# Does an Advanced Degree Reduce the Gender Wage Gap? Evidence from MBAs

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This article uses a longitudinal survey of registrants for the Graduate Management Admission Test (GMAT) to compare the gender wage gap among MBA recipients with the gap among nonrecipients. We find evidence that the gender wage gap is lower among GMAT takers who obtained the MBA than among those who did not. This suggests that women with advanced degrees may face less discrimination in labor markets.

ECONOMISTS AGREE THAT MANY EMPLOYERS USE a job applicant's observable characteristics such as race, sex, and attainment of a degree as a signal about unobservable traits such as ability and motivation. Signaling theory hypothesizes that independent of any effect on a worker's actual productivity, a degree sends a message to employers that the worker is more productive. Statistical discrimination theory argues that employers also use traits such as race and sex as signals of future productivity. Both theories have found empirical support.[1] Yet we know little about how these various signals interact. For example, can a "positive" signal such as advanced education overcome a "negative" one such as being female or a minority member? Few studies have considered whether more educated women and minorities experience less of a wage gap. The question is a difficult one to address empirically. More educated may imply more intelligent, more motivated, more ambitious, and so on.[2] And since characteristics such as ability and motivation are hard to observe, an apparent narrowing of a gender/racial wage gap among the more educated merely could reflect the influence of these unobservables. Any attempt to measure the effect of

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[1] See Lazear and Rosen (1990) and Wood, Corcoran, and Corant (1993) for statistical discrimination and Belman and Heywood (1991) for signaling theory.

[2] Although a compelling study using identical twins suggests that schooling is not positively related to ability and may even be negatively related (Ashenfelter and Krueger 1994).

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education on discrimination must confront the problem of unobserved heterogeneity.

This article tests whether obtaining an advanced academic degree, an MBA, reduces the gender wage gap among people pursuing business careers. To make this test, we compare the gender wage gap among a group of MBA recipients with the gap among another group that considered but did not obtain an MBA. We employ a new data set that is well suited to confronting the econometric dangers, described earlier, of making this kind of comparison. The data come from a longitudinal survey of registrants for the Graduate Management Admission Test (GMAT) sponsored by the Graduate Management Admissions Council (GMAC), the organization that administers the GMAT.[3] There are several reasons why the GMAC survey is a good source of data to evaluate the effects of an advanced degree on discrimination. First, by looking at takers of the GMAT test we focus on a population that is relatively homogeneous in terms of pre-MBA human capital and career goals. Second, because survey responses were matched with test scores and other data from GMAC records, we have good information about scholastic aptitude and quality of education. Third, the survey contains measures of potentially important psychological factors such as self-confidence and attitudes toward work and family. We know of no other study of the gender wage gap that has such extensive controls for worker heterogeneity. Finally, to further address issues of sample selection, we were able to model the decision to obtain (or not obtain) an MBA simultaneously with the determination of wages. We estimate a degree-attainment equation jointly with a tobit model of wages using full-information maximum likelihood (FIML).

The results from our FIML tobit model suggest that women with advanced degrees do have a smaller gender wage gap. We observe a highly statistically significant wage gap among non-MBAs—about 14 percent of wages—but a smaller and statistically insignificant gap among MBAs—about 9 percent of wages. A similar results emerges for African-Americans: Those without MBAs receive 10 to 13 percent lower wages than similarly credentialed whites; those with MBAs are paid as much or more.

When we decompose the respective wage gaps into explained and unexplained portions à la Blinder (1973), Oaxaca (1973), and Oaxaca and Ransom (1994), we get results that do not support our hypothesis. However, when we relax the assumption that the error terms are normal and explore some alternative (limited information) models, the decomposition results

[3] The Battelle Memorial Institute in Seattle, a research and consulting firm, designed the survey and collected the data. Copies of the questionnaires can be obtained from the authors.

support the hypothesis quite strongly. Overall, we interpret the bulk of our evidence to suggest that a woman who obtains an advanced degree will experience a smaller gender wage gap.

## Review of the Relevant Literature

The economic literature offers several reasons for hypothesizing that more educated women might face less discrimination. First, consider Becker's (1971) model of discrimination as a matter of taste. In this view, women and minorities may have poorer employment prospects because of prejudice on the part of employers, coworkers, or customers. Typically, we would expect that a more educated person tends to work with, and for, other more educated people. To the extent that higher education promotes tolerance, a woman with an advanced degree may confront relatively less sexism in her work environment.

A second reason for supposing that an advanced degree can reduce gender discrimination is offered by the theory of statistical discrimination (see Phelps 1972; Aigner and Cain 1977). In this model, employers use observable characteristics such as race and sex to proxy for unobservable ones such as ability and attitudes. Education, which is easily observed, provides a signal to the employer about a worker's innate ability. An employer who negatively prejudges a woman's productivity or motivation may be reassured by an advanced degree; educational screens tend to weed out less capable people. Indeed, they may weed out selectively by gender and race. Borjas and Goldberg (1978) argue that when educational screens are biased against minorities—e.g., culturally biased standardized tests—those screens have a stronger impact on minority members who survive them. In other words, passing through a biased screen is such a strong signal that those (women, by extension) who make it through will get greater rewards to educational credentials. Golbe (1985) predicts a similar effect based on differential cost of obtaining credentials. If, for example, the opportunity cost of an advanced degree is higher for women due to child care responsibilities, that degree will have a higher rate of return for women than for men.[4]

Statistical discrimination theory also predicts that even an employer with no doubts about women's *abilities* may still hire them with some reluctance. Some employers will expect women to experience work interruptions and lower productivity due to future child rearing (Lazear and Rosen 1990;

[4] Golbe's prediction was about minorities, but we extend it to women.

Wood, Corcoran, and Courant 1993). An advanced degree could assuage this concern by signaling a strong commitment to job and career.[5] Overall, the hypothesis that more educated women suffer less discrimination is consistent with the theoretical literature on discrimination.

