitative electives, curtailment is not a problem. As such, the data allow us to address directly the problem of criterion attenuation noted in the introduction. This is achieved by using an F test to determine whether the relationship between GMAT Total and GGPA is similar for students with GMAT scores above, versus below, 480. (An arbitrary cut-off; this is the lower bound in Deckro and Woundenberg [1977].) The equations fitted to the two subsets and the total sample are as follows:

Sub Sample GMAT Total $\leqslant$ 480:	$E(s) = .033T + 50.7$; $r = .19$
Sub Sample GMAT Total $>$ 480:	$E(s) = .053T + 40.8$; $r = .31$
Complete Sample:	$E(s) = .043T + 46.6$; $r = .61$

An F test of the within-group to between-group variance reveals no significant differences, and the assumptions made by Srinivasan and Weinstein (1973), while strong, may be acceptable. However, if there are any differences (and this test is only weak evidence for their absence), the analysis suggests that the rate of change of performance with GMAT is a negative function of GMAT. Thus, the lower

[4]Our GGPA is calculated using unit-weighted percentage grades for each subject (where 50% is a threshold pass).

the GMAT cut-off value, the poorer this value as a discriminator for selection.

The picture is somewhat different at the individual course level. Figures 3, 4, 5, and 6 show how the within individual course and between individual course variance is structured. As expected, performance in Accounting Information is strongly correlated with GMAT Quantitative scores (r_q = 0.52) but less so with Verbal scores (r_v = 0.30), while the pattern is reversed for performance in Human Behaviour (r_q = 0.21, r_v = 0.54).

Table 2 reports the correlation coefficients between performance on each core course and with GMAT Verbal, Quantitative, and Total scores. While the patterns for Accounting Information and for Human Behaviour in Organisations are not unique, there is little reduction in predictive power when GMAT Total is used instead of the appropriate Verbal or Quantitative score for most courses. This appears to further justify the use of GMAT Total scores for selection, even when student performance is measured at the individual course level.

However, this assumes that student failures are approximately uniformly distributed across courses. This is not true for the target organisation, where failures occur most frequently in Quantitative Methods, less frequently in other "quantitative" courses, and rarely in the "verbal" courses. Note that for Quantitative Methods r_q = 0.60, r_v = 0.03 and r_t = 0.30. If student failures are not close to being uniformly distributed across courses, then this would weaken the robustness of the GMAT Total score as a selection criterion and would justify relatively more weight being assigned to the GMAT Quantitative score, as argued by Page and West (1969).

3.2 Probability Models

The analysis above is concerned with behaviour over the whole range of the performance and criterion variables. However, selection simply partitions the applicant set into those who are judged to be acceptable and those who are judged to be unacceptable. Here we consider the Type I and Type II error rates associated with different GMAT Total cut-off points and different levels of satisfactory performance.

Tables 3 and 4 present the data associated with Type I and Type II errors, respectively. Table 3 presents the numbers of students who scored less than or equal to various GMAT Total cut-off levels, and the numbers of these students who also attained each of the three levels of minimum GGPA: 55%, 60%, and 65%. These levels require the marginal student to perform at the Pass, high Pass, and low Credit levels, respectively, for each year in the programme. Type I errors are cases of (rejected) students below the cut-off who would have attained the minimum GGPA level. Table 4 presents the numbers of students who scored greater than the cut-off levels, and the numbers of these students who also failed to attain each of the levels of minimum GGPA. Type II errors are cases of (accepted) students above the cut-off who did not attain the minimum GGPA level.

Figure 7 presents the Type I and Type II error rates for the three levels of minimum GGPA against the GMAT Total cut-off levels. Obviously, as the Total GMAT cut-off is increased, the Type I error rate (the probability of incorrect rejection) rises and the Type II error rate (the probability of incorrect acceptance) declines. For example, with a cut-off of 375 and a minimum average performance of a low Credit (65%), the Type I error rate would be 6.7% and the Type II error rate 39.5%. On the other hand, with a cut-off of 525 and the same minimum performance level, the Type I rate would have climbed to 33.8% and the Type II rate fallen to 14.8%.

It is likely that a Type II error rate of 39.57% would be unacceptable. Whether or not 14.7% is acceptable is moot. Certainly, a 33.8% Type I error rate would at least appear to be unfair to the applicants unless alternative institutions offer equivalent study programmes and also use different selection criteria. If zero cost were placed on Type I errors, the minimum cost solution would be to minimize Type II errors: at cut-off scores of 525, 550, and 600 for minimum GGPAs of 55%, 60%, and 65%, respectively. Conversely, if zero cost were placed on Type II errors, the solution would be to minimize Type I errors at a cut-off score of 350 for a minimum GGPA of 65%.

Examination of Figure 7 shows that GMAT Total is not a particularly good discriminator between those students who would pass (as defined by the three minimum GGPA levels) and those who would fail. This finding supports the warning of the Graduate Management Admissions Council above. Two indicators of effectiveness of the GMAT as a discriminator are (1) the difference in cut-off GMAT scores between the maximum at which the Type I error rate is zero and the minimum at which the Type II error rate is zero, and (2) the minimum simultaneous rate of errors. For a minimum GGPA of 65% (1) the maximum GMAT associated with zero Type I error is 350, while the minimum GMAT associated with zero Type II error is 600, and (2) the simultaneous minimum error is 26.0% at a GMAT of 475. For a minimum GGPA of 60% the figures for measure (1) are 300 and 550, and for (2) 20.0% at 312. For a minimum GGPA of 55%, the data do not provide a comparison.

