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Returns to MBA quality: Pecuniary and non-pecuniary returns to peers, faculty, and institution quality☆

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HIGHLIGHTS

- We investigate heterogeneity in quality characteristics and returns to MBA programs.
- Multiple proxies for quality of institutions, students, and faculty are considered.
- IV, factor analysis and fixed effects help to diminish biases in estimation.
- Substantial effects of quality are found for pecuniary and non-pecuniary outcomes.

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ABSTRACT

A large literature has focused on estimating the returns to schooling and has typically done so by incorporating institutional heterogeneity in quality along merely one dimension (such as average SAT scores). Using longitudinal survey data of registrants for the GMAT exam and school level information from other sources, we create, in the context of graduate management education, multiple indices of school quality, and estimate the effect of these quality measures on multiple indicators of career success. In particular, we create quality measures of MBA programs based on: (1) institutional and curricular factors, (2) characteristics of the student body, and (3) characteristics of the faculty. We create aggregate quality indices by combining individual proxies using factor analysis. We also extend the literature by considering the effects of quality on both earnings and non-monetary outcomes, namely attainment of managerial goals relative to initial individual expectations, self-assessed skill gains, and various measures of job satisfaction. We include several unique individual control variables, and further control for unobserved heterogeneity through the use of instrumental variables and individual fixed effects. Results indicate that the quality of peers and schools may matter most for earnings. When individual fixed effects are included, estimates of quality premiums diminish somewhat, though the estimated premium associated with school quality increases, emphasizing the importance of controlling for selection into programs of varying quality. School quality is also an important predictor of several non-pecuniary outcomes.

1. Introduction

A glaring disjuncture exists in the measures of post-secondary educational quality used by consumers of higher education compared with those employed by social science researchers. Prospective students and their parents consult a proliferation of guidebooks, rankings, and on-line database services, as well as people they know with relevant personal experiences. Typically, though, economists measure latent "educational quality" with a single proxy variable, such as the mean SAT score of an institution's entering class, when considering the effect of quality on student outcomes. This simplistic approach, in addition to being subject to potential selection bias, is likely to underestimate the returns to underlying quality, as any single proxy measures quality with error.[1] Furthermore, it ignores the fundamentally multi-dimensional nature of higher education. Our goals in this paper are to estimate heterogeneity in the returns to higher education with a focus on reducing measurement error with the use of more than a dozen quality measures, to investigate specific dimensions of quality by creating indices of three main quality inputs (peers, faculty, and the institution), and to do so while addressing concerns about selection bias.

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[1] Black and Smith (2006) show this to be the norm, as well as the bias it introduces, but indicate others who use multiple measures, such as Fitzgerald (2000), Monks (2000), Zhang (2005) and Black and Smith (2004, 2006).

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Rather than focus on undergraduates, here we analyze the returns to quality for the third most commonly earned postsecondary degree, the MBA (Masters of Business Administration). Studies of returns to postsecondary degrees are rarely conducted. Attention to MBAs is especially warranted since it is the higher education degree whose value has been most criticized. [2] Five major MBA rankings exist: *Business Week*, *U.S. News & World Report*, *Wall Street Journal*, *The Economist*, and the *Financial Times*. The two most popular MBA rankings in the U.S.—*Business Week* and *U.S. News & World Report*—have a close to zero long run correlation, in part because of the large role played in each by the subjective ratings of business school deans (Dichev, 1999).[3] Dichev (1999) concludes that one should avoid a broad interpretation of the rankings as measures of unobservable "school quality," but rather interpret them more narrowly as "useful but noisy and incomplete data about school performance" (Dichev, 1999, p. 203). Our analyses also reveal close to zero and exceedingly low correlations of changes in *Business Week* and *U.S. News & World Report* MBA program rankings: 0.07 from 1990 to 2012, 0.02 from 1990 to 2000, and 0.13 from 2000 to 2012.[4]

Beyond providing many quality measures, features of our MBA data set allow us to identify the effect on earnings of education, that is to separate the returns to schooling from the effect of observed and unobserved attributes on educational choices and attainment (Brewer and Ehrenberg, 1996; Heckman, 1979).[5] Researchers use five strategies to identify causal effects: exclusion restrictions,[6] sibling and twin data sets,[7] controlling for selection with lots of observables,[8] instrumental variables,[9] and fixed effects.[10] We employ the latter three approaches. The primary data for our analysis comes from the GMAT Registrant Survey, a longitudinal survey in four waves, comprised of individuals who registered to take the Graduate Management Admission Test (GMAT), a standardized exam required by most MBA programs for admission. This dataset offers several advantages in the evaluation of the returns to MBA quality, namely (1) a relatively homogenous group in terms of human capital and career goals, (2) actual, rather than self-reported, GMAT test scores, and (3) a wealth of additional information about individuals both prior to and following their degree, namely college experiences, a detailed work history, pre- and post-MBA earnings, and various self-assessed managerial skills and non-cognitive attributes, such as initiative and self-confidence. Thus, the relatively rich source of data makes a selection-on-observables approach plausible.

Nonetheless, the most important identification attribute of our data is the existence of both pre-degree and post-degree earnings, an anomaly among higher education students.[11] This feature offers a major advantage of studying MBA graduates, as it allows us to estimate individual fixed effects, eliminating time-invariant, individual-specific heterogeneity as reflected in an individual's earnings. Individual fixed effects may be considered an improvement over the selection-on-observables approach, in that observable covariates, however numerous they may be, imperfectly proxy for the actual factors contributing to both educational decisions and education-independent labor market outcomes. Consider, for example, the comparison of person A, who has more innate ability (or ambition, etc.) and interest in attending a highly-rated school, versus person B, who is otherwise observationally identical but has less such aptitude and preferences for program quality. Even controlling for observable characteristics and background, Person A is both more likely to select a higher ranked program and to achieve greater earnings, independent of choosing such a prestigious institution; thus, a simple cross-sectional comparison (or the use of OLS) would lead to upward biased estimates of returns to quality. The fixed effects specification moves beyond this comparison, and instead investigates the "within-individual" variation, not requiring a control group of non-MBAs (or non-highly ranked program graduates) to identify the effect of educational quality on those who obtain an MBA from a highly rated program.[12]

We contribute to the literature on the return to higher education quality in five ways, beyond focusing on the post-baccalaureate MBA degree. First, we use OLS to estimate the return to quality using a large number of individual-level control variables (a selection-on-observables approach), extending the work of Fitzgerald (2000) and Black and Smith (2006).[13] Second, we use factor analysis to create both an index of overall quality proxies and indices of the proxies for the three main inputs: students, faculty, and MBA program characteristics. Here we build on Tracy and Waldfogel's (1997) attempt to distinguish the quality of an MBA program from the quality of its students. [14] This allows us to reduce the effect of error of any particular quality proxy, and provides a convenient way to consider the net effects of different classes of quality variables. Third, we estimate the relative returns to an overall quality index and indices for the three categories of inputs. Fourth, we use techniques to plausibly control for the selection into

[2] For example, Arcidiacono, et al.'s (2008) estimate of a large drop-off in returns to an MBA beyond the nation's top 25 programs is of no help to those considering one of the other over 500 programs. Some studies have concluded that the MBA education is about networking rather than learning (e.g., Mintzberg, 2004) and that earning an MBA did not affect career salaries (Dreher, Dougherty, and Whitley, 1985; Pfeffer, 1977) or career attainment (Pfeffer and Fong, 2002). For a popular press rebuttal, see Yeaple's *Does it pay to get an MBA?* (2006) and *The MBA Advantage* 1994, which include examples of how to use spreadsheets to calculate the net present value of an MBA, including both direct cost and the opportunity cost of foregone earnings.

[3] While *Business Week's* initial ratings of MBA programs in 1988 were based exclusively on the subjective ratings of business school deans, such subjective evaluation continues to constitute forty percent of the current *U.S. News & World Report* MBA ratings system.

[4] Because of differences across years and schools, we used a sample of 17 schools ranked in the top 20 by both magazines in all years. Our correlation calculation is of the change for each school for each two year period in the sample—the same approach as was employed by Dichev (1999).

