

## Features and Information

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WILLIAM WALSTAD, Section Editor

# Forecasting Job Placements of Economics Graduate Students

Alan B. Krueger and Stephen Wu

Each year, academic departments must decide which applicants to admit to their graduate program. Although departments try to maximize a complex set of objectives through their admissions process, one important consideration is the eventual job placement and professional success of their graduates. Research on predicting successful graduate students—however defined—from the pool of applicants is sparse, and in practice, economics departments are often forced to base admission decisions on ad hoc procedures, partial information, and intuition. In this article, we report on a statistical analysis of the determinants of success among more than 300 graduate students who applied for admission to one particular “top five” economics department. Graduate students’ success was measured by the students’ job placement nine years after they would have begun graduate study. This is obviously a narrow and incomplete measure of the success of graduate students (e.g., it excludes their teaching contributions), but it is a quantifiable dimension that many graduate programs care about. Although our results are relevant only for the pool of applicants to this particular graduate program, the application pool consisted of many, if not most, of the applicants to top Ph.D. economics programs in the United States, so the results could possibly be generalized beyond this one school.

Our main findings were that, although there is considerable uncertainty in predicting which applicants will be placed in high-ranking jobs, the math Graduate Record Examination (GRE) score, economics GRE score, and ratings of the admissions committee are useful predictors of the applicants’ subsequent job placement. Perhaps more surprising, a statistical model based on the quantifiable

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*Alan B. Krueger is the Bendheim Professor of Economics at Princeton University (e-mail: akrueger@wss.princeton.edu). Stephen Wu is a graduate student at Princeton University. The authors thank Bill Becker, John Siegfried, and four anonymous referees for helpful comments.*

information in the students' application folders (including GRE scores, undergraduate college, and the prominence of the reference writer) provides a slightly better forecast of successful students than the subjective ratings of the admissions committee. Nonetheless, the ratings of the people on the committee are useful predictors of eventual student placement conditional on the information in the admissions folder, suggesting that an optimal admissions strategy would combine the two sources of information.

Our findings on the efficacy of GRE scores conflict with Sternberg and Williams's (1997) conclusion that the GRE is not a useful predictor of student achievement in the field of psychology. Their sample of students, however, included only those who attended Yale University's graduate program in psychology, and they measured student success by first- and second-year course grades and subjective faculty ratings of student performance. As we show below, if we had limited our sample of economics graduate students to those who attended the top five department and measured their success in terms of course grades, we would also have found that the GRE is a poor predictor of student success. Thus, we think it is premature to conclude that the GRE is not a useful tool for predicting successful applicants to graduate school. Indeed, combined with other information and human judgment, our results suggest the GRE can be a useful resource in admissions decisions.

## CONSTRUCTING THE DATA

An unusual feature of our analysis was that we measured the success of applicants to graduate school by their eventual job placement. Specifically, we have attempted to determine the whereabouts of all the applicants to a given class. Although this approach has its merits, it also poses some potential obstacles. For example, in deciding which cohort of applicants to study, one needs to wait a sufficient period of time until the applicants have had a chance to finish their degrees and obtain jobs. But if one waits too long, the results may no longer be relevant for the current cohort of applicants. For the most part, we focused on the 344 students who applied for admission to this particular economics department in 1989.<sup>1</sup>

In the summer of 1996 and again in the winter of 1999, we attempted to track down the job placements of all of the students who had applied for admission to the program. Determining students' whereabouts turned out to be a major challenge. Many of the applicants may never have attended graduate school, or may have done so in a foreign country, or may have dropped out of their graduate program, or may still have been enrolled. To track down the job placement of applicants, we used the American Economic Association's (AEA) 1995 *Telephone Directory* and 1993 *Survey of Members*, catalog listings of all the top 25 economics departments and business schools (Scott and Mitias 1996), Internet search engines, and input from colleagues at various institutions. After much effort, we were able to track down the job placements of two-thirds of the admitted students but only one-third of the entire applicant pool. Despite the low overall identification rate, we are confident that we

found all applicants who were hired by the top 25 economics departments because we searched each of their faculty rosters from their college catalogs.<sup>2</sup> An in-depth analysis of a small, randomly selected subset of applicants whom we could not find suggests that most never completed or never attended graduate school in economics. We suspect that many of these students were not strongly committed to pursuing graduate education in economics, or were not admitted to a Ph.D. program.