3.3 Additional Analysis

Before discussing the above findings, we report in Table 1 some interesting findings for performance comparisons between core and elective courses. Not surprisingly, mean scores for elective courses are statistically significantly higher than those for core courses. The difference in means (approximately 3.5 percentage points), while not great, would affect the letter grade results of a significant proportion of students. Consider the classes in Accounting Information as an example. In the time period considered, 103 master's students have taken the final examination. Had mean scores been 3 percentage points higher, the distribution of student letter grades would have changed as shown in Table 5. Thus a difference in mean score of 3 percentage points would have been likely to raise the letter grades of nearly one third of the students involved. Note that, from Figure 1, the expected increase in GGPA is 4.3 per cent for each 100 points rise in GMAT Total. The likely balance of electives to core courses in a student's portfolio is therefore important with respect to the use of GMAT as a selection criterion. Where this balance is itself a variable, the selection issue is further complicated.

4. DISCUSSION

4.1 Quantitative versus Verbal Predictor Variables

There has been some discussion in the literature as to whether differential weight should be given to Quantitative versus Verbal GMAT scores in admission criteria [Boldt (1969); Campbell and Casserly (1973); Daft (1978)]. Two methodological issues need to be addressed here. One is the commonly recognised problem of multi-collinearity. The second issue is whether the treatment, in this case an MBA or MPA degree, represents a fixed or variable effect model. Cronbach and Gleser (1965) show that when a process is adaptive (variable effect model) each treatment (portfolio of courses which satisfy the MBA or MPA requirements) has its own function relating performance to criterion scores.

On the core courses (fixed effect), the relationships between Quantitative GMAT, Verbal GMAT, and individual course performance displayed in Table 2 are consistent with commonsense. Multicollinearity is not strong enough to threaten these patterns. On elective courses (variable model), the situation is somewhat different. The relationship between Quantitative GMAT and performance is very weak (see Table 1). Two explanations suggest themselves. One is that students self-select: only students with high Quantitative GMAT scores take such courses. This is a curtailment problem. The other explanation is that this self-selection is compounded by instructors adapting course content and evaluation process to meet the students' abilities.

The key issue, however, is not one of multi-collinearity or even of fixed or variable effects models, but of performance criterion. As reported above, if the performance criterion is GGPA or equivalent, Total GMAT seems to be an acceptable criterion variable and little is to be gained from including its sub-scales. If, however, the performance criterion is to be success (non-failure) on quantitative core courses, the Quantitative GMAT scores should receive more weight than Verbal GMAT scores in the selection process. This implies a relatively higher percentile cut-off on the Quantitative score than on the Verbal.

In contrast, if Mintzberg (1975) is correct and management success is dependent on verbal and communication skills, then, while Quantitative GMAT may be a good selection variable for non-failure on quantitative core courses, it would not be so for future management success. The institution would then need to choose between performance in core courses and managerial success as its output function. The time-lagged and ill-defined nature of managerial success, in contrast to the immediacy and precision of the GPA assessment, make any analysis in this policy area difficult.

4.2 Additional Predictor Variables

While there is some evidence that personality variables such as Need for Achievement [Webb (1965)] or Locus of Control [Nord, Connelly, and Daignault (1974)] predict performance, the relationships are weak. Intuitively, personality should predict performance but, as elsewhere, the findings for personality main effects have been disappointing. Equally, combinations of similar cognitive intelligence measures such as GMAT and GRE add little to the predictive power of GMAT.

The motivation literature in which performance is a multiplicative function of ability and motivation [Vroom (1964)] suggests a different set of predictor variables. Again conventional measures of motivation do not increase the predictive power of the selection models. Instead, arguments are sometimes advanced for conducting interviews to assess motivation. Unfortunately, the research evidence is that interviews are ineffective and very costly [Cronbach and Gleser (1965); Kelly (1954); Webster (1964)].[5]

4.3 Who Takes the Risks?

The primary purpose of this paper is to explore the Type I and Type II error rates contingent on the use of GMAT as a selection device. So far we have not asked who carries the risk. Consider the case, not unknown at top North American schools, in which there are twenty "reasonable" applicants for each student place. The institution can "afford" a high Type I error rate (rejecting many applicants who would have passed) in order to minimise its Type II error rate (accepting students who fail). As noted above, the cost to the rejected student (Type I error) depends on the existence of alternative MBA or MPA programmes with independent entrance requirements. In Australia, with a limited number of programmes, all of which are government funded and hence all likely to be

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[5]A possible alternative is signalled by Fiedler and Leister (1977) on the relationship between stress, experience, and performance. They show that under stress people rely more on experience than on intellect. In low stress situations the converse is true. A state/trait approach with stress as a moderator variable might strengthen the predictive power of GMAT. It might explain and help to reduce Type II error rates.

"required" to adopt similar selection criteria, the cost to the student of Type I errors is higher than is the case in America, and needs to be kept in mind by the selectors.

Not all Type II errors have the same cost. Failure after six, twelve, eighteen, and twenty-four months imposes increasing costs on both student and school.[6] A combination selection/evaluation strategy, with a low Type I error rate and a "high" failure rate after six months is an alternative "selection" criterion. Indeed, students with a high Type II risk could be so warned when offered a place.

5. *SUMMARY*

In this paper we separate analytically the related issues of explaining student performance and of predicting selection errors as a function of a minimum admission criterion. Using Australian data we replicate the typical analysis reported in the literature which shows that GGPA and GMAT Total are positively correlated. We extend this analysis by partitioning GMAT into its Quantitative and Verbal factors and examining students' results in individual courses. This shows that there is little gain in explanatory power when the constituent rather than Total scores are used, even when student performance is measured at the individual course level. The exception to this is that GMAT Quantitative scores dominate Total scores in the explanation of performance in quantitative core courses.

The second theme is concerned with the trade-off between the rates of erroneous acceptance and erroneous rejection contingent on varying GMAT Total cut-off scores. Although academic institutions are probably more concerned about the costs incurred due to errors in acceptance than in rejection, they should recognise the costs to applicants of the latter. Our analysis reveals that while GMAT may provide a good explanation of performance variance, it is an inefficient discriminator for selection purposes, as measured by its ability to realise low Type I and II admission errors simultaneously. Moreover, the Type I error rates are high even for low cut-off scores. For further research in evaluating GMAT and other attributes as selection criteria, we would argue that a probability analysis, such as reported here and not typically found in the literature, is more appropriate than is linear analysis.