[5] Some researchers have attempted to account for self-selection concerns by explicitly modeling the student's choice of the type of institution of higher education to attend (Brewer, Eide and Ehrenberg, 1999; Montgomery, 2002, for full- versus part-time MBA programs) or student's choice of field (Paglin and Rufolo, 1990; Arcidiacono, 2004).

[6] Willis and Rosen (1979) rely on exclusion restrictions in a structural model, using income elasticity estimates for selectivity bias to predict the income associated with each field of study for all students.

[7] Twin studies estimate the value of an additional year of education, controlling for family background and common genetic influences (Behrman and Taubman, 1989; Behrman, et al., 1994, 1996; Ashenfelter and Rouse, 1998).

[8] Researchers use a variety of nationally representative longitudinal data sets on labor market outcomes of distinct cohorts of college graduates; examples include the National Longitudinal Survey of the [High School] Class of 1972 (NLS-72) cohort (James et al., 1989; Grogger and Eide, 1995; Arcidiacono, 2004), the High School and Beyond Longitudinal Study of 1980 Sophomores (H&B-So:1980/1992) cohort (Fitzgerald, 2000), or the Baccalaureate and Beyond study (B&B: 93/97) cohort (Thomas and Zhang, 2005). Also see, Black, Sanders and Taylor (2003) who identify wage differences associated with college majors by comparing workers with identical demographic characteristics (namely age, race and ethnicity), without controlling for either selection into college or the choice of a major (based on data from the 1993 National Survey of College Graduates, NSCG).

[9] Other investigators have relied on instrumental variables, for example proximity to colleges or date of birth, to identify the effect of education on earnings (Angrist and Krueger, 1991; Kane and Rouse, 1995).

[10] Arcidiacono et al. (2008) use individual fixed effects for broad classes of MBA programs with the same dataset we analyze here.

[11] Undergraduates typically attend college directly from high school, as do most law and medical students. Although many other graduate student work prior to obtaining such a degree, we are aware of no study that has used such pre-and post-earnings data, other than with our dataset and that of Boudarbat (2008) in which 43% of the Canadian community college students had worked full-time.

[12] That is, the use of fixed effects allows us, in the language of the treatment effects literature, to estimate the average effect of the treatment on the treated. An additional advantage is that it can do so for multiple treatments, whereas other approaches would likely require multiple instrumental variables or exclusion restrictions. Despite the advantages, the fixed effects framework does require certain assumptions for identification, which are laid out and examined in Arcidiacono et al. (2008) and Grove and Hussey (2011).

[13] As mentioned, Black and Smith (2006) use data on undergraduate students and institutions in an attempt to estimate the returns to multiple proxies (individually and collectively) for school quality. In a similar vein, Fitzgerald (2000) uses the following quality measures: selectivity categories, student–faculty ratios, acceptance rates, size of student body, percent graduate students, private vs. public, geographic location, Carnegie Classifications, spending on instruction and on student services, and whether a historically black institution. He concludes that college quality matters more for women than men.

[14] Tracy and Waldfogel (1997) attempt to distinguish the quality of an MBA program from the quality of the students by including multiple characteristics of the student body and of the institution. They find that high faculty salaries and case-method programs led to greater financial value for graduates.

schools. Motivated by the fact that any particular quality variable is likely to proxy for underlying quality with substantial error, in addition to combining information in individual proxies via factor analysis, we use two stage least squares (2SLS), instrumenting for each quality variable with other available quality proxies. Then, we include individual fixed effects in the earnings regressions in order to control for selection-on-unobservables into programs of varying quality. Finally, we estimate the returns to non-pecuniary outcomes, such as satisfaction with the job, pay, promotion opportunities and enhanced skills, that are likely to be important to students, schools and policy makers. To our knowledge, no other study of the individual returns to educational quality has included such a wide variety of outcomes.

Overall, we find that the effects of MBA quality on student outcomes are substantial. A standard deviation increase in overall quality increases earnings by approximately 10%—an amount that exceeds the estimated total effect of the average MBA degree. The effects of student quality variables on earnings are especially pronounced when estimated by OLS. When fixed effects estimation is used, the coefficients on the quality proxy variables generally decrease, though the estimated premium associated with school quality increases suggesting that program quality is correlated with individuals' unobserved abilities. Taken as a whole, our analysis underscores the importance of simultaneously accounting for substantial measurement error associated with proxy variables for individual quality and for individual selection (on observables and unobservables) into programs of varying quality. Results indicate that the quality of institutions and peers may matter most for salaries. We also find some significant effects of school quality on nonpecuniary outcomes.

2. Data

2.1. MBA sample

We utilize a longitudinal survey of registrants for the Graduate Management Admission Test (GMAT), a standardized test that is a common prerequisite for admissions into graduate business schools. The survey, sponsored by the Graduate Management Admission Council (GMAC), was administered in four waves, beginning in 1990 and ending in 1998. 5885 individuals responded to wave 1 and 3771 responded to wave 4. The survey follows individuals who registered to take the GMAT in 1990, whether or not they even took the test (much less eventually enrolled). Important for our purposes, the survey asks detailed questions about education and earnings. It also asks more subjective questions dealing with self-assessed skills, evaluation of one's business school experience, and attitudes towards one's job, allowing us to consider post-MBA outcomes other than earnings and to include a rich set of control variables. Furthermore, the data was linked to individuals' test registration files, giving us accurate information on both verbal and quantitative GMAT scores. Finally, the presence of pre-MBA earnings observations for much of the sample allows for the use of individual fixed effects, going beyond a selection-on-observables approach to control for the endogeneity of the quality of the school attended.

We limit our sample to those who obtain MBAs sometime within the sample period (about 37% of the initial survey sample), and only include observations if individuals report holding full-time (at least 35 hours per week) jobs and report earnings on the job (as well as other information required to calculate an hourly wage and an annual salary). Dropping missing values for control variables decreases the sample somewhat further. In order to more closely imitate the approach taken in the literature which investigates undergraduate quality, and in accordance with the fact that some of our outcome variables are only available in later survey waves, for much of our analysis we limit our sample to post-MBA observations only. (This sample thus includes observations from either wave 3 or wave 4 or both, because no one in the sample obtained an MBA prior to wave 2 within the sample time frame.) Later in our analysis, we include pre-MBA observations of these individuals in order to include individual fixed effects in earnings regressions. The remaining potential post-MBA sample is 1855 observations. These observations comprise 1321 individuals who completed MBAs from 451 unique programs of varying quality.[15] In practice, sample sizes for regressions will be even lower to varying degrees, given the considerable numbers of missing values for some of the quality proxies (as described below).

2.2. Outcome measures

In line with the literature on college quality, we consider earnings as our primary outcome measure. In particular, we consider both log of hourly wage and log of annual salary.[16] The richness of the GMAT Registrant Surveys also allows us to include several non-pecuniary outcomes in our analysis, focusing on self-reported satisfaction with present job, present pay, opportunities for promotion, and job in general. Wave 4 of the survey contains three of the five Job Descriptive Index (JDI) surveys (excluded are the Supervision and the Coworkers surveys) and the related Job in General survey, used primarily in the field of industrial organizational psychology.[17] Each survey asks respondents to indicate whether particular words or phrases describe their current employment situation. If a “yes” response was indicated and the job attribute was positive, 3 points were given. If “can't decide” was indicated, 1 point was given. If the job attribute was negative and “no” was indicated, zero points were given. The resulting total points for each section of these surveys (as well as an overall total) comprise our outcome measures associated with job satisfaction.

Aside from reported hourly wage and annual salary, we created three additional outcome measures using information in the surveys.[18] The first deals with meeting managerial expectations. In the initial survey wave, respondents were asked about their expectations regarding their managerial status 5 years in the future (i.e., being either a non-manager, an entry-level manager, or a mid- to upper-level manager). In subsequent waves, respondents were asked to indicate their actual managerial status using the same distinctions. We created a variable equal to one if the individual met or exceeded their expectation, and equal to zero if their actual managerial responsibility was lower than their expectation. The second variable deals with one's self-perception of the value of their MBA experience. In Waves 3 and 4, respondents were asked to indicate the extent to which various statements, each related to their MBA experience, were true or false.[19] Each response could vary from −3 to 3, where 3 is most true. We created an index of self-perceived value of the MBA by adding the response values of positive (beneficial) statements and subtracting the response values of negative statements. Finally, the third variable is an index associated with one's self-perceived managerial skills gained through the MBA. In both waves 3 and 4, respondents were asked to indicate (from 1 to 4) the extent to which several attributes or skills (presumed to be relevant

[15] While the distribution of programs attended was broad in terms of quality, the distribution was somewhat skewed, likely in part due to generally larger MBA programs at higher ranked schools. Using our overall quality measure (described in Section 3), 32% of our non-missing survey responses were from individuals who attended programs below the median in quality, while 68% were from individuals who attended programs above the median quality.