*Studies of the Gender Wage Gap among the Highly Educated.* Although we know of no studies that directly test our main hypothesis, substantial literature shows that highly educated women continue to face discrimination in the job market.[6] Early work by Malkiel and Malkiel (1973) suggests that while professional women receive the same pay for the same work, they typically are assigned lower-paying jobs. Fuller and Schoenberg (1991) found a wage gap of 11 to 14 percent among women with BAs in business. A study by Weinberger (1998), which included very good controls for college quality and academic achievement, found a 10 to 15 percent gender wage gap among recent college graduates. Wage gaps have been found in the academic labor market (Ransom and Megdal 1993), even among Ph.D. economists (Singell and Stone 1993). A most interesting analysis of pay differentials among the highly educated comes from Wood, Corcoran, and Courant (1993), who studied male and female lawyers 15 years after graduation from the elite University of Michigan Law School. They found an 18 percent salary gap between men and *childless* women, i.e., women who were unlikely to show the weaker attachment to the labor force that is a common explanation for a wage differential.[7]

The studies described earlier tell us that advanced education does not immunize a woman against discrimination. However, they do not tell us whether, or by how much, it helps *reduce* the gender wage gap. A second class of study sheds some light on this by examining rates of return on educational signals. Belman and Heywood (1991) looked at the sheepskin effect, which is the benefit from acquiring an actual *degree*, as opposed to the education behind the degree.[8] They found that black men and white women had larger sheepskin effects than white males. Similarly, Ohsfeldt,

[5] In fact, theoretical work by Golbe (1985) suggests that in the presence of statistical discrimination, if minorities (and by extension, women) face a higher cost of achieving an advanced degree, then that degree will have a higher rate of return for them than for whites (or men).

[6] Several studies have examined labor market experiences of male and female MBAs specifically: Olson and Frieze (1989); Olson, Frieze and, Good (1987); and Strober (1982). An interesting article by Bertrand and Hallock (2001) looks at the gender gap among top corporate executives.

[7] And because the Wood, Corcoran, and Courant lawyers had similar educational credentials, and because the study controlled for law school performance, the gap could be not attributed to *lower-quality* schooling on the part of women, as had been suggested by Goldin and Polacheck (1987).

[8] See Hungerford and Solon (1987) and Layard and Psacharopoulos (1974) for other examples of empirical examinations of the sheepskin effect.

Culler, and Becker (1987) found that female physicians had higher returns to board certification than male physicians.

All the studies cited earlier shed some light on how education affects the gender wage gap. However, this article directly addresses the hypothesis that obtaining an advanced degree reduces the wage gap a woman faces in the labor market. We conduct this test by estimating wage equations for two groups—those who acquired an MBA and those who did not—within a relatively homogeneous population: people who registered to take the GMAT.

*The Gender Wage Gap and Unobserved Heterogeneity.* Testing the hypothesis described earlier involves some well-recognized econometric dangers. The problem results from unobserved worker characteristics that influence both the wage and the likelihood of acquiring an MBA. To briefly review this familiar problem, consider a personality trait such as career ambition. Suppose that ambitious people have higher educational goals as well as higher job performance but that ambition influences educational goals differently for men and women. Just for purposes of illustration, suppose that in business culture an MBA was more "expected" of a man than of a woman—rather like a bachelor's degree among the upper class a century ago. Under this hypothetical cultural condition, we would expect a male MBA to have lower ambition than an otherwise identical female MBA; he pursued the degree partly in response to a kind of social pressure that she did not face. There is, therefore, an ambition gap, so to speak, between the male and female MBAs. However, because ambition is rewarded with higher wages, this unobserved ambition gap narrows the gender wage gap. That is, the MBA degree will appear to reduce discrimination more than it actually does because part of its apparent impact reflects the higher average ambitions of female MBAs. What this example illustrates is the familiar problem of the self-selected sample. It could result from any number of unobserved worker characteristics.

The literature on discrimination has made substantial progress recently in observing the previously unobserved heterogeneity that corrupts estimates of the gender wage gap. For example, Polacheck and Kim (1994), using person-specific slope coefficients, concluded that "50 percent of the unexplained male-female wage gap can be attributed to . . . unmeasurable individual differences," such as motivation. Long (1995) found that various measures of taste and motivation had statistically significant effects on earnings and that these effects varied by gender. Also, while early studies included mere *quantity* of education—years of schooling—recent work confirms the importance of type and quality of education. Paglin and Rufolo (1990), Gyimah-Brempong, Fichtenbaum, and Willis (1992), and Eide (1994) all found college major to be a factor in the gender wage gap.

While each of the studies cited in the preceding paragraph confirms the impact on the gender wage gap of some aspect of worker heterogeneity—innate ability, quality of education, field of study, academic performance, or attitudes—none was able to control for all these factors simultaneously. A strength of the GMAC survey is that it gathered more information on worker characteristics than has been available to other researchers. We have data on the type and quality of education, school performance, innate ability, and attitudes toward work and family, among others. Moreover, we are able to focus on a population that is relatively homogeneous in terms of career goals.

## Data and Model Specification for the Wage Equations

The GMAT Registrant Survey drew a sample of 7006 individuals who registered to take the GMAT on test dates between June 1990 and March 1991, of whom 5602 actually took the test. The registrants were surveyed in three waves between 1991 and 1994. Our data are drawn from the 4333 registrants who took the test and who responded to all three waves of the survey. From this group we were able to cull 4293 usable observations. Data from the survey questionnaire were supplemented with information from GMAT registration and test records and with measures of educational quality from Barron's *Profiles of American Colleges* and *Profiles of American Business Schools* (1992).

*The Model.* Given the nature of the population we study, our model confronts issues of both censored data and sample self-selection. Our goal is to estimate wage equations for recent completers and noncompleters of graduate management school. We use earnings data from wave 3 of the GMAC survey, conducted 3 to 4 years after test registration, enough time for test takers to complete an MBA program. However, since many GMAT takers never enrolled and since many others attended business school only part time, only a minority actually completed (about 18 percent). Thus our wage equation is based on a self-selected group. Also, not all recent graduates found a job, so the distribution of observed wages is censored below at zero. Thus, by dividing the observations into completers and noncompleters, we have a self-selected samples, and by looking at current wages, we have censored the data.

To illustrate the formal model, we use the example of MBA completers; the model for noncompleters is perfectly analogous. We assume that the hourly wage of completers $w_i^c$ is related to personal characteristics $x_i$ in the usual way:

$$w_i^c = \beta^c x_i + e_i^c \quad e \iota N(0,\sigma_e) \tag{1}$$

The wage distribution is censored below at zero. We assume that completion of the MBA is determined by latent variable $y_i^*$, which is a function of personal characteristics $z_i$.

$$y_i^* = \alpha z_i + u_i \quad u \iota N(0,\sigma_u) \tag{2}$$

The error terms $e$ and $u$ have correlation coefficient $\rho$. The variable $y^*$ is unobservable; we see only whether the MBA was completed, which we represent with dummy variable $d_i$ ($d_i = 1$ if $y^* > 0$, otherwise 0). Greene (1995) shows that the appropriate log-likelihood function for estimating $\beta^c$, $\alpha$, and $\rho$ is

$$\begin{aligned} \ln L = {} & \sum_{d=0} \ln \Phi(-az_e) + \sum_{d=1,\, w^c=0} \ln \Phi_2(-\beta^c x/\sigma_e, \alpha z, \rho) \\ & + \sum_{d=1,\, w^c>0} -\frac{1}{2}\left[\ln 2\pi + \ln \sigma_e + (e/\sigma_e)^2\right] + \ln \Phi\left[\frac{\alpha z + \rho e/\sigma_e}{(1-\rho^2)^{1/2}}\right] \end{aligned} \tag{3}$$

where $\Phi$ and $\Phi_2$ are normal and bivariate normal cumulative density functions, respectively. Equation (3) is the log-likelihood function for a tobit model with sample selection. We estimate the model using full-information maximum likelihood.