Another issue concerns the ranking of the various job placements. For our analysis, we assumed that one goal of admissions and graduate training in economics is to place students in leading research jobs, although we recognize that different departments have different objectives. In ranking academic institutions, we relied primarily on the ranking of the top 100 economics departments based on faculty publications in elite journals produced by Scott and Mitias (1996).<sup>3</sup> Students who were placed in business school jobs were given a rank equal to their university's economics department ranking plus five. (A lower rank signified a more prestigious job placement.) The World Bank, IMF, and Federal Reserve Board received a ranking equivalent to the 40th best economics department. Consulting jobs (e.g., NERA, Abt, DRI) were given a rank equal to the 120th best economics department. Finally, applicants who could not be found were assigned a rank of 150, the worst rank we gave, and treated as censored observations in much of the analysis. Students who held multiple jobs after leaving graduate school were assigned the best rank of all their jobs. Our ranking system was undoubtedly subjective, but we conducted the entire analysis using an alternative ranking scheme taken from a survey by the National Research Council, and we also experimented with using different rankings for consulting jobs, business schools, and government jobs to test the robustness of our findings. Using these alternative rankings, we obtained extremely similar results, and thus our conclusions did not appear sensitive to the choice of ranking system.

From summaries of the applicants' admissions files retained by the department, we were able to obtain information on several relevant predictor variables. Most important, we were able to obtain data on the applicants' math, verbal, and analytical GRE scores; undergraduate college; country of origin; and other graduate schools they listed that they had applied to. For a subset of applicants, we also had the economics subject GRE score. In addition, most of the application folders were read by two members of an admissions committee, and we used the sum of their rating scores as a variable in some of the analysis that follows.<sup>4</sup> Unfortunately, some pertinent information was not retained in the department's files, such as the students' undergraduate grade point average (GPA), relevant coursework, and letters of reference. The folders did list the names of the applicants' letter-of-reference writers, however, so we categorized the letters of reference into three admittedly subjective groups: (1) at least one reference writer was a prominent research economist (i.e., someone who we deemed to be a well-known and respected researcher in the profession); (2) at least one reference writer was an active economist (i.e., an economist who had recently published or who was known for other reasons); and (3) the reference writers were unknown to us.<sup>5</sup>

## WHO IS ADMITTED?

Before analyzing the determinants of job placements, it is useful to describe features of the data and to model the admissions decision. The means of key variables for all applicants as a whole, for the subsample that was found, for the subsample that was admitted, and the subsample that matriculated to the department are reported in Table 1. There were 344 applicants in 1989, 108 (31 percent) of whom were eventually found, 65 (19 percent) of whom were admitted, and 27 of whom chose to attend (a matriculation rate of 42 percent). Fully 58 percent of applicants to this department were foreign born, which is somewhat higher than

**TABLE 1**  
**Means of Key Variables**

Variable	All applicants	Applicants found	Applicants admitted	Applicants who attended
<i>Eventual job placement<sup>a</sup></i>	121.038	57.750	79.108	79.704
<i>Proportion in top-25 job</i>	0.084	0.269	0.246	0.148
<i>Proportion in top-10 job</i>	0.035	0.111	0.108	0.037
<i>Math GRE</i>	742.516	767.282	774.375	763.846
<i>Verbal GRE</i>	568.645	607.670	637.656	606.539
<i>Analytical GRE</i>	654.936	701.165	732.188	702.308
<i>Economics GRE</i>	729.266	771.818	784.314	759.546
<i>Sum of ratings<sup>b</sup></i>	7.381	10.306	13.000	11.926
<i>Reference group 1<sup>c</sup></i>	0.113	0.231	0.338	0.333
<i>Reference group 2<sup>d</sup></i>	0.177	0.185	0.246	0.111
<i>Total schools applied to</i>	4.419	4.647	5.098	5.208
<i>Top 5 schools applied to</i>	1.994	2.314	2.984	2.667
<i>Ivy League undergrad</i>	0.076	0.130	0.185	0.111
<i>Other elite undergrad</i>	0.084	0.083	0.123	0.074
<i>Seven Sisters undergrad</i>	0.026	0.019	0.031	0.000
<i>Female</i>	0.259	0.241	0.292	0.222
<i>Graduate degree</i>	0.399	0.364	0.354	0.519
<i>Foreign undergraduate college</i>	0.519	0.481	0.431	0.593
<i>Region of birth</i>				
<i>United States</i>	0.424	0.481	0.523	0.407
<i>China, Taiwan</i>	0.078	0.019	0.031	0.000
<i>Korea, Japan</i>	0.108	0.102	0.077	0.185
<i>South Asia</i>	0.070	0.074	0.077	0.111
<i>Other Asia</i>	0.061	0.037	0.046	0.037
<i>Europe</i>	0.160	0.176	0.138	0.111
<i>Canada, Latin America</i>	0.076	0.074	0.092	0.111
<i>Australia</i>	0.017	0.037	0.015	0.037
<i>Africa</i>	0.006	0.000	0.000	0.000
<b>Sample size</b>	<b>344</b>	<b>108</b>	<b>65</b>	<b>27</b>