[16] Earnings (including monetary bonuses but not one-time starting bonuses) were reported in the surveys in a number of possible ways (hourly, weekly, bi-weekly, monthly, or yearly). For those not reporting an hourly wage, we used individual reports of how many hours they work in a typical week to calculate a measure of hourly wage, assuming 50 weeks worked per year. A similar calculation was done for annual salary, also assuming 50 weeks worked per year, when earnings were not reported in annual terms. The vast majority of respondents (89%) reported earnings in annual terms, with relatively little variation by quality of MBA program attended.

[17] See Smith, et al. (1987) and the Job Descriptive Index (JDI) website: http://showcase.bgsu.edu/IOPsych/jdi/index.html.

[18] Another possible outcome variable, used in an MBA study by Colbert et al. (2000), is recruiter satisfaction.

[19] For example, such statements include: “My graduate management education has: … Provided me with the right connections to get a good job; … Given me a sense of satisfaction and achievement; … Provided knowledge that will allow me to apply my job skills more effectively; … Been worth my time and investment.”

for effective managerial leadership) were enhanced by their MBA education. We used the sum of their responses to create an “Enhanced Managerial Skills” variable.[20]

2.3. Individual control variables

We include several individual-level variables as controls, in order to account for characteristics that may be related to the quality of MBA program attended and independently related to one's earnings (or other outcome). Descriptive statistics of these variables are displayed in Table 1. Since the survey data was linked to test registration files, we include actual quantitative and verbal GMAT scores. We also include self-reported undergraduate GPA. In an attempt to better control for factors not captured by test scores or grades, we include a self-assessed measure of individual ability or acquired human capital. This “noncognitive attributes index” aggregates the survey responses to various self-assessment questions, as done in Montgomery and Powell (2003).[21] On a four-point scale from 1 to 4, respondents were asked (in Wave I) to evaluate the extent to which they possess sixteen skills or attributes of presumed importance in the business world: oral communication, written communication, ability to delegate tasks, ability to work as a team, etc. The sum of these responses was included in our analysis. Other covariates include: quadratic terms in both age and tenure in the current job; indicator variables for full-time work experience at the time of Wave I of less than one year, between 1 and 3 years, and between 3 and 5 years; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment at the time of Wave 1; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; indicators for selectivity of undergraduate institution attended[22]; indicator variables representing whether or not the individual attended a part-time or executive MBA program[23]; and a variable indicating attainment of another advanced (post-bachelor's) degree.

2.4. Quality variables

We consider several variables which may reasonably serve as proxies for the underlying quality associated with students' MBA experiences. We classify these into three groups: factors representing the quality of the student body attending the MBA program,[24] factors representing the quality of business school faculty,[25] and factors primarily representing characteristics of the schools or MBA programs themselves.[26] Descriptive statistics of these variables are presented in Table 2. These variables were obtained primarily from *Barron's Guide to Graduate Business Schools* (Miller, 1994). The AAUP faculty ratings variable is based on a 1993 salary report by the American Association of University Professors (AAUP). We coded this variable as zero for below average, 1 for average, and 2 for above average, corresponding to the school's range of average salary of for the three ranks of professors by institutional category. The publication count variable represents the total number of papers published by affiliated faculty between 1990

Table 1
Descriptive statistics of individual control variables & outcomes.

Variable	Mean	Std. dev.	25th percentile	Median	75th percentile
Covariates:					
Asian	0.134	0.340			
Black	0.109	0.312			
Hispanic	0.163	0.369			
Female	0.384	0.486			
Experience < 1 year	0.235	0.424			
Experience 1–3 years	0.235	0.424			
Experience 3–5 years	0.176	0.381			
Agriculture, forestries & fisheries	0.144	0.352			
Manufacturing	0.187	0.390			
Service industries	0.180	0.384			
Finance, insurance & real estate	0.120	0.325			
Public administration	0.095	0.293			
Entry-level manager	0.176	0.381			
Mid- to upper-level manager	0.141	0.348			
Highly selective undergrad	0.223	0.416			
Moderately selective undergrad	0.282	0.450			
Other advanced degree	0.084	0.278			
Attend part-time MBA	0.430	0.495			
Attend executive MBA program	0.072	0.259			
Age	33.1	6.18	29.00	31.5	35.75
Tenure (yrs.)	3.42	3.94	0.75	1.92	4.58
Verbal GMAT	30.36	7.41	25.00	31.00	36.00
Quantitative GMAT	30.98	8.07	25.00	31.00	36.00
Undergraduate GPA	3.074	0.407	2.750	3.060	3.380
Self-reported skills	51.72	5.13	48.00	52.00	55.00
Wage ($/hr.), Wave 1	14.99	6.55	10.64	13.91	17.67
Outcome variables:					
Hourly wage ($)	24.19	15.24	16.00	21.50	28.00
Annual salary	59,580	42,526	38,000	51,000	70,000
Overall JDI	115.96	27.11	102.00	122.00	136.00
Work JDI	39.02	10.20	34.00	42.00	46.00
Pay JDI	19.61	6.68	15.00	21.00	25.00
Promotion JDI	16.62	8.77	9.00	18.00	25.00
Enhanced skills	44.87	2.82	43.00	45.00	47.00
Self-evaluation of MBA	15.60	10.03	11.00	17.00	23.00
Managerial goal met	0.321	0.467			

Notes: Statistics involving covariates correspond to Waves III and IV survey responses of the GMAT Registrant Survey for which data on all covariates (other than Wage in Wave 1) and the Hourly Wage outcome were non-missing (N = 1855). Outcome statistics based on the same sample, but restricted to non-missing values of the particular outcome variable, reducing the samples by varying amounts (to a minimum of 1538 in the case of Overall JDI). Experience, industry and management variables refer to Wave 1 (pre-MBA) survey responses.

Table 2
Descriptive statistics of quality variables.

	Mean	Std. dev.	25th percentile	Median	75th percentile	N
Avg. GMAT	548	51.0	512	550	581	1663
Avg. GPA	3.17	0.18	3.1	3.1	3.2	1663
% with work exp.	81.6	16.6	75	87	95	1299
% non-biz. majors	57.0	14.8	75	87	95	1291
% international	16.0	9.9	9	15	22	1367
Publication count	48.5	78.0	0	7	63	1663
% faculty with Ph.D.	89.2	16.2	85	95	100	1510
% faculty full-time	72.2	22.5	59.9	77.8	90.2	1212
AAUP faculty ratings	1.35	0.83	1	2	2	1467
Number of programs	5.35	3.20	3	6	8	1663
Rejection rate	45.0	21.4	27.3	47.3	62.3	1322
Avg. class size	28.9	12.0	21.0	28.0	35.0	1663
AACSB accredited	0.706	0.456				1648

Notes: Sample sizes reflect corresponding post-MBA (Waves III and IV) responses to GMAT Registrant Survey with non-missing values for earnings and all covariates, as well as non-missing values for the relevant quality variable.

[20] We included only those skills/attributes that were commonly asked about in both waves 3 and 4. These included: Ability to motivate others, Ability to adapt theory to practical situations, Ability to work with individuals from diverse backgrounds, Ability to delegate tasks, Ability to organize, Team building skills, and Understanding business in other cultures.

[21] Perhaps more accurate than attributing response values to actual skill levels, Montgomery and Powell (2003) refer to the variable as a “confidence index”.

[22] The more numerous admissions selectivity categories designated in Barron's *Profiles of American Colleges* were collapsed into the following three categories: selective undergrad, middle undergrad, and the omitted category, representing the least selective schools and those not included in the Barron's guide.