*Determinants of the Wage.* The dependent variable in the analysis is the logarithm of the hourly wage on the current primary job at the time of the third-wave interview. For salaried employees (the majority of the sample), we computed hourly earnings by dividing weekly (monthly) earnings by the reported number of hours worked in a typical week (month).[9] The independent variables include work experience, measures of ability, measures of the quality of the undergraduate education, indicators of attitude and motivation, and the standard demographic characteristics.

The personal characteristics that may determine the wage include the respondent's age, marital status, number of children under age 18 living at home, and dummy variables for being Asian or African-American.

[9] Computing an hourly wage in this way may understate the wage gap if men tend to overreport hours worked, as is sometimes suspected. An alternative is to use salary, though this runs the risk of overstating the "wage" gap because men tend to work more hours. It turns out that our data gave similar results either way: There was a smaller and less significant gender *salary* gap for completers of MBAs than for noncompleters.

Experience measures include tenure on the current primary job (in months) and its square. For total labor market experience, we include a set of dummy variables for whether an individual had worked 1 to 3 years, 3 to 7 years, or more than 7 years, respectively, prior to registering for the GMAT.

As controls for academic aptitude, we include the total score on the GMAT test and the undergraduate grade point average. We measure the quality of the undergraduate education using the selectivity of the school as reported in Barron's *Profiles of American Colleges*. This variable, percent of population at less competitive college, is the sample-weighted proportion of registrants who attended a college that was rated by Barron's to be less competitive than that attended by the sample member. It ranges from 0 (least competitive) to 95 percent (most competitive). Thus, for example, a score of 90 indicates that 90 percent of the sample of GMAT registrants attended a less selective college than that of the person in question.

Weinberger (1998) shows that undergraduate major matters when estimating the gender wage gap (at least for white women) among college graduates. We therefore include dummy variables for whether the individual received an undergraduate degree in the humanities, social sciences, or sciences, respectively. The omitted category is having a business major.

A growing body of literature shows that psychological factors such as self-esteem, motivation, and attitudes—factors historically ignored in wage studies—have a significant impact on people's earnings. [See, for example, Goldsmith, Veum, and Darity (1997) and Dunifom and Duncan (1998).] The GMAC survey offers several measures of self-confidence, motivation, and attitudes toward work, family, and other aspects of life. Moreover, the relevant questions were asked in wave 1, prior to experiences in business school or on the post-MBA job market. We constructed three attitude and motivation variables. The first two are dummies that indicate, respectively, whether "one's own family and children" were reported to be "very important" and whether "career and work" were very important. We would expect that considering career very important would be associated with a higher wage. The effect of considering family important is more ambiguous: It might imply that family is permitted to constrain one's career, possibly lowering the wage. However, concern for family also could lead to a stronger work ethic, thereby potentially raising the wage.

The third attitude variable is what we call a *confidence index*. In the wave 1 survey respondents were presented with 16 personal characteristics and skills that would be considered important in "becoming a successful business manager or executive." These personal attributes included, "initiative," "communication skills," "physical attractiveness," "ability to motivate others," "being a team player," "ability to organize," "shrewdness," "good intuition," and others. Respondents were asked to indicate the extent to which they thought they had each of these characteristics or skills: very much = 1; somewhat = 2; not very much = 3; or not at all = 4. From their answers we constructed a confidence index equal to the sum of the responses over all characteristics listed. The index has a potential minimum of 16 (respondent "very much" has every skill) and a potential maximum of 64 (respondent "not at all" has any skill). The mean index for both men and women was 28. This score is equivalent to having, for example, 12 of the traits "somewhat" and 4 "very much." For ease of interpretation, our models include the negative of this index, so a positive coefficient will imply that more confidence increases the wage.

The role of occupation in explaining the gender wage gap has been well documented. [For recent analyses of this question, see Kidd and Shannon (1996) and Preston (1999).] Women receive lower wages in part because they more often work in lower-wage occupations—whether by choice or because of occupational discrimination. To control for employment in a "female" occupation, we matched the three-digit occupation codes of the employed completers with Bureau of Labor Statistics (BLS) data on the percentage of women in each occupation at the national level.

*Determinants of Completion of the MBA.* As discussed earlier, the FIML model estimates the wage equation simultaneously with the decision to complete the MBA. Clearly, many of the factors included in the wage equation also will affect the likelihood of completing an MBA. The completion equation, however, contains some variables that can reasonably be excluded from the wage equation, which is useful in identification of the wage parameters. These include the expected (in wave 1) main source of finance for the MBA: parents, employer, or fellowships, respectively; spouse's income in wave 1; and number of children in wave 1. (Note that the variables for number of children and marital status that appear in the wage equations are measured in wave 3.) Variables in the completion equation also include whether the registrant had a bachelor's degree at the time of GMAT registration and also whether she held a (nonbusiness) graduate degree. We also include a dummy for whether the person valued free time as very important (in wave 1) on the assumption that this would influence how long it eventually would take to complete the degree. As discussed below, the results for the wage model were fairly robust with respect to the specification of the completion model.

