Predicting Management Potential of MBA Program Applicants*

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Abstract : The empirical literature in decision making suggests that the reliability and validity of MBA admission decisions can be enhanced with the aid of actuarial models that relate measures of managerial success to predictors available from the MBA application folder. For a measure of managerial success, we propose the use of annual compensation ten years after the start of the MBA program, adjusted for the effects of individual choice (but not ability) such as geographical location, and employment in the public versus private sector. The results do not change much when adjusted compensation is replaced by a composite criterion consisting primarily of authority level, number of employees supervised, and authority limit on expenditures.

Multiple regression analysis was used to relate compensation to (i) adjustment (individual choice) variables and (ii) model variables drawn from the MBA application folder. Geographical cost of living index was significantly positively related to compensation. Other adjustment variables significantly negatively related to compensation were public sector employment, being self-employed, size of the organization, and the number of years out of the labor force. Among model variables, the quality of the undergraduate institution, subjective ratings of "initiative and drive" and "quality of presentation of the case for admission", undergraduate GPA, and the number of years of significant extracurricular activities were significantly positively related to adjusted compensation, but GMAT scores were significantly negatively related. Experience prior to the MBA showed no relationship to adjusted compensation. The MBA grade point average (unavailable at the time of MBA application) was positively related to adjusted compensation.

A weighted sum of model variables, denoted as MODELSCORE, was obtained from the regression analysis by excluding the adjustment variables and including only the model variables available at the time of application. In comparison to random assignment, the use of MODELSCORE reduces by about a third the

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chances of serious misclassifications, such as predicting an applicant to have a low management potential but the person actually turning out to be highly successful. The average MODELSCORE for past admits is significantly and substantially higher than that for past rejects. The regression coefficients are not significantly different for men versus women and for whites versus minorities, although for the same MODELSCORE, women were paid about 24% less and minorities about 16% less than white males. We emphasize that the use of MODELSCORE to measure management potential would not create such a bias.

Key Words : MBA Admissions, Management Potential, GMAT

1. Introduction

During the past decades, tremendous growth has occurred in the demand for graduate management education in many countries. For many business schools, the number of applicants far exceeds the number of places available. Such a situation presents an excellent opportunity as well as a challenge to select the most promising candidates.

Admissions decisions are usually made on the basis of overall evaluation of applicants by one or more admissions officers. However, an impressive amount or empirical evidence has accumulated in the behavioral literature on decision making showing that actuarial models developed, for instance, using multiple regression are superior in predicting a criterion variable compared to clinical judgments, e.g., an admissions officer's evaluation of applicants on the same criterion (Dawes and Corrigan 1974; Sawyer 1966). This superiority probably results from two sources. First, the model is likely to be more reliable or consistent, since identical predictions will result for two applicants with identical sets of values for the predictor variables. This may not be the case for the judgments of an admissions officer, since the evaluation is probably influenced by the quality of the applicants seen just prior to the one presently considered. Furthermore, an admissions officer's evaluations may become less reliable as a result of boredom, fatigue, and excessive work load whereas a model's predictions are not affected by such factors. The evaluation of different applicants by different admissions officers is likely to further decrease the reliability of the evaluation process.

A second probable reason for the model's superiority is that it is likely to be more valid since it is derived by systematically linking the actual performance of applicants to predictors of that performance. An admissions officer, on the other hand, gets only a limited amount of feedback. The admitted candidate has to be a manager for a sufficiently long number of years before meaningful feedback on managerial success can be obtained. Admissions officers may not even stay on the same job for that many years. Furthermore, the overall desirability of applicants is usually not stated in terms of explicitly defined criteria. There is potential, therefore, to improve the validity of the admissions process by making the criterion variable(s) explicit. Given explicit criteria, predictions of applicants' scores on the criteria can be made using multiple regression based weighting of a set of predictor variables obtainable from the application folder. We believe that model-based predictions will aid in improving the reliability and validity of the admissions process while simultaneously facilitating a more efficient allocation of time spent in evaluating the applications.

It is not the intent of the proposed approach to replace an admissions officer's decisions by mechanized decisions. We believe strongly that there is a moral responsibility to read every application carefully. Our aim is merely to aid and strengthen the admissions decision process by providing predictions on explicit criteria. In addition to model-based predictions, the admissions officer(s) will take into account the unique characteristics of the applicant which may not have been adequately captured by the models. For instance, recognizing that a student's education, in the broader sense of the term, is derived in part from the prior experiences of other students in the program, an admissions officer may justifiably admit a candidate based on his/her unusual background and/or experience, although the candidate may not be as strong as others in terms of explicitly defined criteria.

2. The Overall Approach

We believe there are three major criteria on which MBA admissions decisions are usually based. One criterion applies to the admitted class as a whole while the other two apply to individual applicants.

The breadth of the class is a criterion that is applicable to the class as a whole. Breadth means that the admitted class as a whole should be heterogeneous on a number of factors such as: type of experience, orientation (conceptual versus practical), career goals, backgrounds, undergraduate major areas, gender, race, and nationality. The idea is that the educational experience is enriched by the interaction of a heterogeneous group, in that students will be exposed to ideas, viewpoints, and experiences that they might not otherwise readily encounter.

The other two criteria on which admission decisions are based apply to individual applicants:

- ➢ Potential for successful academic performance in the MBA program.
- ➢ Potential for management success (hereafter referred to as management potential, and operationalized later in this paper).

A model to predict academic performance in the MBA program has previously been developed (Srinivasan, Wittink, and Zweig 2017). It was in use in the admissions process of the Stanford University Graduate School of Business for more than a decade. The academic performance model was used primarily to identity applicants who are likely to be in academic difficulty, since admitting an applicant who does not succeed academically is wasteful both for the school and for that individual. An applicant who is predicted to have a "substantial" probability of poor performance in the MBA program is considered for admission only if his or her management potential is exceptionally high, or other exceptional characteristics emerged from a careful reading of the application. (To repeat, every application is carefully read).

In this paper we develop a model to predict management potential by relating predictors derived from the MBA application folder to data on managerial success collected through a questionnaire sent to graduates of the Stanford University MBA program.

3. Operationalization of Measures of Management Potential

In deciding the MBA classes to collect data on managerial success, two conflicting issues needed to be considered. First, management potential takes time to express itself. Generally, the longer the time after the MBA program was completed, the more valid would be the assessment of managerial success. On the other hand, the more recent the MBA class is on which the data are collected, the more similar it is to current classes, thereby leading to greater confidence in the generalizability of the results to current applicants. Based on these two conflicting considerations, the data on managerial success were collected ten years after the students joined the MBA program.

Questionnaires were mailed out to every graduate of two graduating classes, and to all women and minority graduates of five graduating classes (to increase the sample size of women and minorities). The questionnaires were followed up by two reminders at one month intervals. The overall response rate was 75%.

3.1 Value Added Versus Exit Potential

Three types of management potential are of possible interest. The distinction is based on the idea that a person has a certain amount of management potential at entry to the MBA program (referred to as entry potential), and that going through the MBA program enhances the management potential of the person by an amount we will call the value added to result in the management potential after completing the MBA program (denoted as exit potential).

Since the school is interested in graduating those who are likely to become the most successful managers, one can argue that exit potential, by combining entry potential with value added, is the most relevant criterion. It is the exit potential which is conceptually closest to the eventual success of a manager. Our approach of linking measures of management success to predictors from the application folder amounts to using exit potential as the criterion variable. On the other hand, one can argue that the school is solely in the business of adding value and hence that should be the criterion. Value added is likely to be related to the performance of the student in the MBA program. (We provide empirical evidence in section 8 that the MBAGPA is related to measures of managerial success after controlling for other predictors.) As explained earlier, the overall admissions process ensures a high probability of successful performance in the MBA program. Consequently, the overall approach can be thought of as selecting among applicants with potential for at least a moderate amount of value added, those who are likely to have the highest exit management potential.

