Education and Wage-Based Statistical Discrimination

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Abstract

This study examines the role of statistical discrimination in determining workers' wages. Employers initially have an imperfect knowledge of their employees' true productivity and so may "statistically discriminate" in setting wages, using observed correlates of productivity to estimate its true value. For both holders of bachelors' degrees and MBA graduates, I use the traditional EL-SD test to investigate the existence and importance of various potential bases of discrimination, including university prestige, undergraduate GPA, undergraduate major, gender, and presence of an MBA. I find evidence of discrimination on the basis of undergraduate GPA, especially among women, but little evidence of discrimination on other bases.

1. Introduction

Why does education lead to higher wages? One hypothesis, commonly known as the human capital model of education, sees education as an investment in individual productivity. More education leads to a higher productivity, which in turn commands a higher wage in the labor market. Spence's influential 1973 paper challenged this view by proposing "signaling" as a primary mechanism relating education and wages. In accordance with this model, an individual with a higher inherent productivity obtains a higher level of education in order to signal this productivity to employers. Employers, who cannot observe true productivity, must in turn rely on observed correlates of inherent productivity such as education in determining wages.

Given the considerable practical implications of accepting one of these models over the other – is education indeed a worthwhile investment, or is it just a costly signal? – a large literature has developed attempting to distinguish them empirically. Tyler et al. (2000), for example, estimate a positive signaling value of the GED, net of human capital effects, by using a treatment-control model across U.S. states. Lang and Kropp (1986) investigate the impact of compulsory school attendance laws on those not directly affected. Such laws were found to be correlated with higher educational attainment not only among young dropouts, but also among individuals who already stayed in school beyond the new minimal requirement; the authors conclude that this behavior is consistent with the signaling model of education, but not with the human capital model. Clark and Martorell (2014), on the other hand, use a regression discontinuity approach to evaluate differential wage rates of those who barely passed, and those who barely failed, a high school exit exam required for a diploma. They find no significant evidence that the diploma by itself yields higher wages.

More directly relevant to this investigation is the development of the Employer Learning with Statistical Discrimination (EL-SD) literature. When setting wages for new workers, firms must make a decision in the presence of incomplete information. They do not know the true productivity of their employees and so must form an expectation based on what information they do have. Thus, firms may "statistically discriminate," granting higher wages to workers who display signals correlated with higher productivity. Farber and Gibbons (1996) develop this idea by arguing that when workers enter the labor force, easily observed factors such as level of educational attainment are the primary determinants of their wage. As workers gain more experience, however, hard-to-observe correlates of productivity such as test scores become increasingly associated with wages: employers increasingly learn about workers' true productivity and compensate them in accordance with (an updated belief about) their true value to the firm. Altonji and Pierret (2001) (henceforth AP) develop this model into an empirical test for statistical discrimination. They demonstrate that if firms do indeed discriminate on the basis of easily observed characteristics, then as employers learn more about a worker's true productivity over time, hard-to-observe correlates with productivity should have an increasingly strong association with wages, while the importance of easily observed factors should decline.

This test, which has become standard in the EL-SD literature, offers a new perspective on the question of signaling in education. By proposing a specific mechanism – statistical discrimination on the part of employers – by which signaling functions, one can test for the presence and importance of signaling in determining wages. AP do find that firms statistically discriminate on the basis of years of schooling, though they also note that their test is much more broadly applicable. Indeed, with an appropriate dataset, their model allows for the examination of statistical discrimination on the basis of multiple easily-observed factors, such as gender, race, university prestige, immigration status, and so forth. It is in this vein that my paper represents a contribution to the EL-SD literature. Using a 1990-1998 longitudinal survey of registrants for the GMAT, I investigate the presence of statistical discrimination on the basis of university selectivity, GPA, and undergraduate major. For each of these factors, I study whether firms discriminate differently among workers with an MBA compared to workers with only a bachelor's degree, and whether this discrimination differs by gender. Finally, I test whether gender and the presence of an MBA themselves are used as bases for discrimination. My tests generally reveal little evidence of statistical discrimination among the sample I study. I do find evidence for statistical discrimination on the basis of undergraduate GPA, especially among women, though little evidence on the basis of other factors. Statistical discrimination seems to be no more prevalent among MBA graduates than among college graduates, and with the exception of undergraduate GPA, statistical discrimination does not seem to differ significantly by gender.