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[6]In the case of a government-funded school, the costs of Type II errors are not clearly defined, as the continuing debate in the public finance literature on the opportunity costs of government spending attests.

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Table 1

Regression coefficients and variance explained by GMAT variables, for individual and mean course scores.

	INDIVIDUAL SCORES				MEAN SCORES			
	All Courses	Core Courses	"Verbal" Electives	"Quant" Electives	All Courses	Core Courses	"Verbal" Electives	"Quant" Electives
Mean Score	67.1	66.3	69.9	70.0	67.2	67.1	69.0	69.8
Std Dev	10.1	10.3	8.6	10.4	6.9	7.4	7.9	9.2
Number	1370	1008	165	120	185	183	78	67
Verbal and Quantitative [$E(s) = B_v*V + B_q + c$]								
B_v	.278	.256	.414	.275	.290	.331	.428	.267
(t)	(8.3)	(6.4)	(5.4)	(2.4)	(5.3)	(5.0)	(4.2)	(1.9)
B_q	.295	.357	.039	.346	.290	.269	.090	.179
(t)	(8.3)	(8.4)	(0.5)	(2.6)	(4.9)	(4.3)	(0.8)	(1.1)
r^2	.16	.17	.21	.18	.35	.32	.28	.12
Verbal [$E(s) = B_v*V + c$]								
B_v	.412	.415	.432	.430	.416	.417	.469	.340
(t)	(13.8)	(11.4)	(6.5)	(4.3)	(8.2)	(7.3)	(5.3)	(2.8)
r^2	.12	.12	.21	.14	.27	.23	.27	.11
Quantitative [$E(s) = B_q + c$]								
B_q	.439	.485	.260	.513	.439	.471	.317	.321
(t)	(13.7)	(12.8)	(3.4)	(4.4)	(7.9)	(7.3)	(3.0)	(2.3)
r^2	.12	.14	.07	.14	.25	.25	.11	.07
Total [$E(s) = B_t + c$]								
B_t	.043	.045	.039	.045	.043	.044	.042	.034
(t)	(16.7)	(14.5)	(6.5)	(5.3)	(10.3)	(9.4)	(5.3)	(3.2)
r^2	.17	.17	.20	.19	.37	.33	.27	.14

Table 2

Relationships between GMAT variables taken individually, and individual core course scores.

Course	GMAT Verbal		GMAT Quant.		GMAT Total	
	B_v	r^2	B_q	r^2	B_t	r^2
Common to MBA and MPA:						
Accounting Information	.399	.09	.712	.27	.0503	.20
Price Theory	.408	.07	.763	.23	.0555	.17
Macroeconomics	.271	.11	.279	.11	.0280	.16
Human Behaviour in Organisations	.450	.29	.188	.04	.0358	.24
Industrial Relations	.289	.19	.040	.00	.0198	.11
Marketing	.342	.08	.243	.04	.0318	.09
Quantitative Methods	.054	.00	1.043	.36	.0439	.09
Decision Analysis	.526	.12	.952	.36	.0678	.26
Operations Management	.466	.29	.280	.09	.0396	.27
Management in Society	.415	.24	.275	.09	.0371	.24
MBA Core:						
Finance	.533	.17	.639	.23	.0584	.27
Business Law	.647	.31	.283	.05	.053	.26
Corporate Policy	.766	.45	.733	.37	.0721	.54
MPA Core:						
Administrative Law	.067	.00	-.459	.19	-.0145	.03
Public Sector Systems	.619	.28	-.001	.00	.0351	.13
Public Policy	.515	.21	.538	.29	.0562	.36
Australian Public Policy Formation	.514	.23	.375	.13	.0505	.29

Table 3

Type I Errors

GMAT Total cut-off	Students ≤ cut-off	min GGPA = 55% Students > min	Type I error	min GGPA = 60% Students > min	Type I error	min GGPA = 65% Students > min	Type I error
300	2	1	0.5	0	0	0	0
325	5	4	0.8	2	0.4	0	0
350	7	6	0.857	3	0.429	0	0
375	15	13	0.867	7	0.467	1	0.067
400	25	22	0.888	14	0.560	3	0.120
425	33	29	0.879	20	0.606	5	0.152
450	46	42	0.913	30	0.652	10	0.217
475	57	52	0.912	38	0.667	15	0.263
500	65	60	0.923	44	0.677	18	0.277
525	77	71	0.922	54	0.701	26	0.338
550	87	81	0.931	63	0.724	33	0.379
575	88	82	0.932	64	0.727	34	0.386
600	96	90	0.938	72	0.750	40	0.417
625	100	94	0.94	76	0.760	44	0.440
650	107	101	0.944	83	0.776	51	0.477
675	109	103	0.945	85	0.780	53	0.486
700	109	103	0.945	85	0.780	53	0.486

Table 4

Type II Errors

GMAT Total cut-off	Students > cut-off	min GGPA = 55% Students < min	min GGPA = 55% Type II error	min GGPA = 60% Students < min	min GGPA = 60% Type II error	min GGPA = 65% Students < min	min GGPA = 65% Type II error
300	109	6	0.055	22	0.202	54	0.495
325	106	6	0.057	21	0.198	51	0.481
350	104	6	0.058	20	0.192	49	0.471
375	96	4	0.042	16	0.167	42	0.438
400	86	3	0.035	13	0.151	34	0.395
425	78	2	0.026	11	0.141	28	0.359
450	65	2	0.031	8	0.123	20	0.308
475	54	1	0.019	5	0.093	14	0.259
500	46	1	0.022	3	0.065	9	0.196
525	34	0	0	1	0.029	5	0.147
550	24	0	0	0	0	2	0.083
575	23	0	0	0	0	2	0.087
600	15	0	0	0	0	0	0
625	11	0	0	0	0	0	0
650	4	0	0	0	0	0	0
675	2	0	0	0	0	0	0
700	2	0	0	0	0	0	0