<sup>a</sup>Eventual job placement is rank of first job.

<sup>b</sup>Sum of ratings is the sum of scores given by two members of the admissions committee.

<sup>c</sup>Reference group 1 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed a prominent economist.

<sup>d</sup>Reference group 2 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed an active economist.

Aslanbeigui and Montecinos's (1997) estimate that 52 percent of graduate students in economics in 1995–96 were foreign born.

Attiyeh and Attiyeh (1997) provide a careful analysis of the determinants of admission to graduate school using data from 48 different institutions and five fields of study, including economics. Specifically, for each field they estimate probit models in which admission to the graduate program is a function of GRE scores, undergraduate performance, country of origin, and other variables. Their estimated probit equation for applicants to economics graduate programs is shown in column 1 of Table 2. For comparison, we tried to replicate their model as closely as possible with data from our sample (column 3). Although we did not have exactly the same set of variables as they had (most important, we lacked information on undergraduate grades), the results were notably similar. For example, the top five departments in our sample and in the Attiyeh and Attiyeh sample of departments all tended to place a great deal of weight on the math GRE in admissions; the probit coefficients imply that a 100-point increase in the math GRE is associated with a 10-percentage point increase in the probability of admission in Attiyeh and Attiyeh's sample of economics departments and a 12-percentage point higher probability in our sample.<sup>6</sup> The verbal and subject GREs had a smaller effect on admissions in both samples. Interestingly, the verbal GRE did not appear to be given less weight for foreign applicants in either sample. Black and Hispanic students and women were more likely than nonminorities and men to be admitted to graduate school in both samples. The similarity of most of the coefficients suggests that our sample was fairly representative of other economics departments because they all seem to have used a similar set of criteria in determining admissions decisions.

We included in column (5) some additional variables in our sample. The results indicated that being a foreign student or attending an Ivy League or other elite college (e.g., Stanford, MIT, etc.) did not have a statistically significant effect on the admission rate, other things being equal. On the other hand, students who had more prominent economists write their letters of recommendation had a higher probability of admission, irrespective of the content of the letter.<sup>7</sup> Finally, we do not report models that include the sum of the admissions committee's ratings, but it is unsurprising that this variable is a strong predictor of admission to the graduate program.

## PREDICTING SUCCESS IN THE JOB MARKET

We measured success by the eventual job placement of the student. Although this is clearly an imperfect measure of success, and one might like also to measure success by the long-term job placement, publication record, citations, teaching record, and other contributions of economists, the students' initial placement is nonetheless of interest because a primary goal of top graduate programs is to train students so they can be placed in academic research positions. Moreover, initial job placement is probably highly correlated with future job placement and other measures of success and is a *market-based* indicator.

Tables 3 and 4 present various Tobit estimates where the dependent variable was the rank of the students' job placement as of 1996. Applicants whose job we could not identify or who had not completed graduate school were treated as censored observations, with the censoring point equal to a job rank of 150. Although more sophisticated methods could have been used to analyze the job-rank data, the Tobit models provided a straightforward way of summarizing the relations in the data and in our case, generally yielded similar results to categorical-dependent-variable models. Table 3 presents model results including a variable that measured the sum of the admission committee's rating scores, whereas Table 4 omits this variable. The sample size fell considerably when the economics GRE score was included because applicants were not required to take a subject exam. In addition, the analytical GRE was a less-central requirement for admission. Consequently, we also present models without these variables. In interpreting the Tobits, it is important to note that a lower value of the dependent variable signifies a better ranked position.