[23] Gicheva (2012) shows that labor market dynamics, as well as the likelihood of employer sponsorship of their education, differ significantly between those who attend part-time programs versus full-time programs.

[24] These include average GMAT score, average undergraduate GPA, percent with at least 1 year of work experience prior to business school, percent who had an undergraduate major in something other than business, and percent international students.

[25] These include a variable representing the extent of faculty publications, the percentage of faculty with a Ph.D., the percent of faculty who are full-time, and AAUP ratings of faculty salaries.

[26] These include the percentage of applicants who are rejected, the average class size, an indicator variable for AACSB accreditation, and the number of specialized subject areas that are reportedly available to students.

Table 3
Correlations of quality variables.

	Student characteristics					Faculty characteristics				Program characteristics			
	Avg. GMAT	Avg. GPA	% with work experience	% Non-biz. majors	% interntnl.	Pub. count	% faculty with Ph.D.	% faculty full-time	AAUP faculty ratings	Number of programs	AACSB accredit.	Rejection rate	Avg. class size
Student characteristics													
Avg. GMAT	1.000												
Avg. GPA	0.398	1.000											
% with work experience	0.329	−0.004	1.000										
% non-biz. majors	0.688	0.298	0.531	1.000									
% international	0.115	0.152	−0.163	0.127	1.000								
Faculty characteristics													
Publication count	0.747	0.330	0.319	0.564	0.041	1.000							
% faculty with Ph.D.	0.297	0.088	−0.007	0.061	−0.100	0.105	1.000						
% faculty full-time	0.250	0.278	0.005	0.097	0.022	0.242	0.411	1.000					
AAUP faculty ratings	0.417	0.188	0.360	0.457	0.172	0.356	0.232	0.093	1.000				
Program characteristics													
Number of programs	0.478	0.204	0.238	0.370	0.181	0.497	0.166	0.028	0.356	1.000			
AACSB accredited	0.513	0.191	−0.041	0.238	−0.012	0.356	0.565	0.358	0.130	0.240	1.000		
Rejection rate	0.797	0.357	0.220	0.512	0.078	0.655	0.223	0.247	0.174	0.348	0.382	1.000	
Avg. class size	0.632	0.365	0.208	0.483	−0.030	0.593	0.253	0.263	0.312	0.296	0.419	0.600	1.000

Notes: Correlations based on sample of schools attended by individuals represented in the GMAT Registrant Survey for which information was available for all of the quality proxy variables (N=575).

and 1998 in 24 leading business journals (a measure made available by the School of Management at the University of Texas at Dallas).[27]

We interpret these measures as proxy variables for underlying (and unobservable) MBA quality. The correlations of these variables are shown in Table 3. To the extent that these variables represent underlying overall quality (or particular dimensions of quality), they do so with substantial measurement error, given that their correlations are often considerably less than one.

3. Empirical methodology

Our identification strategy employs three approaches: controlling for selection with lots of observables, instrumental variables, and fixed effects. The selection-on-observables approach requires exceptionally detailed individual information over time as contained in the longitudinal survey we use, conducted in four waves consisting of some pre-treatment and some post-treatment data. In alignment with much of the selection-on-observables literature on college quality, we initially consider the following model of wage determination:

$$\ln\left(w_{ij}\right) = X_i\beta + \gamma Q_j^{\ *} + e_{ij}, \tag{1}$$

where $\ln(w_{ij})$ is the log of current post-MBA earnings (either hourly wage rate or annual earnings) of the *i*th person who attended MBA program *j*, X_i includes a multitude of individual covariates, Q_j^* is an underlying quality variable associated with MBA program *j*, and e_{ij} is an error term. γ is the parameter of interest. However, since Q_j^* is not directly observable, we use individual variables or sets of variables which serve to proxy for a school's quality:

$$q_{kj} = \alpha_k Q_j^{\ *} + u_{kj}, \tag{2}$$

where α_k is an unknown scale coefficient for the *k*th proxy, which allows the covariances of the proxies to differ, and u_{kj} is the measurement error associated with a proxy. This specification follows the generalization of the classical measurement error model presented in Black and Smith (2006).

Several problems present themselves when attempting to estimate an empirical model corresponding to Eqs. (1) and (2). First, our available proxy variables measure latent quality with error, which, as noted, may be substantial in some cases. As is well known, measurement error in the classical sense will lead to attenuated coefficient estimates when OLS is used.[28] Thus, beyond OLS we use two methods to deal with this problem, both used by Black and Smith (2006) in the context of undergraduate quality. First, we use Two-Stage Least Squares (2SLS), allowing other quality proxies to instrument for a particular quality proxy. This is the traditional approach to dealing with classical measurement error.[29] Second, we combine our numerous measures of MBA quality to obtain a measure of Q^* that should be less subject to error. This is done using factor analysis.[30] We construct an index of overall MBA quality by taking a linear combination of all the noisy proxies, where the weight on each variable (the "factor loadings") are chosen by minimizing the expected squared difference between underlying quality and the index. Although not the emphasis of our study, an advantage of using factor analysis to create a quality index is that it allows for easy ranking of MBA programs on the basis of overall quality. Another advantage is that the method allows us to group variables together in ways that correspond to different dimensions of MBA quality. That is, in addition to an overall index, using factor analysis on subgroups of variables, we create three distinct indices: student quality, faculty quality, and program/institutional quality. Thus, we consider the generalized model of post-MBA wage determination:

$$\ln\left(w_{ij}\right) = X_i\beta + \gamma_s Q^{s}{}_j^{\ *} + \gamma_f Q^{f}{}_j^{\ *} + \gamma_p Q^{p}{}_j^{\ *} + e_{ij}, \tag{3}$$

where Q^{s*}, Q^{f*} and Q^{p*} represent potentially distinct dimensions of underlying MBA quality, corresponding to the student body, the faculty, and the program or institution, respectively.

A second problem with estimating an empirical model corresponding to Eqs. (1) and (2) (or Eq. (3)) relates to the scale parameters, α_k, which are not identified. Unless $\alpha_k = 1$, OLS will result in biased estimates of gamma. Since latent quality Q^* lacks a natural scale, a more relevant problem is that the effects of different quality proxies become incomparable when the α_k are not identical. In order to generally compare the magnitudes of our estimates of the impact of quality using different proxies or indices, we normalize each variable or index to have a mean of zero and standard deviation of one.[31] In this case, the magnitudes of our estimates for continuous variables or indices reflect

[27] See http://som/utdallas.edu/top100Ranking/.

[28] This may especially be the case due to our inclusion of a relatively rich set of covariates in X_i. As discussed by Black and Smith (2006), the inclusion of more control variables leads to an increase in the noise-to-signal ratio, which increases the attenuation bias.

[29] See Griliches (1986).

[30] See Spearman (1904) for the original use of factor analysis in the field of psychology.

[31] In the case of AACSB accreditation, a dummy variable, we do no such normalization.

Table 4
OLS estimates of quality impacts on log(wage).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Avg. GMAT	−0.019	0.090**												
	(0.046)	(0.014)												
Avg. GPA	0.021		0.012											
	(0.030)		(0.011)											
% with work experience	0.008			0.054**										
	(0.023)			(0.013)										
% non-biz. majors	0.080**				0.072**									
	(0.030)				(0.013)									
% international	0.012					0.017								
	(0.016)					(0.011)								
AAUP faculty ratings	0.048**						0.087**							
	(0.023)						(0.015)							
Publication count	−0.024							0.080**						
	(0.027)							(0.013)						
% faculty with Ph.D.	−0.012								0.009					
	(0.023)								(0.012)					
% faculty full-time	−0.021									0.010				
	(0.027)									(0.015)				
Rejection rate	0.012										0.060**			
	(0.033)										(0.014)			
Number of programs	0.012											0.055**		
	(0.021)											(0.012)		
Avg. class size	0.035												0.063**	
	(0.025)												(0.012)	
AACSB accredited	0.095													0.072**
	(0.061)													(0.028)
R^2	0.421	0.335	0.334	0.362	0.376	0.346	0.369	0.353	0.335	0.316	0.337	0.345	0.348	0.338
N	575	1663	1663	1299	1291	1367	1467	1667	1510	1216	1322	1663	1663	1648

Notes: Samples cover post-MBA observations of GMAT Registrant Survey respondents. Except for Private and AACSB accredited, each quality measure was normalized to have unit variance. Each regression also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended; and a variable indicating attainment of another advanced degree. Standard errors clustered at the individual level. ** Indicates coefficient is statistically significant at the 5% level.