The means and standard deviations for the variables described earlier are reported in Table 1 by sex and completion status. The human capital variables

TABLE 1

DESCRIPTIVE STATISTICS FOR GMAT REGISTRANTS BY SEX AND WHETHER COMPLETED MBA

| | Completers of MBAs | | | | Noncompleters of MBAs | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| Variable | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Hourly earnings on primary job | 14.48 | 8.30 | 17.22 | 10.83 | 14.11 | 8.16 | 16.78 | 10.48 |
| *Independent variables* | | | | | | | | |
| Age | 25.9 | 5.4 | 27.0 | 5.9 | 26.7 | 5.7 | 27.3 | 5.9 |
| Married in wave 3 | 0.44 | | 0.53 | | 0.51 | | 0.56 | |
| Number of kids under 6 in wave 3 | 0.19 | | 0.37 | | 0.30 | | 0.45 | |
| Asian | 0.15 | | 0.13 | | 0.13 | | 0.14 | |
| Black | 0.16 | | 0.07 | | 0.19 | | 0.09 | |
| Tenure on current job (yrs) | 3.01 | 11.28 | 2.74 | 7.23 | 3.34 | 8.70 | 3.86 | 9.10 |
| Worked 1 to 3 years prior to test | 0.33 | | 0.29 | | 0.30 | | 0.31 | |
| Worked 3 to 7 years prior to test | 0.23 | | 0.29 | | 0.27 | | 0.26 | |
| Worked >7 years prior to test | 0.17 | | 0.23 | | 0.22 | | 0.25 | |
| GMAT score | 492 | 87 | 529 | 94 | 463 | 93 | 499 | 94 |
| Percent of pop. at less selective coll. | 38.8 | 30.2 | 41.2 | 31.9 | 35.5 | 30.6 | 37.9 | 30.8 |
| Undergrad major humanities | 0.11 | | 0.06 | | 0.13 | | 0.06 | |
| Undergrad major soc. science | 0.13 | | 0.20 | | 0.16 | | 0.13 | |
| Undergrad major science | 0.21 | | 0.26 | | 0.19 | | 0.32 | |
| Confidence index | 28.1 | 5.2 | 28.3 | 5.1 | 28.0 | 5.1 | 28.5 | 5.2 |
| Family very important | 0.87 | | 0.87 | | 0.87 | | 0.86 | |
| Career very important | 0.70 | | 0.60 | | 0.68 | | 0.62 | |
| Prop. women in 3-digit occ. | 0.49 | | 0.45 | | 0.49 | | 0.41 | |
| *In completion equation only* | | | | | | | | |
| Married in wave 1 | 0.28 | | 0.37 | | 0.29 | | 0.37 | |
| Spouse's income wave 1 | 8,196 | 21,454 | 5,478 | 13,530 | 8,976 | 22,809 | 5,456 | 12,367 |
| Number of kids wave 1 | 0.25 | 0.73 | 0.32 | 0.78 | 0.30 | 0.79 | 0.39 | 0.93 |
| Employed in wave 1 | 0.52 | | 0.60 | | 0.62 | | 0.65 | |
| Main finance for B-school: parents | 0.15 | | 0.15 | | 0.09 | | 0.07 | |
| Main finance: employer | 0.23 | | 0.21 | | 0.31 | | 0.34 | |
| Main finance: fellowships | 0.16 | | 0.12 | | 0.15 | | 0.12 | |
| Free time very important | 0.52 | | 0.46 | | 0.52 | | 0.49 | |
| At test: had bachelors degree | 0.76 | | 0.74 | | 0.74 | | 0.74 | |
| At test: had other grad degree | 0.02 | | 0.05 | | 0.05 | | 0.08 | |
| Sample | 345 | | 517 | | 1538 | | 1893 | |

show only slight variation among the four groups in the table: The average age for all groups is approximately 27 years, about half are married, and they have around 3 years of tenure on the current job. Male noncompleters have slightly more job tenure, 3.9 years. Some variation is evident in the GMAT score, with male completers averaging the highest (529) and female noncompleters the lowest (463). In addition, the spouses of women had substantially higher income (in wave 1) than the spouses of the men.

## Results

Table 2 presents the coefficients of the FIML model of the joint determination of hourly earnings and the likelihood of completing the MBA and shows the coefficients of the wage equation. Table 3 gives the coefficients for the completion model. Table 4 shows separate wage models for males and females, and Table 5 summarizes our measures of discrimination for the main models. As a check on the robustness of our specification, Table 5 also reports results from some models that relax the assumption that the error terms of the wage equation are normally distributed.[10]

*The Gender Wage Gap Based on a Female Dummy Variable.* First we look at Table 2 for the combined sample of men and women, where the dummy on *Female* represents our indicator of the gender wage gap.[11] The first two specifications are with and without, respectively, the proportion of women in the three-digit occupation. One limitation of these two specifications is that they classify as "noncompleters" the almost 900 sample members who were still actively pursuing the MBA when surveyed in wave 3. This classification may be too restrictive because many had already accumulated much of the human capital associated with the degree. Therefore, a third specification explores the robustness of our results to an alterative definition of obtaining an MBA. In the last two columns of Table 2, the group of completers is expanded to include both those who have finished the MBA and those who were still pursuing it in wave 3. The group of noncompleters is reduced to those who either never attended business school or went and dropped out.[12]

All three models support our hypothesis that the gender wage gap is smaller among GMAT registrants who have an MBA (or, as in model 3, are pursuing one) than among those who do not have an MBA (or, as in model 3, dropped out or never enrolled). For completers of the MBA, *Female* has an effect of 9 percent of the wage when occupation is excluded and of 8 percent when occupation is included; neither coefficient is statistically significant. For noncompleters, being female has a larger effect, 14 percent without occupation and 13 percent with, and both coefficients are highly statistically significant. When we broaden the definition of having an MBA

[10] We also excluded 12 people who were over age 55.

[11] We discuss the coefficients as if they were the marginal effects of the variables, which is slightly inaccurate [see, for example, McDonald and Moffit (1980)]. We computed marginal effects for non-FIML versions of the wage equation and found them to be quite close to the values of the coefficients. We did not, therefore, undertake the computational difficulty of computing adjusted marginal effects for the FIML models.

[12] We are grateful to an anonymous referee for making this suggestion.