**TABLE 2**  
**Probit Estimates for Admissions Decisions: Attiyeh and Attiyeh's (1997)**  
**Sample of Economics Departments and Krueger and Wu's Sample**

Explanatory variable	Attiyeh and Attiyeh (1997)		Krueger and Wu Top 5 department			
	Coefficient	<i>p</i> value	Coefficient	<i>p</i> value	Coefficient	<i>p</i> value
<i>Math GRE</i>	0.005	0.000	0.006 (0.003)	0.029	0.004 (0.003)	0.194
<i>Verbal GRE</i>	0.002	0.000	0.002 (0.001)	0.069	0.001 (0.001)	0.325
<i>Foreign × verbal GRE</i>	0.001	0.000	0.000 (0.001)	0.672	0.001 (0.001)	0.410
<i>Analytical GRE</i>	0.001	0.000	0.003 (0.002)	0.038	0.003 (0.002)	0.090
<i>Economics GRE</i>	0.003	0.000	0.005 (0.002)	0.007	0.004 (0.002)	0.027
<i>GPA</i>	0.572	0.000	—	—	—	—
<i>Institute SAT</i>	0.001	0.000	—	—	—	—
<i>Graduate degree</i>	0.191	0.000	0.409 (0.248)	0.100	0.392 (0.277)	0.152
<i>Related major</i>	0.121	0.072	—	—	—	—
<i>Other major</i>	-0.171	0.001	—	—	—	—
<i>Female</i>	0.107	0.000	0.493 (0.240)	0.040	0.594 (0.274)	0.030
<i>Black or Hispanic</i>	0.489	0.000	1.557 (0.608)	0.010	1.698 (0.679)	0.012
<i>Asian American</i>	-0.145	0.044	0.615 (0.504)	0.222	-0.166 (0.548)	-0.302
<i>East Asian</i>	0.689	0.000	-0.106 (0.521)	0.893	—	—
<i>South Asian</i>	-1.482	0.000	-0.542 (0.540)	0.315	—	—
<i>English-speaking country</i>	0.211	0.005	0.035 (0.480)	0.942	—	—

*(continued)*

TABLE2—continued

Explanatory variable	Attiyeh and Attiyeh (1997)		Krueger and Wu Top 5 department			
	Coefficient	p value	Coefficient	p value	Coefficient	p value
<i>Western European</i>	0.034	0.000	0.606 (0.481)	0.208	—	—
<i>Latin American</i>	0.222	0.001	0.752 (0.643)	0.242	—	—
<i>Other foreign</i>	0.417	0.000	0.125 (0.436)	0.775	—	—
<i>Total schools applied to</i>	—	—	—	—	-0.093 (0.065)	0.151
<i>Top 5 schools applied to</i>	—	—	—	—	0.417 (0.101)	0.000
<i>Foreign undergrad</i>	—	—	—	—	0.340 (0.465)	0.732
<i>Ivy League undergrad</i>	—	—	—	—	0.163 (0.392)	0.678
<i>Other elite undergrad</i>	—	—	—	—	-0.350 (0.401)	0.384
<i>Applications/faculty Reference group 1<sup>a</sup></i>	-0.169	—	—	—	—	—
<i>Reference group 2<sup>b</sup></i>	—	—	—	—	1.333 (0.347)	0.000
<i>Age</i>	-0.009	0.006	-0.061 (0.038)	0.103	0.855 (0.299)	0.004
Sample size	15,159		301		281	

Notes: Dependent variable equals 1 if admitted, 0 if not admitted.

Means used if GRE scores are missing, and a dummy variable is included to indicate whether scores are missing. Standard errors are shown in parentheses. Standard errors for Attiyeh and Attiyeh (1997) are not available.

<sup>a</sup>Reference group 1 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed a prominent economist.

<sup>b</sup>Reference group 2 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed an active economist.

The results of the analysis show that students who were rated more highly by the admissions committee tended to be placed in better jobs. This result held whether or not we conditioned on the applicants' observed characteristics. The coefficient of -6.9 in the last column of Table 3, for example, implies that if a student moves from the 25th percentile to the 75th percentile of the committee's ratings (a movement from 4 to 10), his or her predicted job placement would improve by 41 places.