3.2 Operational Definition of Management Potential Used in the Analysis

Several potential variables from the questionnaire could have been used to operationalize management potential. There is evidence in the literature to support a definition based upon annual compensation. From a survey of graduates conducted at the Graduate School of Industrial Administration (now called the Tepper School) of Carnegie-Mellon University several criteria of managerial success were obtained such as current annual compensation, career satisfaction and organizational level attained. Srinivasan, Shocker, and Weinstein (1973) had three groups of executives compare profiles of managers on these criteria and make paired comparison judgements of overall success. A composite criterion that was inferred, using these judgements, revealed that current compensation was regarded as the single most important criterion. Laurent (1970) arrived at the same conclusion after analyzing several criterion variables by factor analysis. Harrell and Harrell (1984) report that Hemphill's Position Participation Score (Hemphill 1960), which measures how much responsibility and authority a position carries, is significantly positively correlated with annual compensation. Finally, in the present study, compensation has significant positive correlations with other criteria such as authority level ($r = .29$, $p < .001$), career satisfaction ($r = .28$, $p < .001$), and authority limit on expenditures ($r = .33$, $p < .001$). In addition to this empirical support, annual compensation is supported by economic logic and has "face validity" as a criterion of success to managers and to faculty in business schools.

Harrell and Harrell (1973) have used the criterion of reaching general management as a measure of job success. They also report that their criterion is correlated substantially with compensation. However, "general management" has poor scale properties (0 or 1 rather than a continuous scale).

The use of annual compensation as a measure of managerial success suffers, however, from some limitations. For instance, a graduate who chooses a public sector job might receive lower earnings than if he or she had chosen a private sector job. To minimize the undesirable effects of using annual compensation as a measure of managerial success, we have classified job related factors into two categories:

1. *Adjustment Variables* - Those job factors *primarily* affected by individual choice (and not by ability): e.g., type of organization -- government, nonprofit, industry, entrepreneurial, and family owned business; geographical location (cost of living and regional preference considerations).

2. *Ability variables* - Those job factors *primarily* affected by ability (and not by choice): e.g., authority level in the organization; general manager or not.

By *adjusted compensation* we mean the overall annual compensation of the graduate ten years after starting the MBA program, where the effects of adjustment variables (but not ability variables) have been partialed out using multiple regression. *We have chosen adjusted compensation as our operational definition of management success.*

Annual compensation was defined in the questionnaire as the total compensation per year including salary, bonus, commission, stock option, and profit sharing. The frequency distribution of compensation was, as expected, highly positively skewed. A logarithmic transformation (to the base 10) of compensation was made to make the distribution more symmetric. Hereafter, the term compensation refers to the logarithmically transformed annual compensation.

It is conceptually appealing to define total compensation over one's managerial career as the criterion. However, the use of lifetime compensation as the dependent variable creates severe data collection difficulties (one needs to wait for decades after graduation), and makes it less relevant for current applicants. Consequently annual compensation for a single year was used as the criterion.

3.3 Other Measures of Management Success

Besides adjusted compensation, there are several other variables from the questionnaire that could have been used as measures of managerial success (see Table 1). Some of the variables have been transformed to their logarithms to avoid extreme positive skewness.

Table 1: List of Variablesfrom the Questionnaire that are Indicators of Management Success		
LOGCOMP	-	Log[1] Compensation - log of current annual compensation
AUTHLIM	-	Authorization Limit (Log)[1] - log of total dollar amount of company expenditures respondent is permitted to authorize
RATLEVL	-	Relative Authority level - the number of levels of authority below the respondent divided by the total number of levels of authority below chief executive
SUPVEMPL	-	Supervised Employees (Log)[1] - log of number of employees supervised
JOBSATIS	-	Job Satisfaction - rating of satisfaction of present job (7-point scale)[2]
CARSATIS	-	Career Satisfaction - rating of satisfaction of career to date since MBA (7-point scale)[2]
LIFESATIS	-	Life Satisfaction - rating of satisfaction of work and personal (family) life to date since MBA (7-point scale)[2]
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[1]All logarithms are to the base 10		
[2]The categories were: very satisfied (7), satisfied (6), mildly satisfied (5), neither satisfied nor dissatisfied (4), mildly dissatisfied (3), dissatisfied (2), and very dissatisfied (1)		

An exploratory factor analysis of these variables is reported in Table 2. The solution was rotated using a direct Oblimin rotation. The first factor appears to be an extrinsic, objective measure of management success. (This factor includes compensation.) The second factor appears to be an intrinsic, subjective measure of success. These two factors are positively correlated with r = 0.47.

This factor structure of measures of management success has been replicated by Harrell and Harrell (1984). A factor analysis on a set of measures of management success that overlap with those used here produced two factors that have the same interpretations and very similar correlation (.45) to those reported here. Since Harrell and Harrell used data from Stanford MBAs who graduated from earlier classes, and a different but overlapping set of success measures, there is evidence that the factor structure is stable over different cohorts and over a broader class of managerial success variables than used here.

Table 2: Exploratory Factor Analysis of Measures of Management Success[1]		
Factor Loadings after Oblimin Rotation (Pattern Matrix)		
Variable	Factor 1 "Extrinsic Success"	Factor 2 "Intrinsic Success"
LOGCOMP	0.395	0.131
AUTHLIM	0.588	0.005
RATLEVL	0.760	-0.030
SUPVEMPL	0.608	-0.049
JOBSATIS	0.205	0.488
CARSATIS	-0.038	1.016
LIFSATIS	-0.045	0.631
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[1]The correlation between the two factors is r=0.47.		

By examining the results in Table 2, we find that the intrinsic success factor is highly related to career satisfaction. From the questionnaires, we found that 82.5% of the sample were either "very satisfied" or "satisfied" (the top two categories of the seven point scale) with their career. Of the remainder, all but 3.7% of the respondents checked the next category "mildly satisfied." It is reassuring that most of the alumni are satisfied with their careers. However, there is considerably less variation in the data on this factor. In an unpublished study conducted by the senior author with the alumni of another leading business school, the same question on career satisfaction produced much larger variation in the ratings. Consequently, the small variation in the present data is unlikely due to the wording of the question. Thus, in the subsequent analysis the intrinsic success factor is not considered. Instead, we will concentrate on adjusted compensation as the measure of managerial success and examine whether the results remain nearly the same under the alternative definition of managerial success as given by the extrinsic success factor.

4. Overall Approach to Analysis

Denoting by y the annual compensation and by A1, A2, …, A_p the adjustment variables expressed as deviations from the corresponding means, adjusted compensation y* is given by

$$y^* = y - w_1A_1 - w_2A_2 - \dots - w_pA_p \quad (1)$$

where w1, w2, …, wp are the weights (to be determined) which capture the effect or the adjustment variables on compensation. Our intent is to predict y* by using a set of model variables (i.e., predictors collected from the MBA application folder) x1, x2, …, x_q:

$$y^* = c + v_1x_1 + v_2x_2 + \ldots + v_qx_q + u \quad (2)$$

where v1, v2, …, v_q reflect the importance of the model variables (to be determined) in predicting y*, c is a constant, and u is random error. Combining Eq. (1) and Eq. (2)

$$y = c + w_1A_1 + w_2A_2 + \ldots + w_pA_p + v_1x_1 + v_2x_2 + v_qx_q + u \quad (3)$$

Estimates $\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_p$ and $\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_q$ can be obtained by the multiple regression defined in Eq. (3). Since there may be some correlation between the A and x variables, the approach of directly estimating Eq. (3) is superior to the alternative approach of first defining adjusted compensation as the residual of the regression of y on A_1, A_2, …, A_p (see Eq. (1)) and then regressing that residual against model variables x_1, x_2, …, xq (see Eq. (2)).