TABLE 2

TOBIT MODELS OF LOG OF HOURLY EARNINGS: SELECTION-CORRECTED FULL-INFORMATION MAXIMUM-LIKELIHOOD ESTIMATES

| Variable | Model 1 Occupation Excluded | | | | Model 2 Occupation Included | | | | Model 3 Completion Redefined | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Completers of MBAs | | Non-Completers of MBAs | | Completers of MBAs | | Non-Completers of MBAs | | Completed or Still Enrolled | | Dropped Out or Never Went | |
| | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat |
| Female | –0.093 | –1.03 | –0.142 | –3.49 | –0.081 | –0.89 | –0.126 | –3.08 | 0.019 | 0.30 | –0.099 | –2.30 |
| Married in wave 3 | 0.075 | 0.89 | 0.043 | 1.22 | 0.070 | 0.83 | 0.040 | 1.14 | 0.057 | 1.30 | 0.086 | 1.95 |
| Number of children at home | 0.013 | 0.17 | 0.019 | 0.70 | 0.017 | 0.21 | 0.018 | 0.66 | –0.006 | –0.18 | 0.015 | 0.48 |
| Age | 0.005 | 0.42 | 0.001 | 0.23 | 0.004 | 0.31 | 0.001 | 0.21 | 0.015 | 1.70 | –0.012 | –2.56 |
| Asian | –0.102 | –1.01 | –0.015 | –0.26 | –0.099 | –0.98 | –0.017 | –0.28 | 0.049 | 0.55 | –0.036 | –0.62 |
| Black | 0.027 | 0.21 | –0.100 | –1.71 | 0.028 | 0.21 | –0.091 | –1.56 | 0.130 | 1.31 | –0.129 | –2.35 |
| Tenure on current job (mos.) | 0.017** | 2.56 | 0.017** | 8.41 | 0.016** | 2.47 | 0.016** | 8.09 | 0.006 | 1.81 | 0.050 | 18.11 |
| Tenure squared (mos./100) | –0.013 | –2.35 | –0.012** | –10.14 | –0.012** | –2.25 | –0.012 | –9.86 | –0.004** | –2.19 | –0.045 | –20.14 |
| Worked 1 to 3 yrs prior to test | 0.244** | 2.27 | 0.133** | 2.28 | 0.24** | 2.18 | 0.128** | 2.20 | 0.094 | 1.08 | 0.177 | 2.91 |
| Worked 3 to 7 yrs prior to test | 0.408** | 3.24 | 0.192** | 3.10 | 0.40** | 3.15 | 0.190** | 3.06 | 0.130 | 1.34 | 0.243 | 3.79 |
| Worked >7 yrs prior to test | 0.480** | 2.49 | 0.252** | 3.05 | 0.488** | 2.53 | 0.252** | 3.03 | 0.259 | 1.87 | 0.345 | 4.23 |
| GMAT score (00 points) | 0.165** | 2.56 | 0.187** | 8.20 | 0.162** | 2.51 | 0.178** | 8.05 | –0.23** | –6.10 | 0.094 | 2.85 |
| Undergraduate GPA | 0.160 | 1.77 | 0.012 | 0.31 | 0.161 | 1.79 | 0.011 | 0.30 | 0.089* | 1.97 | 0.017 | 0.35 |
| Prop. from less selective coll. | 0.003 | 1.84 | 0.001 | 1.59 | 0.002 | 1.71 | 0.001 | 1.52 | 0.001 | 1.14 | 0.001 | 1.00 |
| Undergrad major humanities | –0.138 | –0.92 | –0.062 | –0.86 | –0.133 | –0.89 | –0.055 | –0.77 | 0.027 | 0.24 | 0.009 | 0.12 |
| Undergrad major social science | –0.191 | –1.82 | 0.068 | 1.11 | –0.183 | –1.74 | 0.073 | 1.20 | –0.063 | –0.71 | 0.065 | 0.96 |
| Undergrad major sciences | 0.013 | 0.13 | –0.031 | –0.64 | –0.011 | –0.10 | –0.069 | –1.43 | 0.189** | 2.46 | 0.035 | 0.72 |
| Career very important | 0.063 | 0.76 | 0.014 | 0.34 | 0.064 | 0.78 | 0.013 | 0.31 | –0.057 | –0.89 | 0.053 | 1.23 |
| Family very important | 0.249** | 2.35 | 0.122** | 2.22 | 0.255** | 2.41 | 0.124** | 2.25 | 0.213** | 2.57 | 0.057 | 0.93 |
| Confidence index | 0.015** | 2.01 | 0.004 | 1.14 | 0.015 | 2.01 | 0.004 | 1.14 | 0.001 | 0.22 | –0.000 | –0.06 |
| Percent women in 3-digit occupation | | | | | –0.325 | –0.87 | –0.33** | –3.27 | | | | |
| No. of noncompleters/completers | 4293 | | 4293 | | 4293 | | 4293 | | 4293 | | 4293 | |
| FIML sample (no. of test takers) | 862 | | 3431 | | 862 | | 3431 | | 1818 | | 2475 | |
| Log likelihood | –3311.0 | | –3310.2 | | –3310.2 | | –6439.9 | | –4984.0 | | –6249.4 | |

*Significant at the 0.05 level.

**Significant at the 0.01 level.

TABLE 3

Probability of Completing the MBA First Stage of the FIML Models in Table 2

| | Probability of Completing MBA | | Probability of Completing or Still Pursuing the MBA | |
|---|---|---|---|---|
| Variable | Coef. | *t*-Stat | Coef. | *t*-Stat |
| Female | –0.046 | –0.93 | –0.107 | –2.69 |
| Age | 0.014 | 1.78 | 0.005 | 0.85 |
| GMAT score | 0.224** | 7.94 | 0.192** | 8.10 |
| Children at home (wave 1) | –0.050 | –1.36 | 0.002 | 0.09 |
| Married (wave 1) | 0.149** | 2.41 | –0.027 | –0.78 |
| Spouse income (wave 1) | –0.000 | –0.93 | 0.001 | 1.31 |
| Had bachelor's degree at test | 0.208** | 2.91 | 0.069** | 2.05 |
| Had a graduate degree at test | –0.188 | –1.58 | –0.011 | –0.16 |
| Asian | –0.018 | –0.26 | –0.028 | –0.48 |
| Black | 0.049 | 0.65 | –0.082 | –1.34 |
| Worked 1 to 3 years prior to test | –0.060 | –0.77 | –0.050 | –0.85 |
| Worked 3 to 7 years prior to test | –0.038 | –0.44 | –0.053 | –0.82 |
| Worked >7 years prior to test | –0.131 | –1.11 | –0.102 | –1.14 |
| Undergrad major humanities | –0.151 | –1.72 | –0.053 | –0.76 |
| Undergrad major social science | –0.002 | –0.03 | 0.030 | 0.53 |
| Undergrad major science | –0.095 | –1.59 | –0.099 | –2.03 |
| Prop. from less selective college | –0.000 | –0.07 | 0.001 | 1.02 |
| Family very important | 0.027 | 0.39 | –0.107 | –1.97 |
| Career very important | –0.003 | –0.06 | 0.009 | 0.22 |
| Free time very important | –0.040 | –0.87 | –0.010 | –0.42 |
| Confidence index | 0.008 | 1.69 | 0.005 | 1.37 |
| Main finance: parents[a] | 0.415** | 5.27 | 0.042 | 1.02 |
| Main finance: employer | –0.264** | –4.48 | 0.039 | 1.26 |
| Main finance: fellowships | 0.052 | 0.74 | 0.085** | 2.56 |
| Employed at time of registration | –0.139** | –2.39 | 0.083** | 2.89 |

Note: Included but not shown are constant terms for both models.
[a]The *expected* main source of finance for business school at wave 1.
**Significant at the 0.01 level.

to include those still enrolled, the results are even stronger. Among sample members who either had an MBA or were still pursuing one, females had the same or higher wages as comparably skilled men. Among those who had dropped out of business school or never enrolled, female wages were lower by a statistically significant 10 percent.[13]

[13] These results for the *Female* coefficient are somewhat sensitive to the specification of the completion model, but only in a way that reinforces our main findings. For example, if we include only demographics in the completion model, the *Female* coefficient for noncompleters becomes even more negative and even more significant ($\beta = -20$, $t = -4.95$), whereas that for completers retains its magnitude and insignificance ($\beta = -08$, $t = 0.47$).