The admissions committee ratings did not reflect all the observable information in the file that could be used to predict job placement (Table 3). Most important, the math GRE and the quality of the references had explanatory power after conditioning on the rating scores of the admissions committee. All else equal, a 50-point increase in the math GRE was associated with an improved job placement of 23 spots. Also, applicants whose reference writers were leading economists obtained jobs that were ranked 60 places better than those whose reference writers were less prominent, all else equal. One possible interpretation of this

**TABLE 3**  
**Tobit Models for Initial Job Placement, Controlling for the Admissions**  
**Committee's Rating of Applicants**

Explanatory variable	Model 1	Model 2	Model 3	Model 4
<i>Sum of ratings</i>	-12.454 (1.764)	-7.847 (2.467)	-8.925 (1.986)	-6.924 (2.143)
<i>Math GRE</i>	—	-0.248 (0.199)	-0.378 (0.159)	-0.457 (0.176)
<i>Verbal GRE</i>	—	-0.039 (0.102)	-0.079 (0.076)	-0.055 (0.089)
<i>Analytical GRE</i>	—	0.039 (0.127)	—	—
<i>Economics GRE</i>	—	-0.345 (0.131)	—	—
<i>Female</i>	—	-11.536 (20.961)	-6.036 (17.227)	-13.576 (17.363)
<i>Age 21–24</i>	—	-82.847 (79.866)	-54.008 (78.497)	-45.332 (78.582)
<i>Age 25 plus</i>	—	-46.902 (80.826)	-24.221 (79.039)	-36.522 (80.124)
<i>Foreign undergrad</i>	—	-2.475 (22.072)	-24.662 (17.185)	5.228 (25.924)
<i>Ivy League undergrad</i>	—	—	—	-11.341 (26.487)
<i>Other elite undergrad</i>	—	—	—	22.772 (25.713)
<i>Reference group 1<sup>a</sup></i>	—	—	—	-59.887 (22.613)
<i>Reference group 2<sup>b</sup></i>	—	—	—	-22.609 (18.677)
<i>Graduate degree</i>	—	—	—	0.454 (18.633)
<i>Total schools applied to</i>	—	—	—	1.339 (4.475)
<i>Top 5 schools applied to</i>	—	—	—	2.558 (6.429)
<i>Korea, Japan</i>	—	—	—	-13.919 (33.349)
<i>South Asia</i>	—	—	—	-22.593 (32.141)
<i>Other Asia</i>	—	—	—	-10.126 (36.288)
<i>Europe</i>	—	—	—	-51.893 (28.801)
<i>Canada, Latin America</i>	—	—	—	-65.076 (36.521)
<i>Australia</i>	—	—	—	-96.655 (49.195)
Sample size	325	203	291	271
Noncensored observations	108	75	102	96
Pseudo <i>R</i> <sup>2</sup>	0.036	0.054	0.045	0.053

*Notes:* Dependent variable: Rank of job placement. A lower value of the dependent variable corresponds to a better-ranked job. Standard errors are shown in parentheses.

<sup>a</sup>Reference group 1 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed a prominent economist.

<sup>b</sup>Reference group 2 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed an active economist.

**TABLE 4**  
**Tobit Models for Initial Job Placement, without Controlling for the Admissions**  
**Committee's Rating of Applicants**