Table 5

Distribution of Letter Grades in Accounting Information

1978 - 1980

Grade	Number actually awarded	Number which would have been awarded	Difference	Number of students affected
HD (85-100%)	5	8	+3	3
DN (75-84%)	12	24	+12	12
CR (65-74%)	31	26	-5	5
PS (50-64%)	53	45	-8	8
PC (45-49%)	2	0	-2	2
Totals	103	103	0	30

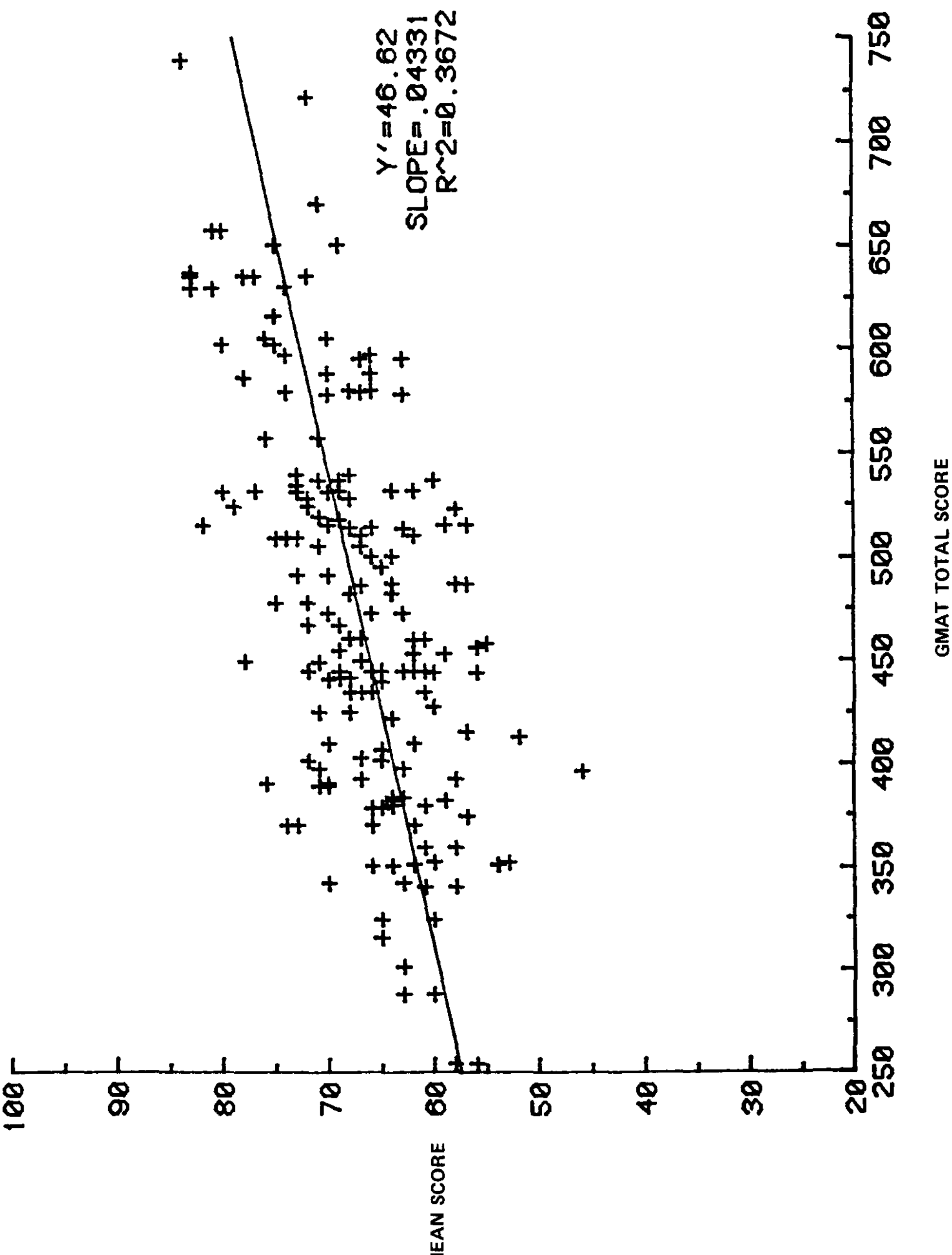

FIGURE 1: MEAN STUDENT SCORES vs GMAT CRITERIA
ALL COURSES: 1978 TO 1980

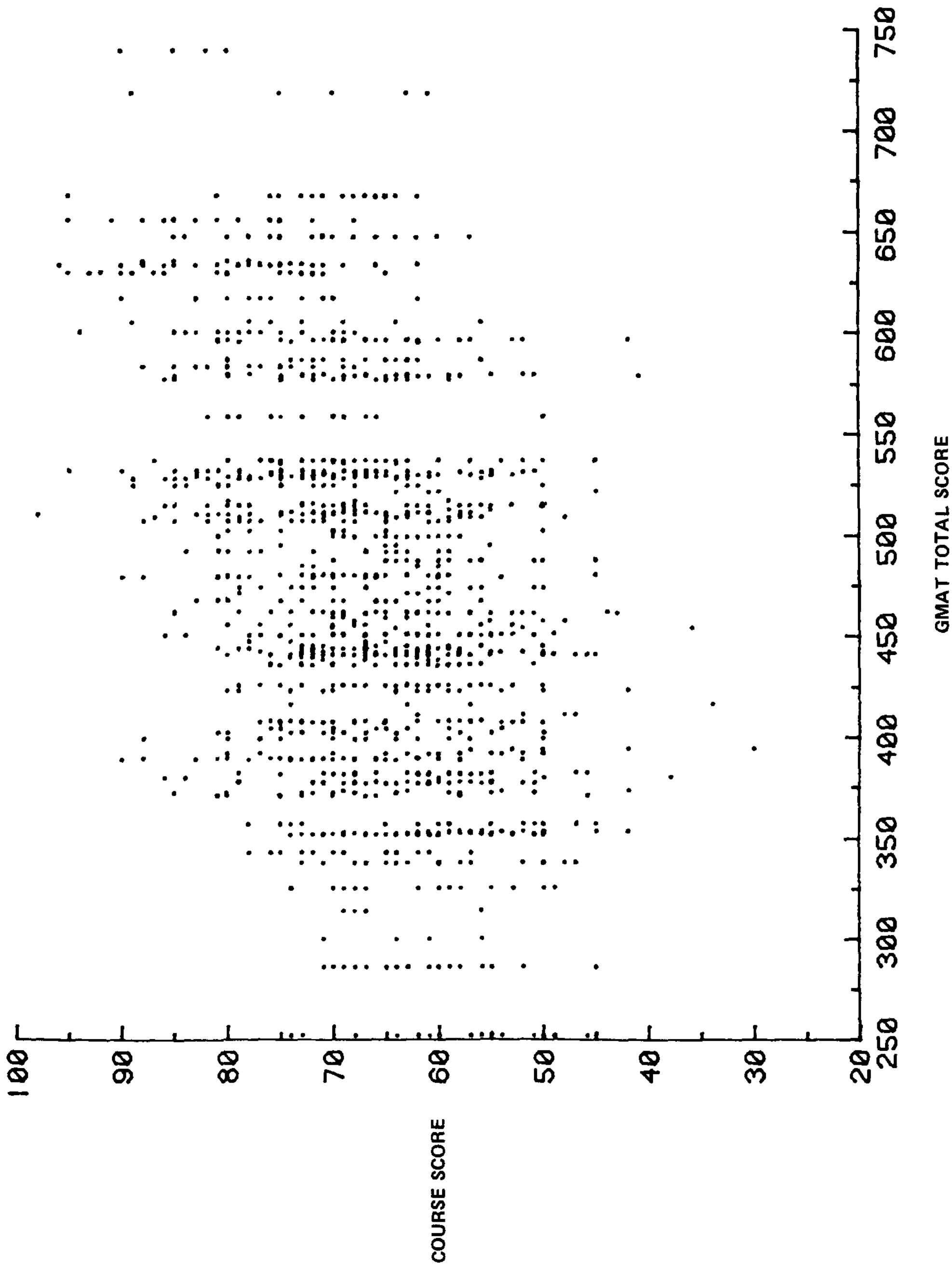