TABLE 4

FIML Tobit Model of Log of Hourly Earnings by Completion Status and Sex (Wage Equation Only)

| | Completers | | | | Noncompleters | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| Variable | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat | Coef. | *t*-Stat |
| Married | –0.016 | –0.12 | 0.172 | 1.51 | –0.018 | –0.34 | 0.094 | 1.87 |
| Number of children at home | –0.097 | –0.67 | 0.001 | 0.01 | –0.043 | –1.03 | 0.044 | 1.25 |
| Age | –0.034 | –1.54 | 0.023 | 1.14 | 0.001 | 0.08 | –0.002 | –0.38 |
| Asian | –0.031 | –0.18 | –0.126 | –0.92 | 0.001 | 0.01 | –0.030 | –0.38 |
| Black | –0.024 | –0.13 | 0.150 | 0.72 | –0.050 | –0.65 | –0.143 | –1.61 |
| Tenure on current job (mos.) | 0.005 | 0.41 | 0.044 | 1.93 | 0.057 | 4.67 | 0.017 | 5.40 |
| Tenure squared (mos./100) | –0.006 | –0.56 | –0.036 | –0.50 | –0.056 | –4.76 | –0.010 | –5.77 |
| Worked 1 to 3 years prior to test | 0.563 | 2.85 | 0.071 | 0.52 | 0.086 | 0.97 | 0.196 | 2.51 |
| Worked 3 to 7 years prior to test | 0.482 | 2.10 | 0.379 | 2.19 | 0.027 | 0.30 | 0.328 | 3.85 |
| Worked >7 years prior to test | 1.002 | 2.65 | 0.225 | 0.84 | 0.031 | 0.27 | 0.410 | 3.46 |
| GMAT score | 0.216 | 1.84 | 0.129 | 1.58 | 0.193 | 5.80 | 0.172 | 5.60 |
| Undergraduate GPA | –0.189 | –1.19 | 0.403 | 3.42 | 0.074 | 1.38 | –0.033 | –0.60 |
| Prop. from less selective coll. | 0.001 | 0.38 | 0.003 | 1.60 | 0.001 | 0.68 | 0.002 | 1.54 |
| Undergrad major humanities[a] | –0.308 | –1.50 | 0.068 | 0.26 | | | | |
| Undergrad major social science | –0.270 | –1.27 | –0.109 | –0.83 | 0.000 | 0.00 | 0.145 | 1.77 |
| Undergrad major science | –0.080 | –0.47 | 0.080 | 0.54 | 0.012 | 0.17 | –0.035 | –0.58 |
| Family very important | –0.037 | –0.25 | 0.125 | 1.18 | 0.036 | 0.55 | –0.004 | –0.08 |
| Career very important | 0.111 | 0.53 | 0.267 | 1.96 | 0.029 | 0.32 | 0.188 | 2.69 |
| Confidence Index | 0.022 | 1.96 | 0.003 | 0.23 | –0.002 | –0.41 | 0.010 | 1.95 |
| No. of completers/ noncompleters | 345 | | 517 | | 1538 | | 1893 | |
| FIML sample | 1883 | | 2410 | | 1883 | | 2410 | |
| Log likelihood | –1344.8 | | –1926.0 | | –2794.7 | | –3600.7 | |

[a]The models for noncompleters refused to converge when this variable was included.

What happens to the gender wage gap when we control for occupation? The results for the occupation variable in Table 2 are consistent with the hypothesis that occupational segregation is less prevalent at higher levels of education. For noncompleters, the occupational variable is highly significant ($t = -3.27$) and implies that moving from an all-male to an all-female occupation lowers the wage by 31 percent. For completers, the effect is about the same size but not statistically significant ($t = -0.87$). Note that for both completers and noncompleters, including the occupation variable reduces the gender wage gap by between 1 and 2 percentage points.

TABLE 5

SUMMARY OF INDICATORS OF DISCRIMINATION IN ALTERNATIVE MODELS

| | Tobit | | Alternative Distributions (with Nonparametric Sample Correction) | | |
|---|---|---|---|---|---|
| | FIML | Two-Stage | Normal | Logistic | Weibull |
| Noncompleters: | | | | | |
| Female coeff. | –0.142 | –0.123 | –0.12 | –0.09 | –0.09 |
| *t*-Statistic | 3.49 | 3.83 | 3.23 | 3.54 | 1.83 |
| Unexp. gap | 0.069 | 0.061 | 0.06 | 0.056 | 0.036 |
| Completers: | | | | | |
| Female coeff. | –0.093 | –0.128 | –0.13 | –0.12 | –0.11 |
| *t*-Statistic | 1.03 | 1.54 | 1.69 | 2.13 | 1.03 |
| Unexp. gap | 0.081 | 0.074 | –0.25 | –0.04 | –1.34 |
| Gaps are equal: *t*-Statistic | 0.32 | 0.26 | –7.10 | –2.66 | –26.5 |

Although not the main subject of this article, it is worth noting what the results in Table 2 suggest about the effect of an MBA on the racial wage gap between blacks and whites. Again, the results are consistent with the hypothesis that obtaining an MBA exposes one to less discrimination. In the wage equations for completers, the coefficient on the *Black* dummy is small, positive, and quite insignificant, but for noncompleters, the wage gap is about 10 percent and modestly significant ($t = -1.71$). In the third model, support for the hypothesis is even stronger. Blacks who have completed or are still pursuing the MBA appear to earn 13 percent *more* than whites, whereas blacks who dropped out or never attended business school earn 13 percent *less*. The statistical significance of the former effect is low ($t = 1.31$) but of the latter is high ($t = -2.35$).