Explanatory variable	Model 1	Model 2	Model 3
<i>Math GRE</i>	-0.445 (0.206)	-0.663 (0.165)	-0.665 (0.176)
<i>Verbal GRE</i>	-0.080 (0.106)	-0.209 (0.077)	-0.148 (0.088)
<i>Analytical GRE</i>	-0.033 (0.129)	—	—
<i>Economics GRE</i>	-0.411 (0.137)	—	—
<i>Female</i>	-22.980 (21.388)	-11.807 (18.211)	-21.355 (17.689)
<i>Age 21–24</i>	-32.327 (83.687)	18.114 (84.001)	11.689 (81.998)
<i>Age 25 plus</i>	12.823 (84.556)	60.448 (84.324)	31.678 (83.103)
<i>Foreign undergrad</i>	1.870 (23.316)	-24.614 (18.377)	14.486 (26.624)
<i>Ivy League undergrad</i>	—	—	-4.352 (27.368)
<i>Other elite undergrad</i>	—	—	18.563 (26.592)
<i>Reference group 1<sup>a</sup></i>	—	—	-76.775 (23.291)
<i>Reference group 2<sup>b</sup></i>	—	—	-34.154 (19.228)
<i>Graduate degree</i>	—	—	-8.824 (18.997)
<i>Total schools applied to</i>	—	—	5.021 (4.520)
<i>Top 5 schools applied to</i>	—	—	-3.886 (6.318)
<i>Korea, Japan</i>	—	—	-30.252 (33.645)
<i>South Asia</i>	—	—	-24.389 (33.142)
<i>Other Asia</i>	—	—	-3.198 (37.087)
<i>Europe</i>	—	—	-72.410 (28.962)
<i>Canada, Latin America</i>	—	—	-80.116 (36.985)
<i>Australia</i>	—	—	-112.156 (50.884)
Sample size	209	302	281
Noncensored observations	75	102	96
Pseudo R <sup>2</sup>	0.044	0.032	0.048

*Notes:* Dependent variable: Rank of job placement. A lower value of the dependent variable corresponds to a better-ranked job. Standard errors are shown in parentheses.

<sup>a</sup>Reference group 1 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed a prominent economist.

<sup>b</sup>Reference group 2 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed an active economist.

result is that a match takes place at the undergraduate level whereby students who are more likely to become successful economists are paired with more accomplished research economists. In addition, more successful research economists could convey more human capital to their students. The data also indicated that women and foreign students tend to be placed in slightly better ranked jobs, although neither of these effects was statistically significant.

There is still a large amount of unexplained variability in placements despite the finding that some variables and the committee's ratings are useful predictors. Even with the variables from the application folder and the rating scores, the pseudo  $R^2$  of these equations is less than 10 percent. Evidently, a great deal of uncertainty is inherent in predicting the future success of applicants to graduate school. This finding should engender some humility among members of admissions committees and should hearten students who are rejected from top programs.

We interacted the ratings of applicants by members of the admissions committee's with eight dummy variables indicating the identity of the faculty member who rated the file. These interactions were jointly statistically insignificant, suggesting that the raters as a whole were equally effective at predicting the success of the applicants. Nevertheless, the interaction term for the chairman of the committee was individually statistically significant. This result suggested that he had particular insight into forecasting the applicants' eventual placement, or that this interaction was significant because he rated a high proportion of the files (which may also have contributed to his insight).

Table 4 presents model results without controlling for the admissions committee's ratings. Our purpose in presenting these models is that they provide the maximum likelihood coefficients that a department could apply to quantitatively rate application files without actually reading them. These models may be a useful input in the admissions process. Qualitatively, most of the explanatory variables had the same direction of effect in the models without the ratings as in the models with the ratings. Foreign students—particularly those from Europe, Australia, Canada, and Latin America—tended to have comparatively better job placements in the model that did not control for the admissions committee's ratings (see column 3 of Table 4).

Table 5 presents logit models where the dependent variable was 1 if the applicant obtained a top 10 job, and 0 otherwise. We limited attention to placement in top 10 jobs because we were confident that every applicant who obtained a job in a top 10 department was correctly identified. In addition, many departments are most concerned about placing students at the top of the distribution. Because these models might be used for prediction, we estimated relatively parsimonious specifications. Interestingly, the results of the top 10 logits were similar to the Tobit equations. For example, students who were highly rated by the admissions committee were more likely to be placed in a top job. The math GRE also had some explanatory power in predicting top placements, even after conditioning on the admissions committee ratings. The verbal GRE, however, was inversely related to the likelihood of placement in a top 10 job. It is interesting that the pseudo  $R^2$  was higher in the model based exclusively on the characteristics in the application folder than in the model based on the subjective ratings of the admissions committee.