For any applicant, management potential can be predicted using Eq. (2) (defined subsequently as MODELSCORE) as

$$\hat{y}^* = \hat{c} + \hat{v}_1 x_1 + \hat{v}_2 x_2 + \ldots + \hat{v}_q x_q \quad (4)$$

We now consider the specification or adjustment and model viriable prior to presenting the results of the analysis.

5. Specification of Adjustment Variables

Table 3: List of Potential Adjustment Variables		
I. Type of organization in which the respondent is employed		
PUBLICORG	-	dummy variable that is 1 if respondent works for a public sector organization and 0 otherwise
NONPROFORG	-	dummy variable that is 1 if respondent works for a non-profit organization and 0 otherwise
SELFEMPL	-	dummy variable that is 1 if respondent is self-employed or sole owner and 0 otherwise
IPARTNER	-	dummy variable that is 1 if respondent is an "investment" partner[1] in current organization and 0 otherwise
II. Size of Organization in which the respondent is employed		
TOTEMPL	-	log of total number of employees in the organization[2]
DIVEMPL	-	log of total number of employees in division or branch office (see text)[2]
III. Other Adjustment Variables		
DEGCOURS	-	number of management related courses taken in degree programs since MBA
EXECPROGRAM	-	number of days of formal management education in nondegree executive programs since MBA
INACTIVE	-	number of years since MBA that respondent has been out of the labor force
CLASS	-	dummy variable that is 1 if respondent graduated from the MBA prgram in the later of two years in the sample and 0 if graduated in the earlier of the two years
IV. Cost of Living Variables		
LCOSTLIV	-	Log of cost-of-living index[2]
SF	-	dummy variable that is 1 if job is in the San Francisco Bay area and 0 otherwise
CAL	-	dummy variable that is 1 if respondent works in California but outside the San Francisco Bay area and 0 otherwise
FOREEMPLD	-	dummy variable that is 1 if employed outside the U.S. and 0 otherwise
FCOSTLIV	-	LCOSTLIV multiplied by FOREMPLD
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[1]The term "investment" partner is used to denote a respondent who has financial investment in the organization. It excludes partners in management consulting, CPA, and law firms.		
[2]All logarithms are to the base 10.		

Table 3 lists the adjustment variables considered in the analysis. As discussed in Section 3.2, adjustment variables are those individual choice (but not ability) related job factors that affect compensation and hence are to be partialed out to define adjusted earnings. Taking as the base case private sector businesses that employ a majority of the MBAs, the first four variables in Table 3 are included to consider the effect on compensation of choosing other types of organizations. It is expected that public and not-for-profit sector managers and those who are self-employed will, on average, earn a smaller annual compensation compared to business managers. The variable IPARTNER is included to take into account the potential effect of the respondent's financial investment in the company on his or her annual compensation.

It is generally believed that larger organizations provide greater job security and hence are likely to have a negative compensation wage differential compared to smaller organizations. The variable TOTEMPL is included to capture this effect. On the other hand, individuals may be willing to take a cut in pay to enjoy the congeniality of working with a smaller sized group. Since the job environment is better captured by the size of the branch office or division rather than the size of the total organization, the variable DIVEMPL is included. (If there is no division or branch office, DIVEMPL is set equal to TOTEMPL.) Since the frequency distribution of employees is highly skewed, a logarithmic transformation is applied to the above two adjustment variables.

The adjustment variables DEGCOURS and EXECPROGRAM are included to capture the potential effect of “investment in human capital” from education subsequent to the MBA. The number of years someone is out the labor force (INACTIVE) is likely to have a negative effect on compensation because of reduced experience. A person may be out of the labor force by choice or may have been forced out of employment because of poor ability. A detailed examination of the questionnaires revealed that with only a couple of possible exceptions, inactivity is mostly due to personal choice. (Two popular reasons seem to be: an MBA leaving a job and taking considerable time before setting up his or her own company; a woman MBA leaving the workforce to raise a child). The variable CLASS was included to adjust for the fact that among the two years of data, the later cohort of graduates had one less year of experience (and hence likely to have lower compensation) compared to the earlier year’s class.

Annual compensation is likely to differ across geographical areas because of cost of living considerations. In order to adjust earnings for areas in the U.S., we used the cost of living indices from “4-Person Urban Family Budgets for a Higher Standard of Living” published by the U.S. Department of Labor. For persons employed outside the U.S. we used the data published by the Union Bank of Switzerland. Their publication “Prices and Earnings around the Globe” included indices for four cities in the U.S. thereby permitting the foreign cost of living indices to be expressed on the same basis as the U.S. cost of living indices. Since annual compensation is expressed in logarithmic form, a logarithmic transformation was also applied to the cost of living index resulting in the adjustment variable LCOSTLIV. To capture the possible differences in the ways the U.S. and foreign indices were measured, the variables FOREMPLD and FCOSTLIV, as defined in Table 3, were included in the analysis. An additional reason for including FOREMPLD was to capture the difference in the levels of compensation for U.S. and non U.S. managers.

The cost of living indices seemed to be intuitively reasonable with exception of those for California which seemed to us and to a former Chairman of the President's Council of Economic Advisors to be too low. Since a large percentage of the respondents resided in California and, in particular, in the San Francisco Bay Area, the dummy variables SF and CAL were included to examine the possible downward bias in the indices for California.

5.1 Other Job Factors as Potential Adjustment Variables

As discussed in Section 3.2, job descriptors such as the level of authority are to a large extent the result of ability or management potential and hence should not be treated as adjustment variables. The same is true or whether a respondent is in a line or staff position, especially given the school's stated objective of preparing students for high level general management. The functional area of work and the industrial classification were not treated as adjustment variables since the job of general management (multifunctional) and a career in management consulting or investment banking are likely to be ability related. As described in the results section, the regression results are insensitive to whether or not hours worked/week is treated as an adjustment variable.

6. Specification of Model Variables

Variables from the MBA application folder used to predict adjusted compensation are referred to as model variables. To determine the pool of variables that could potentially serve as model variables, we examined the following sources:

1. *Previously published studies in the area:* Crooks, Campbell and Rock (1979), Dunnette (1967), Gutteridge (1973), Harrell and Harrell (1973, 1984), Harrell, Harrell, McIntyre, and Weinberg (1977), Korman (1968), Livingston (1971), Marshall (1964), Pfeffer (1977), Reder (1978), Schick and Kunnecke (1981), Strober (1982), Weinstein and Srinivasan (1974), Williams and Harrell (1964).

2. A list of rating scales used by the admissions office at the Stanford Business School Lieberman (1977).

3. The application form for an exhaustive list of potential model variables.

Based on preadmission information, potential model variables were categorized, according to ease of accessibility, as follows:

1. *Directly codable variables:* information is available in numerical form, for example, date of birth, and can be entered directly into a data base, or can

be coded or calculated in a straightforward manner, for example, the number of months of full-time work experience is codable from the employment history provided by the applicant. See Table 4 for a list of directly codable variables.

Table 4: List of Potential Model Variables -- Directly Codable		
I. Education (prior to MBA)		
UGGPA	-	undergraduate grade point average for the freshman, junior, and senior years [1]
CES	-	candidate excellency by school - an index of quality of the student's undergraduate school [2]
MAJOR	-	several dummy variables to identify the undergraduate major area
GRADWK	-	number of months of study in graduate school prior coming to the MBA program
ADV	-	dummy variable that is 1 if the student has an advanced degree and 0 otherwise
II. Test Scores		
GMATV	-	graduate management admission test score (verbal)
GMATQ	-	graduate management admission test score (quantitative)
GMATTOTAL	-	graduate management admission test score (total)
GMATMS	-	dummy variable that is 1 if GMAT was taken more than once [3]
III. Experience (prior to MBA)		
EXPTOT	-	total full-time work experience in months
EXPBUS	-	full-time business experience in months
EXPMIL	-	full-time military experience in months
EXPOTH	-	full-time experience in months other than business and military
EXPPT	-	part-time work experience in months
SUMEXP	-	summer work-experience while in college in months
MAXSAL	-	maximum monthly salary received at the time of application to the MBA program
IV. Other		
AGE	-	age of student (in months) at the time of joining the MBA program
FOREIGN	-	dummy variable that is 1 if the student is not a U.S. citizen and 0 otherwise
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[1]On a four point scale with D = 1, C = 2, B = 3, and A = 4. The sophomore year GPA, unlike the freshman, junior, and senior year GPA, was not found to be a statistically significant predictor of MBA adademic performance (Srinivasan, Wittink and Zweig, 2017, footnote 6.)		
[2]This index is published by the Educational Testing Service. It is computed as the average GMAT(Total) score of all students who took the test from the applicant's undergraduate school.		
[3]The most recent GMAT scores were used for applicants who had taken the test more than once.		