Table 5
OLS estimates of quality impacts on log(salary).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Avg. GMAT	0.015	0.122**												
	(0.052)	(0.016)												
Avg. GPA	0.034		0.031**											
	(0.031)		(0.012)											
% with work experience	0.017			0.062**										
	(0.027)			(0.014)										
% non-biz. majors	0.043				0.093**									
	(0.037)				(0.015)									
% International	0.027					0.030**								
	(0.018)					(0.014)								
AAUP faculty ratings	0.053*						0.106**							
	(0.028)						(0.017)							
Publication count	0.020							0.129**						
	(0.031)							(0.016)						
% faculty with Ph.D.	−0.023								0.019					
	(0.028)								(0.015)					
% faculty full-time	−0.046									0.013				
	(0.031)									(0.016)				
Rejection rate	0.004										.080**			
	(0.037)										(0.016)			
Number of programs	0.01											0.069**		
	(0.025)											(0.012)		
Avg. class size	0.069**												0.017**	
	(0.028)												(0.007)	
AACSB accredited	0.057													0.090**
	(0.067)													(0.031)
R^2	0.474	0.378	0.349	0.369	0.390	0.364	0.393	0.386	0.353	0.344	0.364	0.360	0.369	0.351
N	567	1638	1638	1279	1274	1345	1453	1638	1489	1195	1300	1638	1652	1623

Notes: Samples cover post-MBA observations of GMAT Registrant Survey respondents. Except for Private and AACSB accredited, each quality measure was normalized to have unit variance. Each regression also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended; and a variable indicating attainment of another advanced degree. Standard errors clustered at the individual level. ** Indicates coefficient is statistically significant at the 5% level.

Table 6
IV (2SLS) estimates of quality impacts on wage and salary.

	Log (wage)				Log (salary)			
	IV = all other variables		IV = all variables in category		IV = all other variables		IV = all variables in category	
	Coeff.	Std. err./N	Coeff.	Std. err./N	Coeff.	Std. err./N	Coeff.	Std. err./N
Avg. GMAT	0.122**	(0.030)	0.171**	(0.030)	0.172**	(0.033)	0.221**	(0.033)
		575		1137		567		1121
Avg. GPA	0.148**	(0.054)	0.100*	(0.053)	0.225**	(0.065)	0.156**	(0.063)
		575		1137		567		1121
% with work experience	0.089**	(0.031)	0.128**	(0.033)	0.099**	(0.036)	0.151**	(0.037)
		575		1137		567		1121
% non-biz. majors	0.157**	(0.036)	0.164**	(0.025)	0.227**	(0.041)	0.211**	(0.029)
		575		1137		567		1121
% International	0.042	(0.043)	0.029	(0.051)	0.029	(0.050)	0.078	(0.056)
		575		1137		567		1121
AAUP faculty ratings	0.143**	(0.033)	0.209**	(0.068)	0.190**	(0.039)	0.383**	(0.089)
		575		1012		567		998
Publication count	0.102**	(0.029)	0.235**	(0.074)	0.160**	(0.031)	0.337**	(0.084)
		575		1012		567		998
% Faculty with Ph.D.	0.043	(0.027)	0.033	(0.032)	0.031	(0.030)	0.049	(0.036)
		575		1012		567		998
% Faculty fulltime	0.082**	(0.042)	0.061*	(0.034)	0.107**	(0.053)	0.096**	(0.042)
		575		1012		567		998
Rejection rate	0.073**	(0.031)	0.149**	(0.034)	0.141**	(0.037)	0.199**	(0.039)
		575		1307		567		1285
Number of programs	0.142**	(0.044)	0.232**	(0.056)	0.233**	(0.053)	0.319**	(0.070)
		575		1307		567		1285
Avg. class size	0.128**	(0.034)	0.139**	(0.031)	0.187**	(0.039)	0.179**	(0.036)
		575		1307		567		1285
AACSB accredited	0.102*	(0.061)	0.417**	(0.080)	0.141**	(0.072)	0.557**	(0.099)
		575		1307		567		1285

Notes: Each reported coefficient corresponds to a separate IV regression. Samples cover post-MBA observations of GMAT Registrant Survey respondents. Except for Private and AACSB accredited, each quality measure was normalized to have unit variance. Each regression (first and second stage) also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended; and a variable indicating attainment of another advanced degree. Standard errors clustered at the individual level. ** indicates coefficient is statistically significant at the 5% level.

Table 7
Estimates of quality index impacts on post-MBA earnings.

	Log (wage)					Log (salary)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: With individual controls										
Overall quality	0.101**					0.148**				
	(0.023)					(0.026)				
School quality		0.079**			0.023		0.112**			0.065**
		(0.014)			(0.027)		(0.017)			(0.033)
Student quality			0.110**		0.103**			0.135**		0.134**
			(0.015)		(0.027)			(0.021)		(0.033)
Faculty quality				0.051**	0.000				0.071**	−0.023
				(0.017)	(0.023)				(0.023)	(0.032)
R^2	0.401	0.347	0.398	0.344	0.408	0.455	0.375	0.416	0.389	0.459
N	575	1307	1137	1012	575	569	1291	1127	1005	569
Panel B: No individual controls										
Overall quality	0.108**					0.158**				
	(0.020)					(0.023)				
School quality		0.078**			0.002		0.115**			0.037
		(0.013)			(0.029)		(0.015)			(0.037)
Student quality			0.127**		0.122**			0.163**		0.152**
			(0.014)		(0.026)			(0.018)		(0.031)
Faculty quality				0.070**	0.002				0.101**	−0.011
				(0.016)	(0.028)				(0.021)	(0.035)
R^2	0.190	0.177	0.225	0.161	0.202	0.239	0.208	0.264	0.192	0.245
N	588	1348	1174	1047	588	582	1331	1164	1039	582

Notes: Samples cover post-MBA observations of GMAT Registrant Survey respondents. Each regression in Panel A also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended; and a variable indicating attainment of another advanced degree. Each regression in Panel B also included time and time squared. Overall, School, Student and Faculty quality indices created using factor analysis. Indexes were normalized to have unit variance and zero mean. Standard errors clustered at the individual level. ** and * Indicate coefficient is statistically significant at the 5 or 10% level, respectively.

Table 8
Estimates of quality index impacts on non-pecuniary outcomes.

	Overall JDI	Work JDI	Pay JDI	Promotion JDI	General JDI	Managerial goal met	Self-evaluation of MBA	Enhanced skills
School quality	6.64**	1.25	1.44**	1.95**	1.68*	0.102	1.15*	−0.113
	(3.06)	(1.06)	(0.688)	(0.883)	(1.007)	(0.114)	(0.731)	(0.252)
Student quality	−0.65	0.082	−0.322	0.411	−1.24	−0.03	1.01	−0.050
	(2.88)	(0.935)	(0.681)	(0.842)	(0.977)	(0.111)	(0.691)	(0.223)
Faculty quality	−2.08	−0.562	−0.43	−1.01	−0.348	−0.045	−0.39	0.174
	(2.04)	(0.819)	(0.527)	(0.640)	(0.657)	(0.098)	(0.665)	(0.229)
N	320	337	338	339	338	562	572	572

Notes: Samples cover post-MBA observations of GMAT Registrant Survey respondents (only Wave IV for JDI measures and Waves III and IV for the others). Each regression also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave I survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended; and a variable indicating attainment of another advanced degree. School, Student and Faculty quality indices created using factor analysis. Indexes were normalized to have unit variance and zero mean. Standard errors clustered at the individual level. ** and * indicate coefficient is statistically significant at the 5 or 10% level, respectively.

the average effect of increasing that quality dimension by one standard deviation.