This paper proceeds as follows. In Section 2, I provide an overview of previous findings in the EL-SD literature. In Section 3, I outline AP's model and specify its application to my own study. Section 4 describes the dataset I use in the estimation of the model, the results of which I present and discuss in Section 5. Section 6 provides various secondary results and serves as a robustness check for the results of Section 5, and Section 7 concludes.

2. Literature Review

The conclusions of the existing EL-SD literature have been inconsistent, even among ostensibly similar studies. In the original 2001 paper by AP, the authors see evidence that firms statistically discriminate among American men on the basis of years of schooling. AP obtain strong results by using AFQT scores and sibling wages as unobserved correlates of productivity, although the relevant regression coefficients are statistically insignificant when they use father's education as the unobserved variable. Cheung (2008) examines a comparable sample of men in Australia, investigating the EL-SD hypothesis with test scores and parental education as unobserved variables. In contrast to AP, Cheung cannot conclusively identify statistical discrimination on the basis of schooling regardless of model specification. Moreover, Cheung's estimations suggest that employers do not, in fact, learn about workers in the dimension of their test scores, whereas parental education becomes an increasingly important determinant of wage.

Furthering this contrast, Falter (2007) finds that Swiss firms discriminate on the basis of education, and Pan (2005) finds that Canadian firms do so as well. On the other hand, Strobl (2003) finds no evidence of discrimination for a broad sample of Ghanaians, nor do Bauer and Haisken-DeNew (2001) among Germans. These results suggest that labor markets in different countries may operate fundamentally differently, a result that Broecke (2014) systematically examines across 22 OECD countries. His results too are mixed: Broecke observes (with varying degrees of conviction) evidence of discrimination in ten countries, and inconclusive or contradictory evidence in the remaining twelve. He goes on to suggest explanations for this disparity in results, though he recognizes that his analysis likely does not capture the true complexity of these countries' labor markets.

Indeed, further results from the literature suggest the importance not only of distinguishing among the labor markets of different countries, but also among distinct labor markets *within* a given country. Returning to Strobl, although he finds no evidence of statistical discrimination among Ghanaian workers on the whole, he concludes that education acts a signal among a subset of those workers who obtain employment through "formal" channels. Similarly, when Bauer and Haisken-DeNew further subdivide the German labor market, they find support for the employer learning hypothesis among the lowest-paid blue collar workers in isolation, but not among other types of workers. Galindo-Rueda (2003) detects employer learning, but not statistical discrimination, when studying UK workers collectively; further analysis reveals strong evidence for statistical discrimination among white collar UK workers, but none for blue collar UK workers, in direct contrast to Bauer and Haisken-DeNew's results. Finally, Arcidiacono, Bayer and Hizmo (2010) find evidence of statistical discrimination among American high school graduates, but none for university graduates.

From the above discussion, it is clear that one acquires a complete picture of statistical discrimination in a country only by separately considering various subdivisions of its labor market. This is the first principal contribution of my own research to the literature. My study distinguishes American workers with only an undergraduate education from those that have also obtained an MBA. It is the first paper to compare methodically these two labor markets in the context of the EL-SD literature, and it is among the first EL-SD papers to study business-school graduates as a sample. It is also among the first EL-SD papers to examine systematically how statistical discrimination differs across gender.