*Effects of the Other Variables*. Table 2 shows that a number of what we call quality variables have sizable and significant effects and that their inclusion influences the measured wage gap.[14] The GMAT score has a large positive and statistically significant effect for both completers and noncompleters. A 100-point increase in GMAT score increases the wage by about 17 percent for both groups. (An exception is in model 3.) Also, like Goldsmith, Veum, and Darity (1997) and Dunifom and Duncan (1998), we

[14] An interesting finding, not shown in these tables, is that once we control for these quality variables, the MBA itself has no significant effect on wages. At the suggestion of an anonymous referee, we ran a tobit model for all sample members and discovered that once the quality variables in Table 2 are included, completing the MBA raises wages by less than 2 percent, and the effect is insignificant ($t = 0.35$). Variables such as GMAT score and the selectivity of the undergraduate school remain quite statistically significant. These results are available from the authors.

find that attitudes matter. The confidence index was significant for both completers and noncompleters. An MBA holder who claimed she "very much" had all 16 personal attributes in the index would have 32 percent higher wages than someone who only "somewhat" had these traits. For non-MBAs, the effect was half as large and somewhat less significant. Interestingly, considering family very important significantly increased wages; considering career important did not. Perhaps commitment to family is indicative of other positive attributes, such as a strong sense of responsibility and caring for others.

*The Completion Equation*. Although, again, not the main focus of this article, some results for the completion stage of the FIML are also worth discussing. Table 3 reports coefficients from two runs: the probability of completing the MBA (models 1 and 2 in Table 2) and the probability of completing or being enrolled (model 3 in Table 2). The complementary equations—the probability of not completing or of having never attended/dropped out—are mirror images of these and therefore are not reported. Most of the signs of the coefficients for the probability of having completed the MBA are consistent with intuition. People with high GMAT scores are significantly more likely to have completed the MBA, as are married people. People who had jobs when they took the GMAT were less likely to have finished the degree—they would be more likely to have pursued it part time—particularly if they expected financial help from an employer. Some of the coefficients change when we expand the definition of "completing" to include those still pursuing the MBA. Women were significantly less likely than men to be in this category; i.e., they were more likely to never have gone to business school or to have dropped out. The effect of being employed in wave 1 switches sign between the two models in Table 3, as does the effect of expecting one's employer to help with tuition. Neither change is surprising because those getting help from an employer are more likely to attend business school part time and therefore to take longer completing the degree.

*Separate Models for Women and Men*. A recognized problem with using the specification in Table 2 to gauge the gender wage gap is that it assigns men and women identical rates of return on all human capital attributes. This assumption is very restrictive. For example, wage discrimination could take the form of lower rewards to women for attributes such as education or ability. A widely used alternative method of measuring discrimination is to estimate separate wage equations for men and women and decompose the wage gap (Oaxaca 1973; Blinder 1973). It is important for us to explore this alternative method because a likelihood-ratio test rejects, at the 0.01 level, the hypothesis that all the coefficients in Table 2 are equal for men and women. Moreover, a meta-regression analysis by Stanley and Jarrell (1998) shows that studies using the Oaxaca-Blinder decomposition consistently report smaller estimates of the gender wage gap than studies relying on a female dummy.

Table 4 shows the results of the wage equation when the model is estimated separately for men and women. (Only the wage results are reported in the table.) The estimated returns to some key human capital and ability variables differ between men and women. For example, women appear to get higher rewards for academic aptitude. An extra 100 points in GMAT score raises a female MBA's wage by 22 percent and a male MBA's wage by only 12 percent. For non-MBAs, that 100 points adds 21 percent to the wage for women and 15 percent for men.

On the other hand, women appear to get a *smaller* return on pure signals. Attending a more selective undergraduate school has a significant effect on the male wage but not the female wage. This was a curious finding. To explore it further, we ran a model for the completer sample alone (not reported) that included a measure of the selectivity of the MBA-granting institution: the average GMAT score of its students. For a man, an extra 100 points in the school's average GMAT—the difference between, say, Berkeley and California State at Hayward—raised his wage by 21 percent ($t$ = 1.73). For women, the effect was only 9 percent and was statistically insignificant ($t$ = 0.51). This result seems to contradict the Borjas and Goldberg (1978) hypothesis that minorities and women enjoy higher returns to educational screens.[15]

Finally, in contrast to some published hypotheses, the impact of job tenure differs only slightly between men and women. For completers, for example, an extra year on the job raises women's wages by about 5 percent and men's by about 4 percent.[16] For noncompleters, the effects are 1 percent for women and 2 percent for men. Because our completers are generally just starting their post-MBA careers, this result bears on an argument made by Becker and Lindsay (1995a, 1995b) that the apparent gender gap in starting pay actually may reflect voluntary behavior on the part of women. They argue that women may choose to bear a larger share of firm-specific human capital investment. If so, say Becker and Lindsay, we should observe higher

[15] On the other hand, one could argue that because affirmative action in admission reverses the traditional disadvantages, this result supports Borjas and Goldberg. However, using these same data, Montgomery (2002) found that while blacks and Hispanics had an advantage in business school admissions, women did not.

[16] Evaluated at the mean tenure for each group, as reported in Table 1.

returns to women in tenure on the job. Our results do not support this hypothesis.

*Decomposing the Wage Gap*. With the coefficients from separate models for men and women, as in Table 4, we can decompose the gender wage gap into "explained" and "unexplained" portions. To briefly review the well-known technique, suppose we estimate wages $w$ for males ($M$) and females ($F$) with ordinary least squares (OLS) equations:

$$\ln w_M = \beta_M X_M + e_M$$
$$\ln w_F = \beta_F X_F + e_F$$

Because the mean of the error terms in an OLS equation is zero, the observed difference in mean log wages must equal

$$\overline{\ln W_M} - \overline{\ln W_F} = \hat{\beta}_M \overline{X_M} - \hat{\beta}_F \overline{X_F} = \left[\hat{\beta}_M\left(\overline{X_M} - \overline{X_F}\right)\right] + \left[\left(\hat{\beta}_M - \hat{\beta}_F\right)\overline{X_F}\right] \quad (4)$$

where bars indicate mean values and hats indicate estimates. The first term in square brackets is the explained portion of the wage gap, and the second term is the unexplained portion.[17] The unexplained portion is attributed to discrimination because it results not from differences in human capital between men and women but from differential rewards to human capital.