FIGURE 2: INDIVIDUAL COURSE SCORES vs GMAT CRITERIA
ALL COURSES: 1978 TO 1980

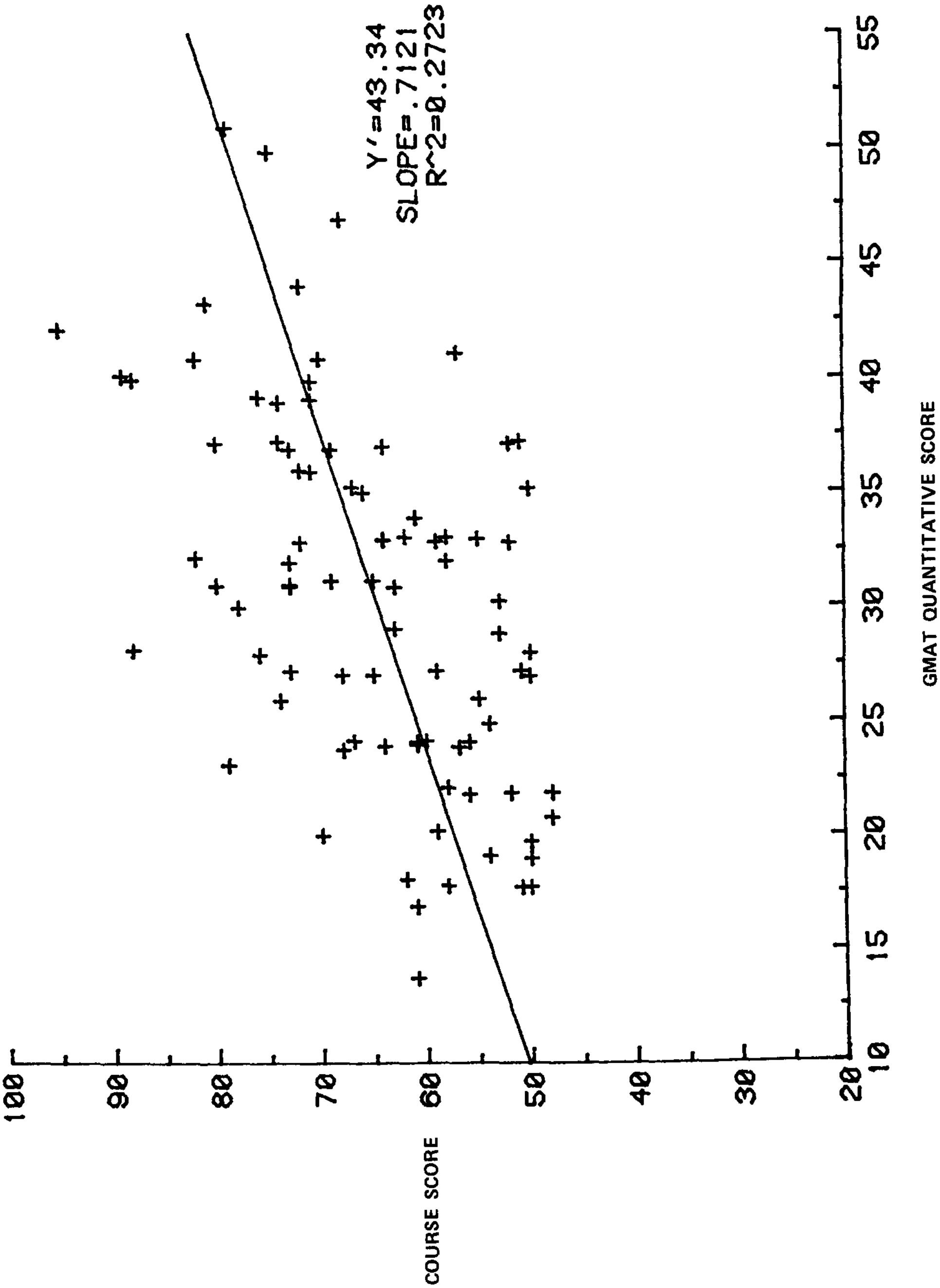

FIGURE 3: INDIVIDUAL COURSE SCORES vs GMAT CRITERIA
ACCOUNTING INFORMATION: 1978 TO 1980

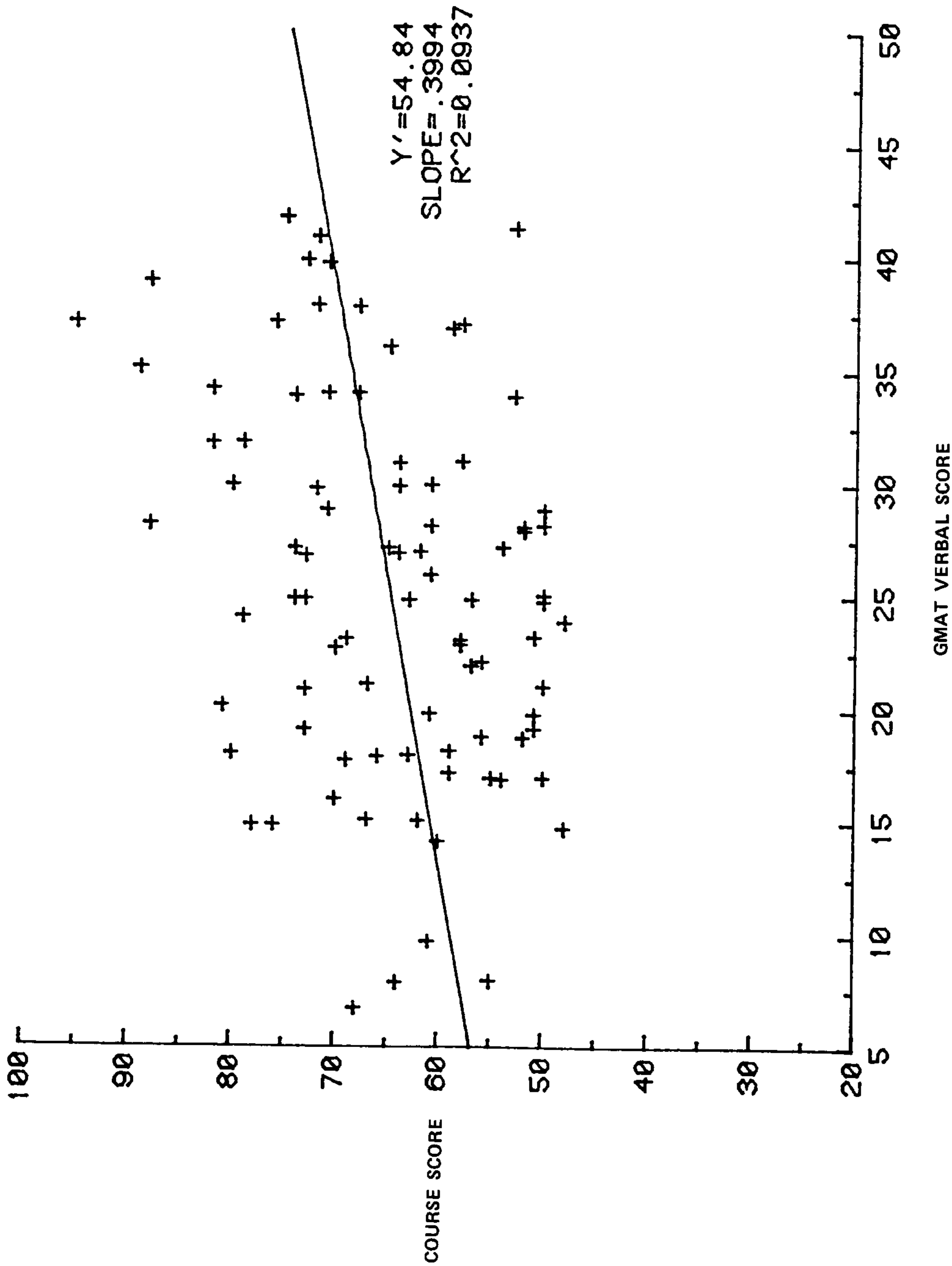