Equally important, however, is the range of potential bases of discrimination that I examine. A deficit of much of the existing literature is its almost exclusive focus on discrimination by years of schooling. Of the studies mentioned above, only AP and Pan address any factors beyond years of schooling (examining the role of race and immigration status, respectively). Among the few papers that do address other factors, Gill (2012) studies the EL-SD roles of gender, immigration status, and ethnicity for a sample of New Zealand workers. Bordón and Braga (2013) find evidence for discrimination by prestige of Chilean workers' undergraduate institutions, and Heisz and Oreopoulos (2002) find AP's model inconsistent with their EL-SD study of the rankings of Canadian law schools and MBA programs. My paper thus represents an important contribution to our understanding of statistical discrimination on the basis of less-studied factors. It is among the first to apply AP's test to university selectivity and gender, and it is the very first (to the best of the author's knowledge) to examine statistical discrimination on the basis of undergraduate GPA, undergraduate major, and the presence of an MBA.

3. Model

I test for statistical discrimination using the model developed in AP. Consider a model for worker productivity as follows:

$$y_{it} = rs_i + \alpha q_i + \Lambda z_i + \eta_i + H(t_i). \quad (1)$$

Here, y_{it} is the log of labor market productivity, separated into four components: s_i are variables observed by the both the employer and the econometrician, q_i are variables observed by the employer but not the econometrician, z_i are variables observed by the econometrician but not by the employer, η_i are variables observed by neither the employer nor the econometrician, and $H(t_i)$ is some function of the experience of the worker. Employers initially have imperfect knowledge of a worker's productivity and so may statistically discriminate on the basis of known information, q_i and s_i. Employers form expectations of z_i and η_i conditional on q_i and s_i, and they use these expectations to estimate a worker's overall productivity. In a competitive labor market, firms pay a worker an initial wage equal to his expected productivity, namely

$$W_{it} = E(y_{it}|q, s, t) = b_s s_i + b_q q_i + H(t). \quad (2)$$

Employers may gradually learn more about a worker's true productivity, allowing them to rely less on s_i in assessing the unobserved factors of the worker's productivity. The econometrician can therefore estimate a log-wage model of the form

$$w_{it} = E(w_{it}|s,z,t) = \ b_{st}s_i + b_{zt}z_i + H(t), \tag{3}$$

allowing the coefficients on *s* and *z* to vary over time. As underlying ability is increasingly revealed, one might expect the coefficient on s_i to decrease in magnitude over time, while the coefficient on z_i becomes increasingly important in predicting wages. AP formalize this intuition by showing that, in the presence of statistical discrimination, if *s* and *z* are positively correlated and *z* is positively associated with productivity, b_{st} is nonincreasing in *t*, and b_{zt} is nondecreasing in *t*. Similarly, if *s* and *z* are negatively correlated and *z* is positively associated with productivity, b_{st} is nondecreasing in *t*, and b_{zt} is also nondecreasing in *t*. I attempt to verify this prediction for various dimensions of education by estimating (2) with the following specifications:

$$w_{it} = \ \beta_0 + \ \beta_s s_i + \ \beta_z z_i + \beta_{st} s_i x_{it} + \ \ \beta_t f(x_{it}) + \ \beta^T \theta_i + \ \varepsilon_{it} \tag{4}$$

$$w_{it} = \ \beta'_0 + \ \beta'_s s_i + \ \beta'_z z_i + \beta'_{st} s_i x_{it} + \beta_{zt} z_i x_{it} + \ \ \beta'_t f(x_{it}) + \ \beta'^T \theta_i + \ \varepsilon_{it}. \tag{5}$$