A final issue of importance when estimating such models relates to the endogeneity of quality. Individuals do not randomly select into MBA programs of varying quality. Rather, certain types of individuals will be drawn to certain types of programs. Similarly, admissions committees are likely to consider personal attributes that are related to the wage one can command in the labor market when they make their admissions decisions. In the methods described previously, we attempt to ameliorate this problem by including a rich set of control variables in the regressions. Nonetheless, an omitted variable that is positively related to both earnings and MBA quality will lead to an upward biased estimate of the returns to quality. To address this possibility, we exploit the fact that, unlike the case of undergraduates, a large percentage of MBAs obtain work experience prior to enrolling in MBA programs. The presence of pre-MBA earnings for the majority of our sample allows us to include individual fixed effects in earnings regressions, which eliminates the effects of time-invariant, unobserved heterogeneity.

4. Results

4.1. OLS and 2SLS: earnings results

OLS regression estimates of the impact of each quality proxy are shown in Table 4 with log wage as the dependent variable and Table 5 with log salary as the dependent variables. Due to space constraints, we only show coefficients for the quality variables but not for the extensive set of control variables which are listed at the bottom of each table.[32] Some of the variation in researchers' estimated returns to undergraduate educational quality merely reflects the different proxies used, as shown by Zhang (2005).[33] We find similar results in the case of individual MBA quality proxies. On their own, most variables are significant at the 5% level, and most coefficients have magnitudes in the range of .03 to .13 (columns 2–14 of Tables 4 and 5), so that a standard deviation increase in most quality variables is associated with higher post-MBA wages of between 3 and 13% (since the quality variables are normalized to have unit variance and the dependent variable is the logarithm of wage or salary). When included collectively in a single regression (column 1 of Tables 4 and 5), the vast majority of the coefficients on the quality variables are not significantly different from zero, which is perhaps not surprising due to the often substantial correlations among the variables and the small sample size due to the fact that many respondents did not provide information about those variables. Nonetheless, both the percentage of non-business majors and faculty salary variables are positive and significant. Furthermore, the coefficients on the quality proxies are jointly significant ($F = 3.18$ for column 1 of Table 4 and $F = 5.00$ for column 1 of Table 5).

Because each proxy variable measures underlying quality with error, we now turn to the use of instrumental variable techniques. Table 6 shows the results from 2SLS estimation. For both wage and salary, we try two sets of instruments for each particular variable. First, all the other quality proxies are included as instruments. Second, only those other variables in the same quality category (i.e., students, faculty, or school) were used as instruments. The magnitudes of the coefficients of interest are often substantially higher than they were when OLS was used, suggesting that substantial measurement error plagues individual proxy variables. In this case, most coefficient estimates range from .10 to .20 and higher. Overall, quality seems to be a very important driver of post-MBA earnings, even after controlling for the large number of factors relating to individual ability, prior employment and accumulated human capital.

We now consider separate dimensions of MBA quality by combining several quality indicators into indices through the use of factor analysis.[34] We created an overall quality index and indices reflecting school, student, and faculty quality.[35] Table 7 panel A includes the results of including these indices in earnings regressions. A standard deviation increase in overall quality is associated with about 10% higher wages and 15% higher salaries of graduates. These numbers are somewhat higher than those for the typical single quality variable using OLS, suggesting that the combination of information on quality using factor analysis has helped to decrease the attenuation of estimates due to measurement error. When included individually, each quality index was statistically significant, with the faculty index about half the magnitude of the student and school indices (columns 2–4). When all three indices are included together in the regression, though, only student quality

[32] Throughout each of our specifications, estimated coefficients on the omitted variables are generally as predicted. In particular, age positively affects earnings at a decreasing rate, work experience and tenure are generally positively related to earnings, women earn significantly less than men (about 10%). As has been shown in prior research (e.g., Arcidiacono et al., 2008), quantitative test scores (but not verbal scores) positively relate to earnings. Undergraduate quality and GPA, managerial status, and the non-cognitive attributes index also positively and significantly relate to earnings.

[33] Zhang (2005) uses a common data set (the Baccalaureate and Beyond study, B&B: 93/97) for his estimates of the return to college quality but does so with the different measures of quality used by scholars, namely Barron's selectivity categories, mean SAT scores of the entering freshmen class, tuition and fees, and Carnegie Classifications. He finds that using SAT scores tends to result in lower returns to quality than does the use of Barron's ratings categories.

[34] For each index, the data only supported the use of a single factor. Including indices in the regression models based on two factors did not change our results substantively.

[35] The correlations between the school, student and faculty indices were each around 0.6. The resulting quality indices were consistent with a priori beliefs regarding program quality. Rankings based on the obtained index values are shown in Appendix Table 1, and comparison rankings by *U.S. News* and *Business Week* are shown included in Appendix Table 2. Note, however, that due to missing values of some quality variables, several schools which may have otherwise entered this list are not present (for example, Harvard University in the case of study body characteristics). Furthermore, it should be emphasized that classification of quality along these dimensions is inherently arbitrary, as some specific variables are likely to affect multiple quality dimensions, either directly or indirectly.

Table 9
Log(wage) panel estimates of returns to MBA and quality indices.

	OLS					Fixed effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overall quality	0.090**					0.092**				
	(0.019)					(0.018)				
School quality		0.078**			0.013		0.068**			0.046
		(0.013)			(0.027)		(0.011)			(0.030)
Student quality			0.099**		0.090**			0.062**		0.060**
			(0.014)		(0.027)			(0.013)		(0.030)
Faculty quality				0.073**	0.002				0.072**	0.000
				(0.016)	(0.027)				(0.013)	(0.028)
MBA	0.107**	0.058**	0.077**	0.036	0.081**	0.080**	0.057**	0.056**	0.027	0.048
	(0.037)	(0.023)	(0.028)	(0.030)	(0.037)	(0.038)	(0.023)	(0.026)	(0.027)	(0.038)
R^2	0.532	0.494	0.511	0.485	0.534	0.575	0.575	0.580	0.565	0.575
N	1259	2902	2539	2277	1259	1273	2955	2590	2326	1273

Notes: Each specification (column) included earnings observations from MBA sample for each wave (1–4), when available. Overall, School, Student and Faculty quality indices created using factor analysis. Coefficient on each index corresponds to index interacted with MBA. Indexes were normalized to have unit variance and zero mean, so that MBA coefficient represents return of "average" quality program, and coefficient on index represents effect of a standard deviation increase in quality. Each regression also included quadratics in time and tenure, and an indicator variable for possession of another advanced degree. Specifications (1)–(5) also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended. Specifications (6)–(10) include individual fixed effects. ** and * indicate coefficient is statistically significantly different from zero at the 5 and 10% levels, respectively.

was significant with log(wage) as the dependent variable and both student and school quality in the salary regressions (column 5) with the student effect twice as large as the school effect. These results run counter to those of a number of studies at the undergraduate level, which have identified teacher quality as a key to student learning (Murnane, 1975; Betts, 1995; Grogger, 1996; and Hanuschek, Kain and Rivkin, 1998; Lindahl and Regner, 2005).

In panel B of Table 7, to investigate the effect of individual control variables on the quality estimates, we ran similar regressions to panel A but which only included the quality indices and a time trend. Larger quality estimates for individual indices and the overall index suggests that, as expected, individuals positively select into programs of higher quality. However, while the effect of student quality on earnings decreases from 0.152 to 0.134 and of wages from 0.122 to 0.103 when individual controls are included (column 10 and 5 panel A versus panel B of Table 7, respectively), the effect of school characteristics becomes more pronounced and statistically significant for salary with the addition of individual controls. This trend continues when we further control for selection into programs using individual fixed effects (discussed below in Section 4.3).

4.2. OLS and 2SLS: non-pecuniary results

Individuals consider more than just prospective earnings when choosing between MBA programs. Similarly, the goals of school administrators undoubtedly extend beyond increasing the earnings potential of their graduates. We now turn to consideration of several nonmonetary outcomes, made possible by the richness of the GMAT Registrant Survey data.

The first five columns of Table 8 show estimates of school, faculty and student quality impacts on the four Job Description Indices, i.e., Work, Pay, Promotion and General, and their combination in the Overall JDI. The arbitrary scale of the responses don't allow for any meaningful interpretation of the magnitude of the coefficients. However, in the case of the Work JDI and Pay JDI, as well as the overall index, the coefficient on school quality is positive and significant. The point estimates of the effect of school quality on both the Work and General Satisfaction indices are also positive, though not quite significant at conventional levels. Unlike the results for wage and salary, student quality variables are not significant.