2. *Rating scale variables:* these are qualitative (subjective) variables for which systematic rating procedures were developed to obtain quantitative assessments; for example, in evaluating an applicant's leadership activity as an undergraduate. A detailed examination of 30 application folders was useful in defining the rating scale variables and in providing detailed instructions

to raters. Inter-rater reliabilities, computed using 30 applicants, were used as diagnostics to improve the definitions and to clarify the instructions. In addition, composites were created as weighted sums of the rated variables. For instance, level of experience was coded for each job held by an applicant on a 1-9 ordinal scale (footnote 1 in Table 5). To summarize the amount of experience of the applicant, while simultaneously taking into account the level of experience, a weighted total experience variable (EXPSUM) was defined by summing over the different jobs the number of months of experience, multiplied by a weight reflecting the level of experience for each job. The weights were arrived at by averaging the subjective judgments of three faculty members. See Table 5 for a categorized listing of Rating Scale variables.

Table 5: List of Potential Model Variables - Rating Scales		
I. Experience (Prior to MBA)		
EXPSUM	-	sum of work experience in months, weighted by "level of experience"[1]
EXPHI	-	weight for highest "level of work experience"[1] prior to entry into MBA program
EXPGRO	-	career growth prior to entry = EXPHI / (total number of months of full-time experience)
II. Participation in Sports and Other Activities		
SPORTHI	-	number of years of sports participation at high level while at college (for example, varsity sports)
SPORTMED	-	number of years of sports participation at medium level while at college (for example, intramural sports)
SPORTLO	-	number of years of sports participation at low level while at college (for example, tennis with friends)
SPORTSUM	-	sum of SPORTHI, SPORTMED, and SPORTLO, weighted by 1.0, 0.38, and 0.19
OTHACT	-	number of years of other activities (for example, social and service clubs)
III. Leadership		
LEADHI	-	number of years of leadership activity at high level while at college (for example, college elective leadership)
LEADLO	-	number of years of leadership activity at low level while at college (for example, officer of residence hall)
LEADSUM	-	sum of LEADHI and LEADLO, weighted by 1.0 and 0.4
EXTRACUR	-	LEADSUM + SPORTHI[2]
IV. Recommendation Letters[3]		
ACHIEVE	-	relative achievements
COMMUN	-	communication ability
RELATE	-	relationships with other people
V. Ratings Based on Essays and the Overall Application (on five-point scales 1-5)		
GOALS	-	ability of candidate to define career goals
INITIATIVE	-	demonstrated initiative and drive
PRESENT	-	quality of presentation of case for admission
UNDSTD	-	candidate's demonstrated understanding of the Stanford MBA prgram
WHYMBA	-	clarity of candidate's statement of reasons for wanting to pursue an MBA program
INITPRESENT	-	INITIATIVE + PRESENT[2]

[1]Work experience was classfied into nine levels: (1) executive responsibility (250 or more employees), (2) executive responsibility (less than 250 employees), (3) management responsibility (50 or more employees), (4) management responsibility (less than 50 employees), (5) professional and technical support, (6) administrative specialist, (7) administrative/management trainee or intern, (8) clerical and sales, and (9) other. Weights were assigned to each of the categories to reflect the level of management skills required for jobs in that category (see text, Section 6).

[2]These compound variables were defined during analysis to reduce esimation error (see text, Section 7).

[3]These variables, derived from recommendation letters, are defined as the weighted averages of the scores on a four-point scale (1-4) provided by at most four evaluators of the cadidate; weights for the evalulators were based on the nature and frequency of contact. Data were available for the more recent graduating class of the two years in the sample, but generally were unavailable for the earlier year.

6.1 Reliability of Rating Scale Variables

Table 6: Reliability Scores for Rating Scale Variables		
Variable	Intra-rater[1] reliabitiliy (n = 30)	Inter-rater[1] reliability (n = 30)
ACHIEVE	.724	.412
COMMUN	.633	.749
EXPSUM	.999	.886
GOALS	-.049	.343
INITIATIVE	.505	.452
LEADSUM	.967	.782
OTHACT	.987	.826
PRESENT	.726	.485
RELATE	.306	.647
SPORTSUM	.997	.883
UNDSTD	____[2]	.639
WHYMBA	-0.128	.248

[1]The reliability scores were computed for two different sets of applicants. Intra-rater reliabilities were obtained for one judge (A) who made independent ratings separated by six months. Two different judges (B and C) were used to obtain inter-rater reliabilities.

[2]Reliability score could not be computed since there was no variation on this variable for the 30 applicants in the sample.

For the rating scale variables to be useful as predictors, we need both intra- and inter-rater reliability. Based on additional samples of thirty applicants each, (Pearson) correlation coefficients were computed for most of the rating scale variables. If there is more than one measure of the same variable (e.g., experience), only the measure considered most relevant was used in the computation of reliabilities. The results reported in Table 6 suggest that both the intra- and inter-rater reliabilities are high for most variables, but unacceptably low for some other variables. In particular, GOALS and WHYMBA suffer from a lack of consistency. Both variables are obtained from information scattered throughout the application folder. It may be expected therefore that these variables posed serious difficulties for raters. For UNDSTD no intra-rater reliability score could be computed due to the lack of variation across applicants in the sample of 30 applicants chosen for estimating reliability. In general, variables that have been indicated in previous literature to be the most relevant had high enough reliability scores to be of potential value as predictor variables. Further improvements in the definitions and instructions may be useful in improving the reliabilities. The application form may also have to be modified to elicit some of the information more readily.

7. Approach to Estimation of Model

As described in Section 4, the overall research approach requires the estimation of a multiple regression model with annual compensation as the dependent variable and adjustment and model variables as predictors. As seen from Tables 3 through 5, there is a large list of potential predictors. The predictors were grouped into non-overlapping groups hierarchically ordered in terms of their potential importance, as indicated by the previous literature in the area (referenced in Section 6). We examined the sets of predictors in order of importance, starting with the most important. At each stage we added predictors (or deleted predictors included in previous steps) based on the additional explanatory power of a predictor, and our knowledge of previous empirical literature. Hence the procedure we used for model development was analogous to a guided regression procedure (Mosteller and Tukey 1977) where we combined our knowledge of the problem with the data to produce a final model in a step by step manner.

In developing the model predictors were combined in some cases. For instance, the two rating scales INITIATIVE and PRESENT when simultaneously included in the model had regression coefficients that were close to and not statistically significantly different from each other. Since these two rating scales were substantially inter-correlated ($r = .68$), the estimation error is likely to be reduced by combining them, i.e., by replacing the predictors INITIATIVE and PRESENT by their sum INITPRESENT. (This amounts to setting the regression coefficient for INITIATIVE equal to that for PRESENT). Likewise SPORTHI was combined with LEADSUM to define EXTRACUR.

To ensure that the regression results are robust, i.e., the results do not change very much by the addition or deletion of a few observations, we used a procedure analogous to "winsorized regression" (Yale and Forsythe 1976), whereby residuals which are greater than three standard errors were reset to three standard errors. This way a few outliers would not unduly influence the estimation results.