FIGURE 4: INDIVIDUAL COURSE SCORES vs GMAT CRITERIA
ACCOUNTING INFORMATION: 1978 TO 1980

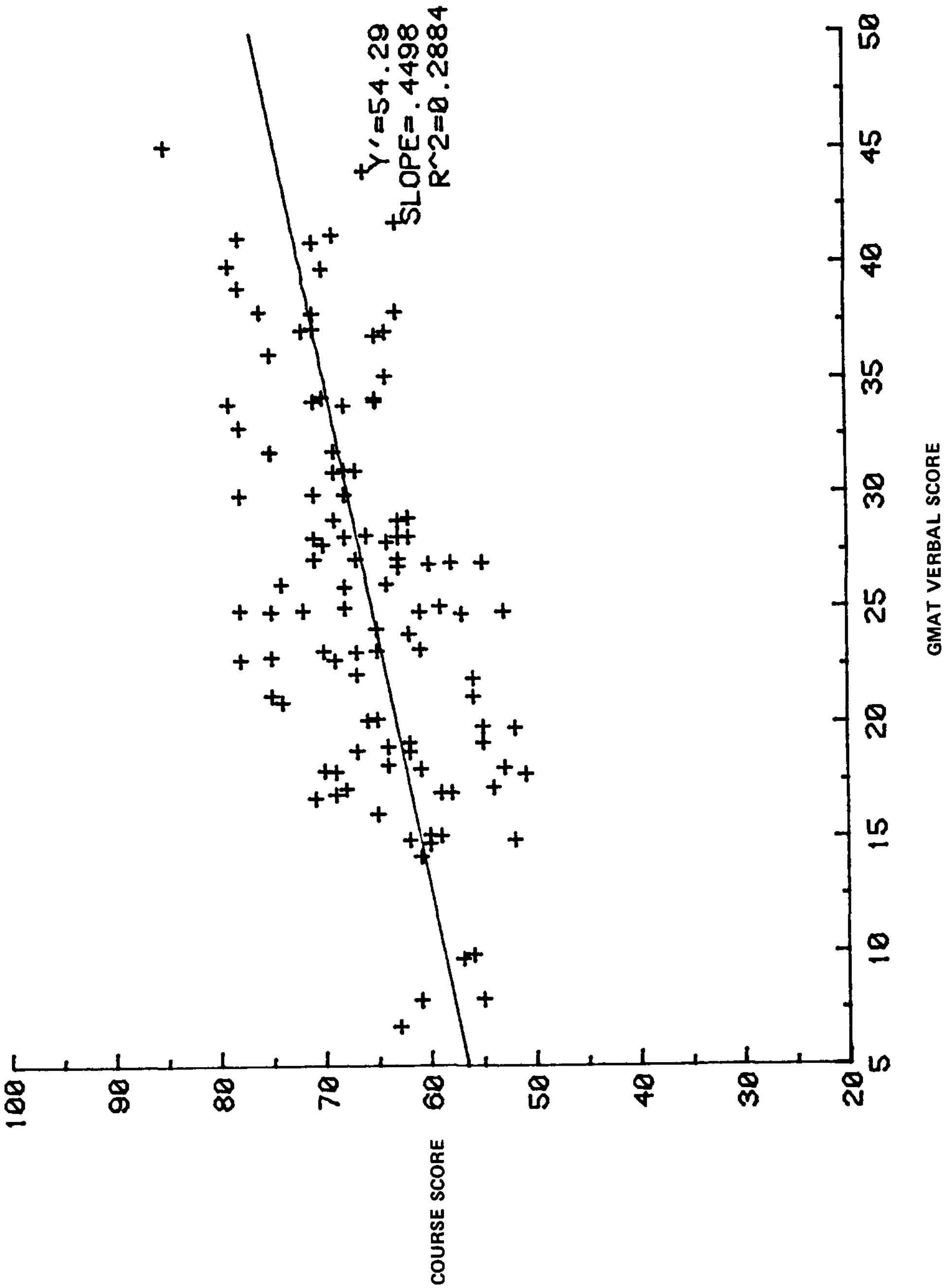

FIGURE 5: INDIVIDUAL COURSE SCORES vs GMAT CRITERIA
HUMAN BEHAVIOUR IN ORGANIZATIONS: 1978 TO 1980

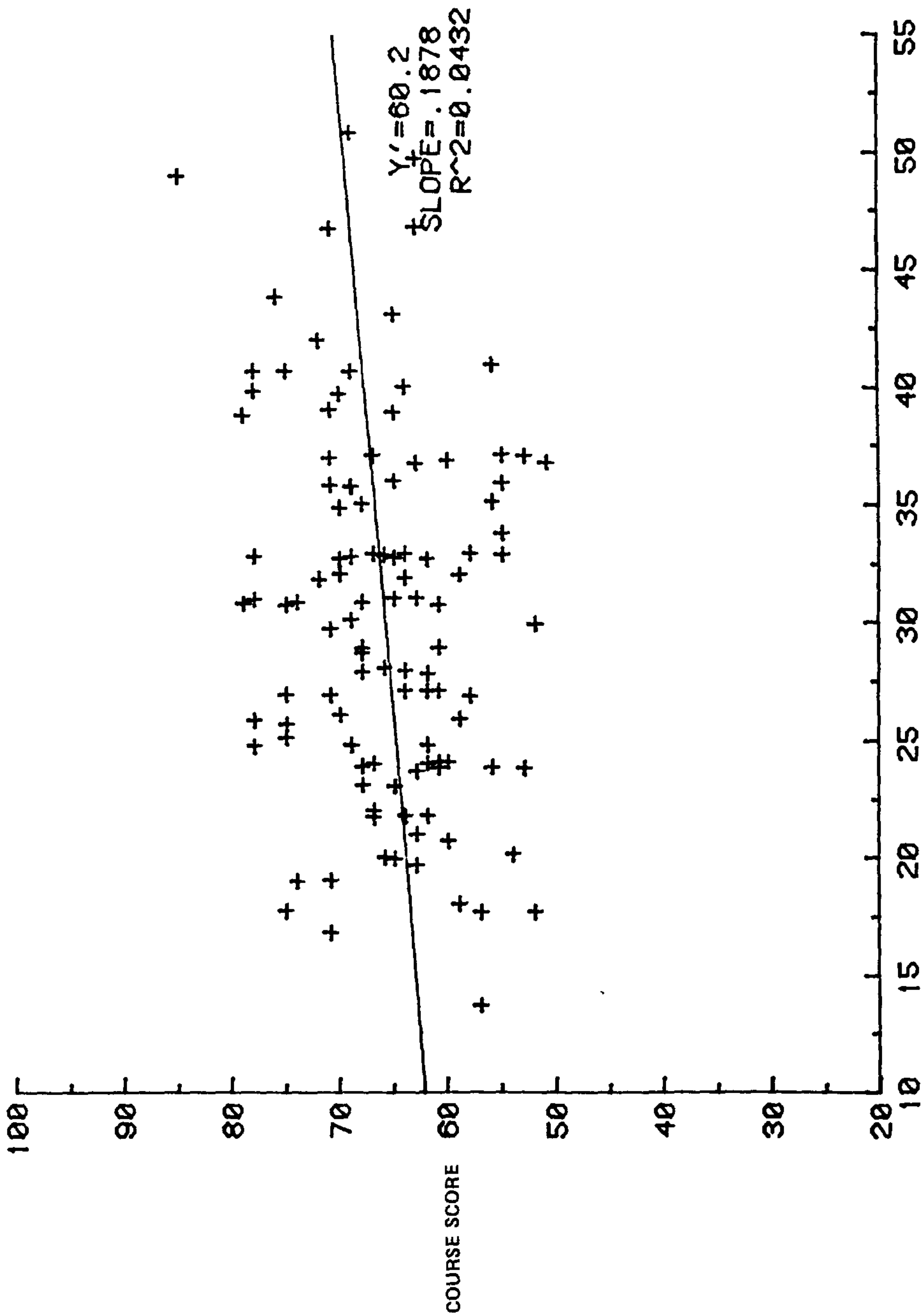