School quality is also positively related to the index encapsulating one's self-evaluation of their MBA experience. No dimension of quality significantly impacted the likelihood of meeting one's initial expectations of future managerial status. Similarly, none of the quality indices positively impacted one's reported skill gains through business school.

4.3. Fixed effects results

We have, until this point, mimicked the literature on college quality by including only post-graduation observations in our analysis. A richer analysis is made possible by the panel nature of our dataset, and the fact that some observations occur prior to MBA attainment. We first extend our OLS estimation presented in Table 7 to the full panel data context, including the same rich set of control variables, as well as an indicator variable for MBA, equaling zero prior to MBA completion and one following MBA completion. Each quality index was included in the regression by interacting it with the MBA variable. We then relax the assumption of selection into MBA programs of varying quality purely on the basis of observables, and consider the role of unobserved heterogeneity in influencing our previous results. We thus repeat our earnings regressions, but now include individual effects.[36] Under certain assumptions, fixed effects estimation will result in consistent estimates of the average effect of attending an MBA program of a given quality, for those who chose to attend that program.[37] One possibility that would undermine the fixed effects identification strategy would be a differential in experience-earnings profiles prior to MBA enrollment on the basis of program quality. That is, higher quality programs may admit people already on higher earnings trajectories. We investigated this possibility in our sample, using individuals with multiple (up to three) earnings observations prior to MBA attainment. No significant differences in earnings trajectories were observed between individuals who went on to earn MBAs from programs above versus below the median in our overall quality index. Furthermore, the coefficient on an interaction between eventual overall program quality and prior earnings trajectory was found to be insignificant.

Columns (1) through (5) of Table 9 show the effect of our quality indexes on wage, as estimated by OLS. Consistent with our earlier results, quality is shown to be extremely important in generating higher earnings following the MBA. In particular, while the average quality

[36] Note that, because the non-pecuniary variables we consider are not present in more than one survey wave (i.e., both before and after MBA completion), we are not able to include fixed effects in those regressions.

[37] That is, in the terminology of the treatment effects literature, we attempt to estimate the average treatment effect on the treated. See Arcidiacono et al. (2008) for a detailed discussion of the required assumptions underlying the fixed effects model in a similar context.

Table 10
Log(salary) panel estimates of returns to MBA and quality indices.

	OLS					Fixed effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overall quality	0.132**					0.097**				
	(0.022)					(0.024)				
School quality		0.114**			0.041		0.098**			0.072*
		(0.015)			(0.030)		(0.015)			(0.041)
Student quality			0.128**		0.118**			0.062**		0.050
			(0.018)		(0.033)			(0.017)		(0.041)
Faculty quality				0.095**	−0.005				0.074**	−0.008
				(0.021)	(0.036)				(0.018)	(0.038)
MBA	0.115**	0.082**	0.092**	0.057	0.074*	0.061	0.039	0.044	0.022	0.024
	(0.046)	(0.029)	(0.033)	(0.037)	(0.045)	(0.050)	(0.030)	(0.035)	(0.037)	(0.051)
R^2	0.503	0.461	0.450	0.431	0.505	0.536	0.527	0.507	0.492	0.536
N	1228	2811	2470	2222	1228	1243	2865	2521	2272	1243

Notes: Each specification (column) included earnings observations from MBA sample for each wave (1–4), when available. Overall, School, Student and Faculty quality indices created using factor analysis. Coefficient on each index corresponds to index interacted with MBA. Indexes were normalized to have unit variance and zero mean, so that MBA coefficient represents return of "average" quality program, and coefficient on index represents effect of a standard deviation increase in quality. Each regression also included quadratics in time and tenure, and an indicator variable for possession of another advanced degree. Specifications (1)–(5) also included: quadratics in time, age and tenure; indicator variables for less than 1 year of accumulated full-time work experience at the time of Wave 1 survey, between 1 and 3 years of experience, and between 3 and 5 years of experience; indicator variables for Asian, black, Hispanic and female; indicator variables for five major categories of industry of employment; indicator variables for entry-level manager and upper-level manager at the time of Wave 1; quantitative GMAT score, verbal GMAT score, skill index; undergraduate GPA and indicators for highly selective and moderately selective undergraduate school attended; indicator variables for part-time and executive MBA program attended. Specifications (6)–(10) include individual fixed effects. ** and * indicate coefficient is statistically significantly different from zero at the 5 and 10% levels, respectively.

MBA generates a return on one's wage of 10.7% (the coefficient on MBA in column 1), attending an MBA program with quality one standard deviation above the mean results in almost doubling that return, increasing it by an additional 9.0 percentage points. We observe the largest effect of student quality, both when included individually and along with the other quality indexes. Generally, the estimated coefficients on the quality indexes diminish somewhat from those in Table 7. These estimates generally diminish even further when we control for selection into programs of various quality with the inclusion of individual fixed effects (columns 6 through 10). The largest difference in the fixed effects versus OLS estimates occurs in the student quality index. While this index remains the sole significant index in column (10), the magnitude drops to 0.060 (from 0.090), suggesting that average student quality is highly correlated with the individual's (observed and unobserved) skills or abilities. When OLS is used, the student quality index may be picking up characteristics of individuals that are positively associated with their earnings. Nonetheless, the effect of the student quality index remains a substantial component of the returns to an MBA degree.

Table 10 displays the panel estimates (OLS and FE) resulting from regressions over annual earnings. The results are comparable to those found for hourly wages. Each quality index is positive and significant when included separately in the regressions, though the estimates decrease somewhat with the fixed effects regressions. The magnitude of the FE coefficient on student quality individually, at 0.062, is less than half of the estimate resulting from OLS. This coefficient actually becomes insignificant when all three indexes are included (in column 10). In the case of the annual earnings FE regressions, our preferred specification, only the school quality index remains marginally significant.

Overall, although student quality measures are generally observed to have the largest effect on the economic returns to an MBA, the school quality index surpasses that of student quality in our preferred specification of fixed effects and annual earnings. The results found in Table 7 and in Tables 9 and 10 emphasize the importance of adequately controlling for individual selection into programs of varying quality when attempting to estimate quality premiums. For example, focusing on the salary effects of the student quality index (which includes average GMAT score, a variable similar to variables typically used in the returns to college quality literature), we began with an OLS estimate of 0.152 when virtually no control variables were included (Table 7, Panel B, column 10). Adding a rich set of control variables lowered this estimate modestly to 0.134 (Table 7, Panel A, column 10), dropped further to 0.118 when the full panel of data (including pre-MBA observations) was used (Table 10, column 5), and dropped substantially further to 0.05 when individual fixed effects were included (Table 10, column 10).

5. Conclusion

Our analysis provides a number of important substantive findings about the effect of educational quality on post-MBA outcomes. A large number of quality proxies are considered both individually and collectively—more than any previous work to our knowledge. We employ both a selection-on-observables approach, as well as the use of individual fixed effects in order to control for selection into programs of varying quality. Instrumental variables techniques, as well as the creation of an overall quality index with the use of factor analysis, were carried out in order to deal with the attenuating effect of measurement error in quality proxies. Departing from the typical view in the literature on college quality of using a single measurement, we create three quality indices corresponding to student, faculty, and institutional characteristics.

We find that quality has a large and significant impact on the earnings of MBA graduates, such that individuals attending the highest quality programs may enjoy a return on earnings several times higher than that received by individuals at lower quality programs. Indeed, the typical graduate from an MBA program below the median in quality is observed to earn a very modest or even zero return to the degree. Student quality measures are generally observed to have the largest impact on the pecuniary return to an MBA. However, the school quality index surpasses that of student quality only when considering our preferred specification, with fixed effects and annual earnings as the outcome variable.

In addition to OLS and 2SLS estimation, we perform a fixed effects analysis, made possible because we use a dataset of individuals with years of prior full-time employment and earnings, an anomaly in the returns to higher education literature. Fixed effects estimation almost universally diminishes the magnitudes of estimates of the quality premiums, except regarding school quality measures emphasizing the importance of adequately controlling for selection into programs of varying quality. Failing to do so is likely to result in upward biased estimates of the effects of program quality, as program quality will likely partially reflect an individual's latent ability.