7.1 Estimation and Validation Samples

The total sample from the two graduating classes was $n = 580$. About 75% of the graduates returned the questionnaires and about 93% of the respondents reported their current compensation. All the relevant adjustment and model variables were available for about 91% of those with data on compensation. The final sample size was 364 (= 580 x .75 x .93 x .91), which is about 63% of the total sample. The potential biases introduced by non-respondents and missing compensation data are discussed in Section 9.3.

Since we are interested in testing the model's predictive validity, approximately 20% of the sample (n = 76) was set aside as the validation sample. The remaining n = 288 respondents constituted the estimation sample.

The model with the entire estimation sample remains nearly the same when restricted to U.S. graduates working in the U.S. The results with the entire estimation sample are cumbersome to present since they include a dummy variable FOREIGN to consider non-U.S. graduates, and variables FOREMPLD and FCOSTLIV to consider those who work outside the U.S. To simplify presentation, the results in the next section consider only the estimation subsample of n = 233 U.S. graduates who work in the U.S.

8. Results

Table 7: Results of Multiple Regression with Compensation (log) as the Dependent Variable [1]		
	Regression Coefficients [2]	
Predictor	Without MBAGPA as a Predictor [3]	With MBAGPA as a Predictor [3]
Adjustment Variables [4]		
PUBLICORG	-28.7***	-29.0***
SELFEMPL	-19.6**	-18.7**
TOTEMPL [5]	-5.4**	-5.4**
INACTIVE	-18.7***	-18.7***
CLASS	-12.3**	-12.5**
LCOSTLIV [6]	11.1***	11.5***
Model Variables [7]		
UGGPA	10.7*	8.6
CES / 100	12.7**	11.9**
GMATOTAL / 100	-10.7**	-11.5***
EXTRACUR	4.0**	4.0**
INITPRESENT	4.0**	3.8**
MBAGPA	----	29.4
Adjusted R^2	0.191	0.191

[1]Based on the estimation subsample of n = 233 U.S. graduates working in the U.S.

[2]For convenience, regression coefficients have been transformed so that they can be interpreted as the percent increase in compensation per unit increase in the predictor, other things remaining equal. See Section 8 for an interpretation of the results. (To transform the regression coefficient b to percent increase p, the transformation is $p = 100\,[10^b - 1]$.)

[3]*** $p < .01$, ** $p < .05$, * $p < .10$. Since the selection of the final set of predictors was, in part, based on the same data, the p-levels should be interpreted merely as crude indications of statistical significance.

[4]Adjustment variables are listed in Table 3.

[5]Since TOTEMPL is the number of employees expressed in logarithmic form to the base 10, a unit increase in this predictor is the same as the tenfold increase in the number of employees.

[6]For convenience, the unit increase in LCOSTLIV is defined to be the increase in cost of living index from 100 to 110, i.e., a 10% increase in the cost of living.

[7]The first three model variables are listed in Table 4; the last two are listed in Table 5.

Table 7 presents the coefficients for the multiple regression model developed by the approach detailed ln Section 7. For ease in interpretation the regression coefficients have been transformed so that they can be interpreted as the percent increase in annual compensation ($) per unit increase in the predictor, all other predictors remaining equal. Throughout this paper, whenever we refer to regression coefficients we mean the numbers in the middle column of Table 7, i.e., the model without MBAGPA as a predictor[1]. The top half of the table refers to adjustment variables and the bottom half refers to model variables.

Turning attention first to adjustment variables, the type of organization the MBA works for has a substantial effect on compensation. Public sector organizations pay about 28.7% less than private sector organizations, and being self-employed costs the MBA about 19.6% in compensation. Larger organizations, on the average, tend to pay less. A ten told increase in the number of employees in the organization decreases compensation by 5.4%. As a point of reference, it may be noted that the median number of employees per organization in the present sample is about 900. If the MBA is inactive for a year, i.e., out of the labor force, the compensation drops by 18.7%. Not surprisingly, graduates of the later year's class (CLASS = l) earn about 12.3% less than graduates of the earlier year. Finally, compared to the average urban U.S., working in an area with a 10% greater cost of living increases compensation by about 11.1%.

Turning attention now to model variables, a unit increase in undergraduate GPA (say, from 2.5 to 3.5) increases compensation by 10.7%. To interpret the regression coefficient for CES, the Candidate Excellence by School index, consider an MBA who is an undergraduate from San Jose State University and compare him or her with one who is the same in all other respects except that he or she is a Stanford University undergraduate. San Jose State's CES score is 453 (i.e., San Jose State undergraduates obtained, on average, 453 points on the GMAT total) whereas Stanford's CES score is 569. Thus the increase in CES score is 569 – 453 = 116 so that CES/100 goes up by 1.16. Consequently, the model predicts that the compensation would go up approximately by 1.16 x 12.7 = 14.7%. A 100 point increase in GMAT total decreases compensation by 10.7% (more on this in Section 8.1). A year of significant extracurricular activity while at college (e.g., college elective leadership or varsity sports) increases compensation by 4.0%. To interpret the coefficient for INITPRESENT, consider an MBA whose "demonstrated initiative and drive" and the "quality of presentation of the case for admission" get rated as 3 each on the 1-5 rating scales. Then another MBA who is the same in all other respects, except for getting a rating of 4 on one of the two scales will have 4% larger compensation.

[1] The MBAGPA is obviously not available at the time of application and hence could not be used in predicting management potential.

The Stanford business school uses a grading system with H = 1.0, P+ = 0.5, P = 0, P- = -.3 and U = -1. Since the regression coefficient for MBAGPA is 29.4, a P+ average in the MBA program compared to a P average increases compensation approximately by 0.5 x 29.4 = 14.7%. There were no real differences in the effects of grades in core courses versus electives or in quantitative versus managerial courses, so that only the effect of overall MBAGPA is reported in Table 7. Our result differs from the finding reported in Harrell and Harrell (1984) that second year grades (nearly the same as elective grades) but not first year grades (nearly the same as core course grades) are related to compensation.

Most of the regression coefficients in Table 7 are statistically significant at the 5% level or better. Some of the regression coefficients in the model with MBAGPA are not significant because MBAGPA, UGGPA, CES, and GMAT are substantially inter-correlated. Although the selection of predictors was guided by previous research, it was in part based on the data in the estimation sample. Thus the reported statistical significance levels should be viewed only as a rough guide.

8.1 The Negative Effect of GMAT on Compensation

We now consider the result that other things remaining equal high GMAT scorers tend to earn less[2]. ETS (Educational Testing Service 1983) has always maintained that GMAT scores are not designed to predict career success, but are only measures of an applicant's ability to succeed in graduate work. However, a study by the ETS of graduates of eleven MBA programs (Crooks, Campbell, & Rock 1979, Tables 4 and 5) found that the effect of GMAT scores on compensation was negative for line managers but positive for staff managers. In our sample the relationship was found to be negative for both line and staff managers with the relation being more negative for line managers[3].

A negative relation between GMAT and earnings has also been reported in data collected on Stanford MBAs who graduated in the early 60's (Harrell and Harrell 1974; Harrell, Harrell, McIntyre & Weinberg 1977; Harrell and Harrell 1984). A possible explanation for this finding is presented in Harrell and Harrell (1974) who examined differences between high and low scorers in GMATV on several personality variables. They reported that lower scores on the GMATV were associated with:

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[2] To provide a frame of reference, it may be noted that the GMATTOTAL for 80% of the sample was between 500 and 700. So the negative relationship is only over such a range. The result should not be interpreted to mean, for example, that an MBA with a 300 GMATTOTAL will earn much more than another MBA applicant with a 750 total score.

[3] Two measures of the line/staff designation were used. One was a self-report obtained from the questionnaire. Alternatively, a person was defined to be a staff manager if he or she supervised ten or fewer employees and considered to be a line manager otherwise. The results are unaffected by which measure of line/staff was used.