**TABLE 5**  
**Logit Estimates for Placement in Top 10 Job**

Explanatory variable	Model 1	Model 2	Model 3
<i>Sum of ratings</i>	0.247 (0.080)	—	0.211 (0.138)
<i>Math GRE</i>	—	0.042 (0.025)	0.037 (0.025)
<i>Verbal GRE</i>	—	-0.007 (0.005)	-0.013 (0.007)
<i>Female</i>	—	-0.601 (1.081)	-0.843 (1.109)
<i>Age 21–24</i>	—	2.249 (1.224)	2.423 (1.245)
<i>Foreign undergrad</i>	—	0.172 (1.454)	-0.122 (1.529)
<i>Ivy League undergrad</i>	—	2.097 (1.352)	2.890 (1.485)
<i>Other elite undergrad</i>	—	0.819 (1.548)	1.106 (1.610)
<i>Reference group 1<sup>a</sup></i>	—	1.860 (1.174)	1.765 (1.192)
<i>Reference group 2<sup>b</sup></i>	—	0.513 (1.119)	0.243 (1.107)
<i>Graduate degree</i>	—	1.160 (1.050)	1.500 (1.095)
<i>Total schools applied to</i>	—	-0.450 (0.272)	-0.330 (0.273)
<i>Top 5 schools applied to</i>	—	0.455 (0.402)	0.296 (0.421)
Sample size	270	270	
Pseudo R <sup>2</sup>	0.130	0.384	0.413
Log-likelihood	-37.915	-26.629	-25.943

*Notes:* Dummy variable equals 1 if placed in top 10 job, 0 if not. Standard errors are shown in parentheses.

<sup>a</sup>Reference group 1 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed a prominent economist.

<sup>b</sup>Reference group 2 is a dummy variable that equals 1 if at least one letter-of-reference writer was deemed an active economist.

Moreover, when we performed a “split sample” exercise and estimated the Tobit model using a randomly selected half of the sample and then used this model to predict job placements for the other half of the sample, we found that the model continued to perform at least as well as the subjective ratings of the committee.

As a final approach, we divided job placements into six ordered categories: (1) top 10 job; (2) 11–25 job; (3) 26–50 job; (4) 51–100 job; (5) 101–120 job; and (6) 150 not placed or placement not found. We then fit ordered logit models to these categories. As in the Tobit models, a lower value of the dependent variable in this categorization signified a better job (Table 6). The model in the first column used the committee’s rating as the only predictor variable, while the model in column 2 excludes the human ratings and predicted placement from the other explanatory variables from the admissions file. Finally, the model in column 3 included both the human ratings and the measured characteristics

**TABLE 6**  
**Ordered Logits**

Explanatory variable	Model 1	Model 2	Model 3
<i>Sum of ratings</i>	-0.203 (0.031)	—	-0.137 (0.045)
<i>Math GRE</i>	—	-0.011 (0.003)	-0.008 (0.003)
<i>Verbal GRE</i>	—	-0.003 (0.001)	-0.001 (0.002)
<i>Female</i>	—	-0.343 (0.325)	-0.229 (0.328)
<i>Age 21–24</i>	—	-0.212 (1.303)	-1.151 (1.330)
<i>Age 25 plus</i>	—	0.183 (1.317)	0.885 (1.354)
<i>Foreign undergrad</i>	—	-0.565 (0.377)	-0.524 (0.386)
<i>Ivy League undergrad</i>	—	-0.287 (0.500)	-0.380 (0.504)
<i>Other elite undergrad</i>	—	0.575 (0.514)	0.606 (0.520)
<i>Reference group 1</i>	—	-1.383 (0.415)	-1.119 (0.426)
<i>Reference group 2</i>	—	-0.632 (0.362)	-0.495 (0.370)
<i>Graduate degree</i>	—	-0.047 (0.354)	0.006 (0.360)
<i>Total schools applied to</i>	—	0.135 (0.083)	0.056 (0.086)
<i>Top 5 schools applied to</i>	—	-0.167 (0.115)	-0.014 (0.124)
Sample size	270	270	
Pseudo $R^2$	0.074	0.091	0.109
Log-likelihood	-296.086	-290.882	-284.96

*Notes:* Dependent variable: Job placement group: Group 1: Top 10 job (10 observations); Group 2: 11–25 job (13); Group 3: 26–50 job (27); Group 4: 51–100 job (13); Group 5: 101–120 job (33); Group 6: not found (174). Standard errors are shown in parentheses.

from the application folder. The human ratings were highly significant predictors of placement in better jobs. Once again, however, the math GRE had predictive power after controlling for the human rating scores. It is also interesting to note that applicants who had prestigious letter-of-reference writers and applied to relatively more top economics departments were placed in better-ranked job categories.