The models estimated in Table 4 will not permit a true decomposition of the wage gap using the methodology of previous studies. The error terms in the FIML tobit will not necessarily sum to zero, which implies that the bracketed terms in Equation (4) will not necessarily sum to the wage gap. There will be an extra term: ($e_M - e_F$). Nevertheless, our interest here is less in the absolute size of the unexplained wage gap than in how it compares between completers and noncompleters. In particular, we would like a statistical test of whether the unexplained wage gap is smaller for completers. That is, we want to know if

$$\left(\hat{\beta}_M^C - \hat{\beta}_F^C\right)\overline{X}_F^C \prec \left(\hat{\beta}_M^N - \hat{\beta}_F^N\right)\overline{X}_F^N \quad (5)$$

where superscripts $C$ and $N$ refer to completers and noncompleters, respectively.

In the literature, the Oaxaca-Blinder components of the wage gap generally are taken at face value. However, we propose a straightforward method

[17] Some studies have questioned the assumption that $\beta_M$ reflects rates of return for both sexes in the absence of discrimination (Neumark 1988; Oaxaca 1973; Oaxaca and Ransom 1994). For simplicity, however, we adhere to this traditional approach.

of testing whether completers have a lower unexplained wage gap. Our approach requires that we estimate a model for *all* registrants that includes a full set of slope dummies for female completers, male noncompleters, and female noncompleters, respectively. The hypothesis in Equation (5)—restated as an equality—can then be formulated as a linear restriction on the parameters in that model. To see this, suppose that we transform our $n \times k$ matrix of independent variables $X$ into an $n \times 4k$ matrix $X'$ that has three sets of slope dummies:

$$X' = X[I, D_F^C, D_M^N, D_F^N]$$

where $D_F^C$ is an $n \times n$ matrix whose diagonal elements comprise a dummy for being a female completer and whose other elements are zero. $D_M^N$ and $D_F^N$ are defined similarly, and $I$ is an $n \times n$ identity matrix. Using $X'$, we estimate parameter vector $\Omega$ from

$$\ln W = \Omega X' + \varepsilon$$

and test the linear restriction $R\Omega = 0$, where $R$ is the $1 \times 4k$ row vector

$$R = \left[0 \ldots 0, -\overline{X}_F^C, -\overline{X}_M^N, \overline{X}_F^N\right]$$

The appropriate $t$-statistic is $R'\Omega/[RVR']^{1/2}$, where $V$ is the variance covariance matrix of $\Omega$.

The result of the preceding test for the FIML model is reported in the first column of Table 5. For the FIML models (those reported in Table 4), the estimated unexplained gap is slightly larger for completers, 0.081 versus 0.069. Column 2 shows that the same is true if we run our tobit models as two-stage Heckit models: Completers have a wage gap of 0.74, and noncompleters have a gap of 0.061.[18] Thus our decomposition results are not consistent with those from using the female dummy.

*Robustness of the Estimates under Alternative Distributions.* The tobit model assumes that the errors in the wage equation are normally distributed. We evaluated this assumption using a conditional moment test, as suggested in Skeels and Vella (1999), and rejected it at the 0.01 level. It seemed appropriate, therefore, to rerun the wage models under alternative assumptions about the distribution of the errors. Columns 3 through 5 of Table 5 refer to censored-dependent-variable models that assume that the errors have, respectively, (1) a normal distribution, (2) a logistic distribution, or (3) a Weibull distribution. These three models also relax the assumption of

[18] In the Heckit model, the inverse Mills ratio from the completion probit is included as a independent variable in the tobit equation.

normality in the selection equation—implicit in the Heckit method—and employ a nonparametric sample correction approach, as suggested by Deaton (1997).[19]

The results for the non-FIML models in Table 5 generally are consistent with those of the FIML models in Table 2; the coefficient on the female dummy is always highly significant for noncompleters and insignificant for completers (except for the logistic model). The decomposition results for the alternative models quite strongly support our main hypothesis. For the normal, logistic, and Weibull distributions, the unexplained wage gap for noncompleters is negative, whereas for completers it is positive. That is, these models find that among MBAs, women get higher returns on their human capital than men do. (So strongly, in fact, that in the case of the Weibull model, the result is outside the range of plausibility.) The difference in wage gaps is highly statistically significant in the three alternative-distribution models.

What light do the alternative models shed on the FIML results? Certainly they suggest that if we use the *Female* wage dummy to assess the gender gap, limited-information models are more modest in supporting the view that highly educated women experience a smaller gender wage gap. For wage decomposition, on the other hand, the limited-information models actually conclude that for highly educated women the gap is reversed. The latter implication may seem improbable. At the very least, however, it seems safe to claim that the results from the alternative models, taken as a whole, do not contradict the conclusions reached from the FIML model.

## Conclusions

This article compares the gender wage gap for holders of an advanced degree with the gap for those with only a college education. We used a selection-corrected tobit model on a population of GMAT takers to test whether women who acquired an MBA faced less wage discrimination than women who did not. The weight of our evidence suggests that they do. We found a highly statistically significant wage gap for noncompleters of the MBA but a smaller and insignificant one for those who completed the degree. When we expanded the group of "completers" to include those still pursuing the degree, their gender wage gap entirely disappeared, whereas that of the "noncompleters" remained significant. On the other hand, when we performed the standard Blinder-Oaxaca decomposition of the wage gap, our

[19] In this approach, one estimates the vector $\alpha$ in Equation (2) with a probit, but instead of constructing an inverse mills ratio, one enters $\alpha Z$ in the wage equation in polynomial form—in our case, cubically.

results did not support the hypothesis: Both completers and noncompleters had roughly the same portion of the wage gap that was "unexplained" (and therefore possibly attributable to discrimination). This changed, however, when we made alternative assumptions about the distribution of our error terms. Under several different distributional assumptions, we found that completers had *negative* unexplained wage gaps, implying that women got *higher* returns on their human capital than men. For noncompleters, the gaps were still positive. On balance, we think our evidence supports the hypothesis that women who obtain an MBA face less wage discrimination in the job market.[20] It would be useful to see these results extended to other graduate degrees.

Other aspects of our results bear on hypotheses presented in the discrimination literature. Using relatively good measures to separate academic aptitude from signals about aptitude, we found women to receive lower returns to such signals rather than higher, as predicted elsewhere (Borjas and Goldberg 1978; Golbe 1985; Bellman and Heywood 1991). Also, our evidence was not consistent with the hypothesis that women get lower starting wages because they voluntarily shoulder more of the cost of firm-specific training than men do (Becker and Lindsay 1995a, 1995b).

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[20] A word of caution should be sounded in that our GMAT test takers were relatively young, age 26 on average, and many had little experience in the professional market. Our results do not necessarily contradict those of researchers such as Wood, Corcoran, and Courant (1993), who have found evidence of long-term wage discrimination against highly educated women.

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