...a socially desirable personality pattern of higher social extroversion, higher social boldness or ascendance, and [being] more often chosen as a preferred friend. (pg. 10)

The same personality variables were reported by Harrell and Harrell (1974) to be related to management success. In their ten-year follow-up of the Stanford MBA classes of 1961-1963, Harrell and Harrell (1974) found that compensation was negatively related to GMATV but unrelated to GMATQ. In their twenty year follow-up of the same classes, Harrell and Harrell (1984) report that compensation is negatively related to GMATQ and GMATTOTAL but unrelated to GMATV. In the present study, compensation was negatively related to both the verbal and quantitative components of GMAT.

An additional explanation of the negative relationship of GMAT to compensation is that high scorers on the GMAT tend to be in staff jobs that often pay less than jobs in line management. However, it is worth noting that GMATTOTAL was negatively related to compensation even among staff managers.

8.2 Path Diagram

The negative relationship between GMAT and compensation is intriguing given that GMAT is positively related to MBAGPA (Srinivasan, Wittink, and Zweig 2017) and as seen from the last column of Table 7, MBAGPA is positively related to compensation. To facilitate understanding, Figure 1a presents the path diagram linking the relationships between the predictors, MBAGPA and adjusted compensation (see Eq. (1)). We find that the direct effect (partial correlation) of GMATTOTAL on adjusted compensation is -0.16, but after taking into account the indirect positive effect GMATTOTAL --> MBAGPA --> Adjusted Compensation of .01 (= .21 x .07) the net effect is -.16 + .01 = -.15 (see Figure 1b). This result is consistent with the fact that the coefficient for GMATTOTAL in Table 7 is more negative when MBAGPA is included than when it is excluded. For the other model variables, viz., UGGPA, CES, EXTRACUR and INITPRESENT, both the direct and indirect effects are positive. Since prior experience is emphasized for admission to the Stanford Business School, the effect of EXPTOT (total work experience in months prior to the MBA) is also represented in Figure 1. We find that both the direct and indirect effects of EXPTOT are negligibly small[4].

[4] The percentage of the sample who had prior experience of greater than or equal to 6 months, 1 year, 2 years, or 4 years were 90%, 64%, 50%, and 33%, respectively.

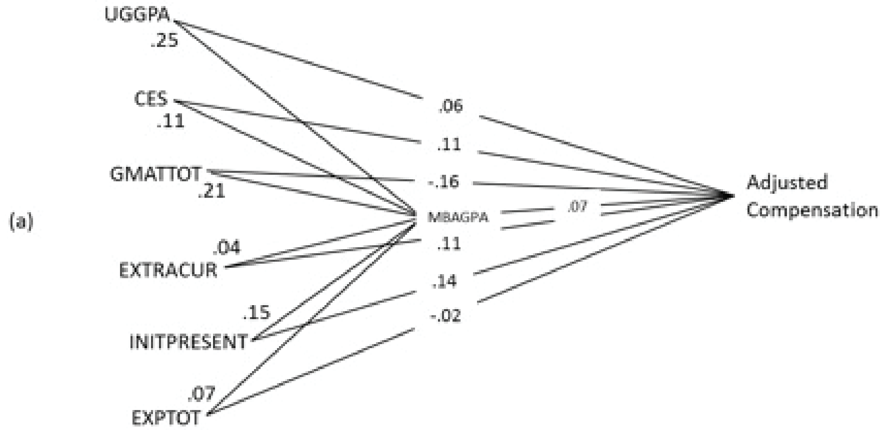

Figure 1a: Path Diagram Linking Predictors, MBAGPA and Adjusted Compensation

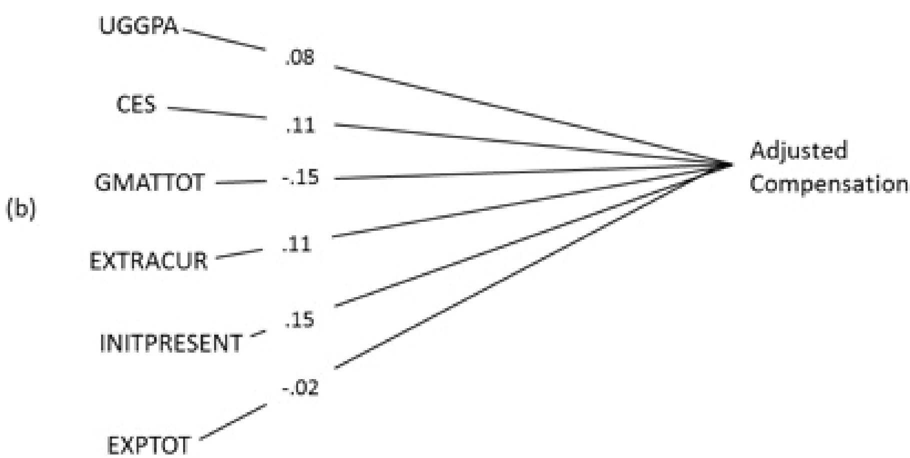

Figure 1b: Total Effects (Direct plus Indirect) of Predictors on Adjusted Compensation

8.3 Variables Unrelated to Compensation

In addition to the experience variables listed in Tables 4 and 5 we also considered the following, but those considerations did not change the main conclusion that prior work experience does not affect compensation:

1. A new set of experience variables representing months of experience at levels 1-4, 5, 6-7, and 8-9 (see footnote 1 in Table 5).
2. Based on the idea that experience might make a difference for persons with little experience, but for persons with much experience the exact amount of experience might not matter, EXPTOT was logarithmically transformed. (This transformation would shrink the high end of the scale relative to the low end of the scale.)
3. The possibility that the effect of MBAGPA on compensation may depend on prior experience was also investigated. This is based on the hypothesis that prior experience increases what a person gets out of the MBA program, since a person can more readily relate course material to real world situations. This hypothesis was tested by creating an interaction variable that was the product of an experience variable and MBAGPA (three experience variables were considered: EXPTOT, EXPSUM, AGE). In no case did the addition of an experience variable and the interaction term add significantly to the final model that includes MBAGPA.

The absence of any relationship between prior experience and compensation may be the result of the fact that MBAs often take jobs unrelated to their experience prior to the MBA. It is also possible that there is an "adverse selection problem", i.e., those who choose to leave their jobs and apply to the MBA program after a few years of experience were not as successful in their jobs as those who decided to stay on their jobs and not pursue an MBA.

It may be instructive to examine the lists of Tables 3 through 5 and understand which adjustment and model variables were not significantly related to compensation. In addition to prior experience just considered, the following may be worth emphasizing. Not-for-profit organizations were found to pay about 13% less than businesses, but the difference was not statistically significant. The absence of any effects of the dummy variables corresponding to San Francisco and California suggests that the downward biases in the cost of living indices referred to in Section 5 are roughly offset by the willingness of Stanford MBAs to take a pay cut, if necessary, to work in sunny California. Undergraduate major areas do not seem to make a difference although there was some indication (not statistically significant) that engineers earned a little less than others (consistent with the findings reported in Harrell and Harrell, 1984). Among the letters of recommendation variables, the only variable which had some modest relationship (although not statistically significant) was the rating of relative achievements (ACHIEVE) of the applicant compared to others. This finding is consistent with the presence of the INITIATIVE (and drive) variable in the model in Table 7.

8.4 Other Variables of Interest

Hours worked per week was significantly positively related to compensation ($p < .01$), increasing the adjusted R2 of the model from 0.19 to 0.23. Working an additional ten hours per week increases compensation by about 10%. The addition of this variable leaves the regression coefficients in Table 7 essentially unaltered.

The only industry effect that was statistically significant was that MBAs in the banking and investment industry received 29% higher compensation compared to others. Again the introduction of this variable into the multiple regression model left the regression coefficients in Table 7 essentially unaltered.