FIGURE 6: INDIVIDUAL COURSE SCORES vs GMAT CRITERIA
HUMAN BEHAVIOUR IN ORGANIZATIONS: 1978 TO 1980

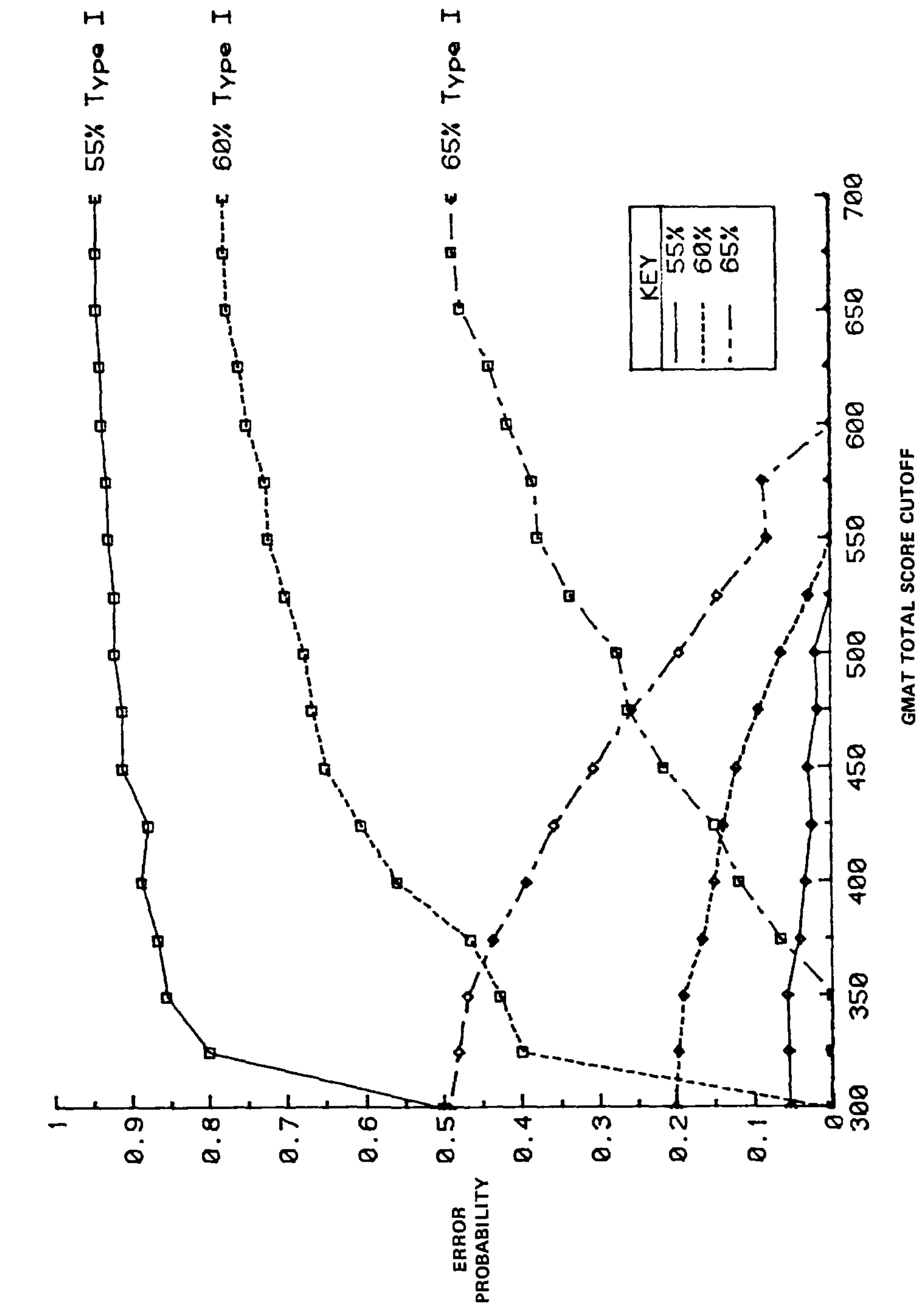

FIGURE 7: TYPE I AND TYPE II ERRORS FROM ADDING GMAT TOTAL TO EXISTING CRITERIA: VARIOUS MINIMUM GGPAs