As in the earlier logit model, the pseudo  $R^2$  was slightly higher in column 2 (based on measured characteristics from application) than in column 1 (based on ratings), suggesting that a model based solely on the applicants' characteristics did a better job explaining placement than the model that was based on the human ratings alone.<sup>8</sup> Because the human ratings are a useful predictor of applicants' job placement conditional on their measurable characteristics, an

optimal strategy for selecting students may be to combine the two sources of information.

### GRADES OF MATRICULANTS

We analyzed grades in graduate courses for the small sample of matriculants. The results of a bivariate regression of the students' second-year cumulative GPA on their math GRE scores were:

$$\text{GPA} = 1.241 + .002 \text{ Math GRE} \quad R^2 = .038 \quad n = 22.$$

(2.075) (.003)

For this sample, the math GRE did not have a statistically significant association with GPA. The GRE score was still insignificant if we controlled for the type of college the student attended (Ivy League or other elite college), or whether the student was foreign. This result, however, was not inconsistent with our previous finding that the GRE was a useful predictor of job placement. In particular, to study grades, one must restrict the sample to matriculants, so the sample selection may distort the predictive ability of GRE scores. Moreover, course grades may be a poor predictor of job performance. In light of these results and our earlier findings of the efficacy of GRE scores for predicting job placement, we regard Sternberg and Williams's (1997) finding that GRE scores are not useful predictors of success with considerable caution, because their sample was limited to matriculants of one school and their measure of success was based on course grades and subjective evaluations.

### CONCLUSION

The results of our study may be of use in selecting applicants for admission to graduate programs in economics. In particular, the subjective ratings of the admissions committee, GRE scores, and the prominence of reference letter writers are statistically significant predictors of applicants' subsequent job placement. Nonetheless, there is considerable uncertainty in forecasting which applicants will be successful economists. Evidently, unobserved factors or pure chance play a large role in student job placements.

The positive association between GRE scores and job placement found in this study is particularly difficult to interpret. On the one hand, the test scores could predict job placement because they measure the skills that are relevant for becoming a successful economist. That is, the scores may reflect students' acquired economic knowledge, or their capacity to learn and apply skills in graduate school. On the other hand, the scores may be completely uncorrelated with the students' abilities and capacities and matter in our equations because they demonstrate that most top graduate programs rely heavily on GRE scores in making admissions decisions, and that attending a top graduate school is often a prerequisite for obtaining a job at a top department early in one's career. In the latter case, the GRE scores only serve as a screen, without improving allocative

efficiency. These two interpretations obviously have different implications for the way GRE scores should be viewed in the admissions process, and we unfortunately are unable to sort between them. A worthy topic for future research would be to investigate the reasons why GRE scores predict successful job placement of applicants to graduate school.

#### NOTES

1. To preserve confidentiality, we have not revealed the name of the department, but there is little reason to suspect that the application pool is substantially different from the pool of applicants to top economics departments in general.
2. Because Siegfried (1998, Table 3) estimates that 58 percent of all assistant professors in economics departments join the AEA, and a higher proportion of assistant professors at top ranked departments join, the AEA *Telephone Directory* should contain most of those placed in academic jobs.
3. Ranking economics departments is an inherently subjective task. For example, one could question the arbitrariness of the journals included in the Scott and Mitias (1996) ranking. Nonetheless, the various rankings are generally highly correlated. For example, Dusansky and Vernon (1998) found that the Pearson correlation coefficient between the Scott and Mitias ranking and seven other economics department rankings ranged from .71 to .85. For our purposes, our main results were not very sensitive to using an alternative department ranking such as the National Research Council's ranking.
4. In the admissions process used by the department, each faculty reader assigned a score to the application file. The faculty readers were supposed to score the files independently, without knowledge of the other readers' score. We have converted this score to a 1–10 scale, with 10 indicating the best score possible. The correlation between the two raters' scores was 0.51—positive but not as large as one might expect.
5. These groups were mutually exclusive. Reference writers could only be classified in group 2 if they were not in group 1. We classified the reference writers without knowing the name of the applicant.
6. These derivatives were calculated at the mean admission rate in our sample.
7. The letters were not available, so the recommendations may have been positive or negative.
8. As with the Tobit estimates, a split sample experiment indicated that the ordered logit model predicted job placement at least as well as the human ratings when the model was estimated using one half of the sample to form predictions for the other half.

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