9. Tests of Assumptions in Estimating the Model

Least-squares estimation of the multiple regression model provides best linear unbiased estimates of the parameters provided certain assumptions are satisfied. One assumption is that the variance of the error term is constant across observations (homoscedasticity). A plot of residuals versus predicted values showed no evidence of heteroscedasticity. In addition partial residual plots were made for each predictor, i.e., the residual was plotted against the predictor after the predictor in question was partialed out of the effects of all other predictors. The partial residual plots showed no evidence of the variance of the error term depending on any of the predictor variables, although there was a slight decrease in residual variance as TOTEMPL increased.

Statistical testing of the model coefficients is based on the assumption that the errors are normally distributed. To check this assumption, a normal probability plot of the residuals was produced. No significant deviations from normality were observed.

The model used assumes that predictor variables enter the model in a linear fashion. As a check of whether some non-linear functions of the predictors might add explanatory power to the model we used "smooths" of the partial residual plot for each predictor[5]. No significant departures from linearity were found.

[5] The "smooth" of a plot of y against x removes much of the "noise" in y so as to display the systematic relationship of y to x. A local linear smoother was used (Cleveland 1979). In our context, y is the residual of the dependent variable in the multiple regression (Table 7) and x is the residual of the predictor after it is regressed on all other predictors.

We conclude that the assumptions of the regression model are met to a satisfactory degree in this data set.

9.1 Collinearity of Predictor Variables

High collinearity of the predictor variables can make parameter estimates unstable. We looked for collinearity by calculating for each predictor variable the auxiliary R^2, which is the R^2 of the regression of the predictor in question on all remaining predictors. The largest auxiliary R^2 was .38 for the adjustment variable SELFEMPL, which is obviously negatively correlated with TOTEMPL. Since the auxiliary R^2 are "small", multicollinearity is not a problem in the estimated model.

9.2 Curtailment

The analysis so far has been carried out on applicants who were admitted and who enrolled in the MBA program. This group is selected on the basis of certain criteria and is, therefore, likely to be systematically different from other applicants. Therefore, if we consider only the enrollees, we may not capture the variation in predictor variables in the entire applicant pool, which is the population to which the models are to be applied. Such curtailment problems (Lord and Novick 1968) have been addressed previously by Srinivasan and Weinstein (1973) in a context similar to the present one. Basically, restricted variation in predictor variables tends to reduce the magnitudes of the correlations, t-ratios, and beta weights.

To examine the incidence of curtailment, we collected data from the same classes on the predictor variables for a subset of the remaining applicants, i.e., those who were rejected and those who were accepted but did not enroll.

Define Q = SA / SE, where SA is the estimated standard deviation of a predictor variable in the entire applicant pool, and SE is the standard deviation of the same predictor variable for all enrollees. If Q is substantially above 1, curtailment is indicated so that beta weights and t-ratios may be understated. On the other hand, if Q is substantially below 1, values for the t-ratios and beta weights based on the enrollees may be overstated.

For each potential predictor variable (Tables 3 - 5) a Q-value was computed. If the Q-value was substantially above 1 ($Q > 1.2$) and the predictor was not included in the model, the t-value by including the predictor variable in the final model was examined. In all such cases the t-values and beta weights were small so that even with an adjustment for curtailment these predictor variables would not be statistically significant. The Q-value for one predictor included in the model (INITPRESENT) was greater than 1.2 (=1.34) indicating that INITPRESENT may be more important in the entire applicant population than indicated in our analysis. For no predictor variables included in the final model was the Q-value substantially below 1 ($Q < 0.8$) so that we can conclude that the t-ratios are unlikely to be overstated. The results indicate that no curtailment correction is necessary.

9.3 Non-response Bias

We investigated whether there is bias in our results from not being able to include persons who did not return the questionnaire or did return the questionnaire but did not report their current compensation. It may be suspected that non-respondents may not have been as successful in their careers as those who responded to the survey. To examine this possibility, we computed the average predicted management potential for the various groups. As seen from Eq. (4) the predicted potential is given by a weighted linear combination of the model variables, with the regression coefficients given in Table 7 serving as the weights. The predicted potential had an almost identical average for respondents and non-respondents so that the bias, if any, created by non-respondents is likely to be minimal.

The predicted management potential was, on the average, higher for those who provided the annual compensation information compared to those who returned the questionnaire but did not provide information on compensation. However, the difference was not statistically significant. Given that only about 7% of the respondents did not provide information on compensation the bias created is likely to be minimal.

10. Model Validation and Related Issues

Throughout this and the following section, the term MODELSCORE denotes the weighted sum of the model variables, with weights given in the bottom half of Table 7 (i.e., without the weights for adjustment variables). As explained in Eq. (4) of Section 4, MODELSCORE is the predicted management potential, operationalized as the predicted adjusted compensation.

10.1 Face Validity

The results in Table 7 make intuitive sense and, as detailed in Section 8, are broadly consistent with previous research. The coefficients have the right signs and the magnitudes of the coefficients are not unreasonable.

10.2 Consistency with Past Admissions Decisions

Using data from the two classes for which we had data on applicants who were rejected, or were accepted but did not enroll, we found that the mean MODELSCORE for the admitted applicants was about one standard deviation higher than the mean MODELSCORE for the rejected applicants, with the standard deviations being almost identical for the two groups. The difference in the two means is substantial and highly statistically significant. Thus there is some agreement between the model's predictions and past admissions decisions.

10.3 Explanatory Power

The models listed in Table 7 have an adjusted R2 of about .20, i.e., they explain about 20% of the variation in compensation. (The percent explained goes up by about four percentage points when hours worked/week is included as an additional predictor.) The magnitude of the adjusted R2 is not unreasonable considering that the unit of analysis is an individual and not an aggregate entity and that information from application was used to predict compensation ten years later. Further, a large improvement over chance in terms of the proportion of successful admits can be obtained even with a low R2 since in the present situation the ratio of the number of applicants to the number of admits is large (Taylor and Russell 1938).

Several factors could account for the unexplained variation. First, compensation itself is considerably error prone and the relationship between managerial performance and compensation is positive, but weak (Loomis 1982; Seligman 1984). Luck, good and bad, plays an important role in managerial careers (Seligman 1981). A significant income differential can be attributed solely to the height of a person (Keyes 1980). Socioeconomic status (Pfeffer 1977) and family relationships to owners and presidents probably make a difference in managerial careers.

A potentially useful set of factors, viz., personality variables, have been ignored in our models except in so far as personality traits are related to the model variables used in the analysis. Several studies have shown significant relationships between personality variables and managerial success (Dunnette 1967; Harrell and Harrell 1973, 1974; Harrell, Harrell, McIntyre & Weinberg 1977). However, a difficulty in using personality variables as predictors of management success is that the questions one might use in an application form to measure desirable personality traits may be transparent, i.e., applicants may figure out what the "right" answers are and game the system.

10.4 Predictive Validity

Table 8: Cross-Classification of Predicted versus Actual Adjusted Compensation[1]

		Actual Compensation			
		Low	Medium	High	
Predicted Compensation	Low	13.2 (15.0)	11.8 (10.9)	7.9 (7.4)	32.9
	Medium	11.8 (10.9)	6.6 (11.5)	14.5 (10.9)	32.9
	High	7.9 (7.4)	14.5 (10.9)	11.8 (15.0)	34.2
		32.9	32.9	34.2	100.0

[1] The top number in each cell is the percent of the validation sample (n = 76) that was in each category, for example, 13.2% of the validation sample had low predicted and low actual adjusted compensation. The sample sizes for "low", "medium", and "high" for both variables were 25, 25, and 26 respectively. The bottom number in each cell (in parentheses) is the theoretical percentage assuming a correlated bivariate normal distribution for Actual and Predicted Compensation.

= cells corresponding to serious misclassifications.