We also extend the literature by investigating the impact of educational quality on multiple non-pecuniary outcome measures. School quality positively influences post-MBA measures of job satisfaction, as well as individual attitudes towards the value of their MBA experience. These non-monetary effects suggest that focusing on earnings outcomes is likely to underestimate the net benefits of investing in higher education quality, both at the individual and institutional levels.

Particular limitations of our analysis include the fact that the last survey occurred less than four years, on average, after completing the MBA program, when graduate's average age was 35. Differences in lifetime returns to particular quality dimensions may vary substantially over a longer time frame. We measure the three dimensions of educational quality using publically available data, rather than generating our measures. The advantage of our approach is the transparency of the quality data and replicability of our results. The disadvantage is that these data inadequately measure the true underlying quality of the faculty, students and the MBA program. For example, no available data assess faculty effectiveness in terms of multiple aspects of student learning outcomes. Similarly, MBA program reliance on the case study method varies widely, as do the quality and use of the alumni network and recruiting by the career services center. Since the returns to educational quality literature has focused on, and made impressive progress regarding, methodology and identification strategies, better measurement of the quality of professors, the student body, and the MBA program would greatly contribute to our understanding of the payoff to attending schools with differing qualities and price.

Appendix A

Appendix Table 1
Index values and implied school rankings using factor analysis of quality variables.

Rank	Overall quality:		School characteristics:		Student body characteristics:		Faculty characteristics:	
	School	Index	School	Index	School	Index	School	Index
1	University of Michigan	11.92	UC–Berkeley	2.04	Yale University	4.21	University of Michigan	3.59
2	UCLA	10.93	Arizona State	1.91	Dartmouth College	3.82	University of Texas–Austin	3.18
3	University of Texas–Austin	10.40	UCLA	1.90	UCLA	3.79	MIT	3.12
4	Duke University	9.03	Ohio State University	1.86	University of Pennsylvania	3.74	Columbia University	2.73
5	UNC Chapel Hill	8.71	University of Michigan	1.80	Duke University	3.19	New York University	2.56
6	University of Washington	8.60	UNC Chapel Hill	1.80	University of Michigan	3.19	Northwestern University	2.50
7	Dartmouth College	8.40	U. Wisconsin–Madison	1.72	University of Illinois–Chicago	3.11	Harvard University	2.49
8	Carnegie Mullon	8.33	Georgia Tech	1.70	Stanford University	3.02	Ohio State University	2.20
9	University of Southern Calif.	8.25	University of Georgia	1.66	UNC Chapel Hill	2.98	University of Minnesota	2.20
10	UC Berkley	7.75	University of Texas–Arlington	1.65	Columbia University	2.97	Purdue University	2.12
11	Ohio State University	7.60	University of Washington	1.63	University of Washington	2.96	Duke University	2.10
12	Yale University	7.51	Dartmouth College	1.62	University of Chicago	2.96	UCLA	2.10
13	University of Rochester	6.55	Michigan State	1.62	Georgetown University	2.94	Stanford University	2.07
14	University of Minnesota	6.52	Carnegie Mellon	1.58	Carnegie Mellon	2.80	University of Washington	1.94
15	University of Maryland	6.49	University of Maryland	1.57	UC–Davis	2.80	University of Southern Calif.	1.84
16	UC–Irvine	6.32	University of Pennsylvania	1.57	University of Illinois	2.77	Carnegie Mellon	1.82
17	Purdue University	6.18	University of Texas–Austin	1.56	University of Texas–Austin	2.63	UNC Chapel Hill	1.78
18	Indiana University	6.12	University of Arizona	1.56	UC–Irvine	2.61	Cornell University	1.59
19	Washington University	5.86	Emory University	1.56	New York University	2.56	University of Iowa	1.53
20	University of Pittsburgh	5.75	Washington State	1.55	University of Virginia	2.55	University of Colorado–Boulder	1.49
21	Case Western	5.16	Oklahoma State	1.55	University of Southern Calif.	2.50	University of Rochester	1.40
22	Georgia Tech	5.13	Miami University (Ohio)	1.53	Brigham Young University	2.50	U. Wisconsin–Madison	1.39
23	Georgetown University	5.02	Pennsylvania State	1.53	University of Rochester	2.48	UC–Berkeley	1.38
24	UC–Davis	4.92	Washington University	1.51	U. Mass.–Amherst	2.32	University of Maryland	1.35
25	University of Virginia	4.80	University of Illinois	1.49	University of Maryland	2.30	Rutgers University	1.33

Notes: Index values created using factor analysis over the relevant quality proxy variables, using a single factor. Factor loadings were used to create index values, even for MBA programs out of the GMAT Registrant Survey sample. Note that, due to missing values for one or more of the quality proxy variables, many schools that may have made these lists are not present.

Appendix Table 2
Ordinal rankings comparisons.

Rank	Overall quality:			School characteristics:		
	Quality index	USNews	BW	Quality index	USNews	BW
1	University of Michigan	Dartmouth	Yale	UC–Berkeley	MIT	MIT
2	UCLA	Duke	Berkeley	Arizona State	Pennsylvania	Yale
3	University of Texas–Austin	Virginia	UCLA	UCLA	Dartmouth	Berkeley
4	Duke University	Berkeley	Virginia	Ohio State University	Duke	Pennsylvania
5	UNC Chapel Hill	Michigan	Michigan	University of Michigan	Virginia	UCLA
6	University of Washington	UCLA	Dartmouth	UNC Chapel Hill	Berkeley	Virginia
7	Dartmouth College	Carnegie Mellon	Carnegie Mellon	U. Wisconsin–Madison	Michigan	Cornell
8	Carnegie Mellon	Yale	UT–Austin	Georgia Tech	UCLA	Michigan
9	University of Southern Calif.	UNC–Chapel Hill	Rochester	University of Georgia	Carnegie Mellon	Dartmouth
10	UC Berkley	UT–Austin	Indiana	University of Texas–Arlington	Cornell	Carnegie Mellon
11	Ohio State University	Purdue	UNC–Chapel Hill	University of Washington	Yale	UT–Austin
12	Yale University	Indiana	Duke University	Dartmouth College	UNC–Chapel Hill	Rochester
Rank	Student body characteristics:			Faculty characteristics:		
	Quality index	USNews	BW	Quality index	USNews	BW
1	Yale University	Pennsylvania	Chicago	University of Michigan	MIT	Harvard
2	Dartmouth College	Stanford	Stanford	University of Texas–Austin	Stanford	Stanford
3	UCLA	Dartmouth	Yale	MIT	Harvard	MIT

(continued on next page)

Appendix Table 2 (*continued*)

Rank	Student body characteristics:			Faculty characteristics:		
	Quality index	USNews	BW	Quality index	USNews	BW
4	University of Pennsylvania	U. of Chicago	Berkeley	Columbia University	Northwestern	Yale
5	Duke University	Duke	Pennsylvania	New York University	Dartmouth	Northwestern
6	University of Michigan	Virginia	UCLA	Northwestern University	Duke	Berkeley
7	University of Illinois–Chicago	Berkeley	Virginia	Harvard University	Virginia	UCLA
8	Stanford University	Michigan	Michigan	Ohio State University	Berkeley	Virginia
9	UNC Chapel Hill	Columbia	Dartmouth	University of Minnesota	Michigan	Cornell
10	Columbia University	UCLA	Carnegie Mellon	Purdue University	Columbia	Michigan
11	University of Washington	Carnegie Mellon	UT–Austin	Duke University	UCLA	Dartmouth
12	University of Chicago	Yale	Rochester	UCLA	Carnegie Mellon	Carnegie Mellon

Note: Rankings based on quality index values created using factor analysis over the relevant quality proxy variables, using a single factor. U.S. News (USNews) and Business Week (BW) rankings are from 1995, and include only those schools with non-missing values for the constructed quality index. For example, MIT and Harvard were the number one ranked schools by U.S. News and Business Week, respectively, but they are not included in the overall quality rankings here due to missing values of at least one variable comprising the overall quality index.

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