Minor differences in MODELSCORE are probably unreliable in comparing the management potential of one applicant to another. Consequently, it would be better to utilize MODELSCORE defined as a few categories. Considering the small size of the hold-out sample (n = 76), it was divided into three nearly equal numbers of graduates corresponding to low, medium and high values of MODELSCORE (= predicted adjusted compensation). For the same graduates, we also computed their actual adjusted compensation i.e., the reported compensation minus the weighted sum of adjustment variables with the weights given in the top half of Table 7. As in the predicted categories, the actual values were also classified into equal low, medium and high categories. Given the predicted and the actual categories, we can cross-classify the 76 observations of the validation sample into the nine cells of a 3 x 3 table.

There are misclassification costs whenever the predicted category is not equal to the actual. However, the costs of misclassifying a low to a medium or a high to a medium are much smaller than the two serious misclassifications, viz., we predict someone to have a high potential and the person turns out to have low success (adjusted compensation) or conversely someone who turns out to be highly successful was classified by the model to have a low potential.

If the MODELSCORE were totally unrelated to actual success, then each cell in the table will be expected to have 1/3 x 1/3 = 1/9 = 11.1% of the observations. As seen from the boxed cells in Table 8, the serious misclassifications of a high to a low and a low to a high each drop from 11.1% to 7.9%. The reduction in total serious misclassifications from 22.2 to 15.8% (approximately by a third) is statistically significant ($p < .10$).

The percent correctly classified (the three diagonal cells in Table 8), does not improve as one would have liked. (The percent correctly classified = 13.2 + 6.6 + 11.8 = 31.6% is actually a little worse than the base rate of 3 x 11.1 = 33.3%). However, as argued earlier, small misclassifications do not matter anywhere as much as serious misclassifications. Furthermore, the results of a theoretical analysis also noted in Table 8 indicate that the percent correctly classified is likely to be about 41.5% as opposed to the 31.6% obtained in the present data. (The lower value is possibly due to sampling fluctuations).

The modest reduction of about a third in serious misclassifications is encouraging. As discussed in the previous subsection, there are structural reasons, such as the errors in compensation itself and the effects of luck, that a prediction of success ten years later is bound to be error-prone.

10.5 Homogeneity of Model Coefficients for Private and Public Sector Managers

To investigate the differences between the regression coefficients of the final model for public versus private sector managers, a statistical test was conducted (Chow 1960; Fisher 1970). The resulting F statistic was less than one indicating that there are no statistically significant differences in the regression coefficients between the private and public sector models.

10.6 Robustness of the Model Results to other Measures of Management Success

In Section 3.3, an alternative measure of managerial success was developed. The Extrinsic Success factor (EXTRINSIC) is a weighted combination of the following indicators of management success: relative authority level (RATLEVL), authority limit on expenditures (AUTHLIM), number of employees supervised

(SUPVEMPL), compensation (LOGCOMP), career satisfaction (CARSATIS), and job satisfaction (JOBSATIS)[6].

We performed a regression using EXTRINSIC as the dependent variable and using as predictor variables the adjustment and model variables in Table 7. With EXTRINSIC as the dependent variable the effects of UGGPA and EXTRACUR (which were less important predictors with compensation as the dependent variable) dropped off considerably. The three remaining model variables had the same signs as they did in the model predicting compensation and the magnitude of the t-ratios were likewise very similar.

We checked to see if any additional model variables would add explanatory power to the model for EXTRINSIC. We found that a dummy variable representing engineering undergraduate major had a significant ($p < .05$) negative effect on EXTRINSIC, i.e. engineering majors did worse than other majors, replicating the finding reported in Harrell and Harrell (1984). No other variable added even a moderate amount of predictive power to the model.

These results suggest that the model developed using adjusted compensation as the definition of management success is generally consistent with the alternative definition of management success as well.

10. 7 Applicability of the Model to Women and Minorities

Statistical tests were conducted (Chow 1960; Fisher 1970) to investigate potential differences in the regression coefficients for men versus women (Strober 1982), for whites versus minorities (Brown and Ford 1977), and for whites against different subgroups of minorities (Blacks, Chicanos, and Asian Americans). This analysis was restricted to U.S. citizens. The total sample consisted of 173 white males, 68 women, and 56 minorities.

After allowing for differences in intercepts (see below), there were no significant differences in the regression coefficients for men versus women, for whites versus minorities, and for whites versus different minority groups. Consequently, the model of Table 7 is applicable to women and minorities as well.

Since the regression coefficients may be assumed to be the same, we calculated MODELSCORE for each person, and an adjustment score, which is the linear combination of adjustment variables given by the final model (top half of Table 7). LOGCOMP (compensation) was adjusted by subtracting the adjustment score

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[6] EXTRINSIC = .440 RATLEVL + .241 AUTHLIM + .223 SUPVEMPL + .127 LOGCOMP + .110 CARSATIS + .096 JOBSATIS. The numbers in this equation are factor score coefficients. They are different from the factor loadings given in Table 2 expressing the regression relationship of each variable to the two factors. Note that the satisfaction measures have a lower weight in determining EXTRINSIC.

from it, to result in adjusted compensation (ADJCOMP). To examine whether compensation is biased against women and/or minorities (i.e., the possible differences in the intercepts of the regression model), we estimated the model:

$$\text{ADJCOMP} = A + B\ \text{MODELSCORE} + C\ \text{WOMAN} + D\ \text{MINORITY} + E\ (\text{MODELSCORE} * \text{WOMAN}) + F\ (\text{MODELSCORE} * \text{MINORITY}) + \text{Error} \quad (5)$$

where WOMAN = 1 for female MBAs and 0 otherwise, and MINORITIES = 1 for minorities and 0 otherwise[7]. We obtained a statistically significant ($p < .01$) negative estimate for C indicating that for the same MODELSCORE, women are paid 24% less[8]. A statistically significant ($p < .10$) negative estimate for E was obtained which means that the bias in compensation against women gets worse for more qualified women. We also obtained a statistically significant ($p < .10$) negative estimate for D indicating that for the same MODELSCORE, minorities get paid 16% less (Brown and Ford 1977). (There were no significant differences among subgroups of minorities, and the coefficient F in Eq. (5), although slightly negative, was not statistically significant.)

Several factors may be related to the bias in compensation against women and minorities. The bias is less likely due to ability, since our model includes several ability related variables (see bottom half of Table 7), although it is possible that we have excluded some relevant ability factors. The bias in compensation against women cannot be explained away by the fact that women tend to leave the workforce for longer periods of time, because this effect has been already adjusted for in defining ADJCOMP in Eq. (5). Men and women MBAs work nearly the same number of hours/week so that the length of work week is not an explanation. A part of the bias in compensation against women is related to the fact that a fraction of male MBAs tend to have nonworking spouses giving the male MBA an advantage, and this is related to higher compensation (Pfeffer and Ross 1982). By contrast, most female MBAs had working spouses. The bias in compensation against women and minorities may also be the result of discrimination. For these and other reasons, the MODELSCORE over-predicts compensation for women and minorities. It is important to emphasize that the use of MODELSCORE is not biased against women and minorities.

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[7] Dummy variables were included to adjust for the different years of graduation, but these are not shown in Eq. (5).

[8] Since MODELSCORE was expressed in the form of deviation from the mean, this result means that a women MBA with an average value for MODELSCORE gets paid 24% less salary than a male MBA with the same average value for MODELSCORE.

11. Concluding Remarks

From the results presented earlier, we may conclude that the MODELSCORE has reasonable validity in assessing management potential. It should be emphasized, however, that the objective assessment of an applicant's management potential is not meant to replace the admissions officers' subjective assessment of management potential, but to supplement it. The subjective and objective assessments of management potential each have their strengths and weaknesses. The subjective assessment can take into account more of the information about the applicant, especially unusual or unique aspects. On the other hand, for reasons discussed in the introduction, an objective assessment such as MODELSCORE is likely to provide a more reliable and valid indication of management potential.

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