As before, w_{it} is the log wage of worker *i* at time *t*. I denote by s_i the (scalar) basis of statistical discrimination I wish to test and by z_i a (scalar) variable known to the econometrician but not to the firm; in the context of this paper, z_i is always positively associated with productivity. I represent the cumulative experience of worker *i* at time *t* as x_{it}, $f(x_{it})$ is a quadratic function of x_{it}, and θ_i is a vector of control variables. I first estimate (4) as a baseline. If the coefficient on *s* changed over time only as a result of the experience profile, it would be sufficient to verify that $\beta'_{st} \leq 0$ (in the case of positive discrimination) or $\beta'_{st} \geq 0$ (in the case of negative discrimination) in equation (5). However, since other factors might influence their change over time, I must compare these coefficients to their baseline values in (4). Thus, if firms positively discriminate on the basis of *s*, then in (5), I should see $\beta_{zt} \geq 0$ (suggesting employer learning in the dimension of *z*) and $\beta'_{st} \leq \beta_{st}$ (suggesting discrimination on the basis of *s*). On the other hand, if firms negatively discriminate on the basis of s, then in (5), I should see $\beta_{zt} \geq 0$ and $\beta'_{st} \geq \beta_{st}$.

4. Data

To estimate the above models, I use a longitudinal survey of registrants for the Graduate Management Admissions Test (GMAT), a requirement for admission to most business schools. The survey, administered from 1990 to 1998, tracks 7,006 registrants through four waves of questionnaires. Of these registrants, 5,602 eventually took the test and 3,249 responded to all four questionnaires, providing a wealth of information about their demographic characteristics, employment history, and experience applying for, and attending, graduate management school. I restrict all my analysis to those who took the GMAT.

This dataset is particularly well-suited to the proposed analysis. In addition to the extensive background information available for each respondent (including gender, race, and family characteristics), one can track each respondent's employment history over a nearly eight-year time period. For each recorded job, one can observe the respondent's current salary, weekly hours of work, job start date, and job end date. There are up to twelve wage observations for the 1,624 respondents that eventually graduated from a graduate management program, seven of which occur prior to matriculation into the program, and I record up to eight observations for those that never graduated from an MBA program. The survey records the tenure (in months) for each job, which allows me to construct a monthly measure of potential cumulative work experience since graduating from an undergraduate institution. For ease of interpretation, I rescale the units of this experience measure to years. I then construct hourly wages for each respondent, first transforming yearly and monthly salaries into weekly salaries under the assumption of fifty business weeks per year and four business weeks per month.

In the context of the models described above, the dataset offers a number of *s* and *z* variables to use in my specifications. The data provides respondents' undergraduate GPA and category of undergraduate major (one of business, social science, humanities, science, and engineering), both of which may be important bases of statistical discrimination.[1] The dataset also identifies the undergraduate institution from which each respondent graduated, as well as the business school the respondent attended. I use university rankings from a *Barron's Guide* to construct a proxy for the prestige of these institutions: a business school is a "top" school if it falls in the top 25 places in the *Barron's* ranking, while undergraduate institutions are ranked from 1 (least competitive) to 9 (most competitive). These rankings allow me to test for discrimination on the basis of school prestige as well.

I identify three *z* variables that could be used for an analysis of statistical discrimination: GMAT scores, father's education, and an individual's stated dedication to his career. For the regressions, I standardize GMAT scores across the sample, and I represent father's education as a dummy for whether or not the father attended college. The first wave of the survey asks respondents to rank how highly they value various aspects of their life, including career, wealth, and family. "Dedication" is a dummy variable that denotes whether a respondent gave the highest possible ranking to both "career" and "wealth." It is highly unusual for firms to ask applicants about GMAT scores, regardless of whether or not they have an MBA. It is also

[1] AP's model assumes that all jobs have the same skill requirements. Accordingly, throughout this paper, I interpret different workers' wage paths to be a function of how firms estimate each worker's underlying "general skills." This is especially important in the test for discrimination by college major, as one might argue that different majors are informative about different sets of underlying skills. For discussion of a "multiple skills" extension to AP's model, see Light and McGee (2012).

unlikely that a firm will know the educational attainment of an applicant's father, or an applicant's subjective dedication to his career. As these variables satisfy the necessary hypothesis that they are known to the econometrician but not observed directly by the firm,[2] they serve as candidates for bases of employer learning over the course of an individual's career. I find that the GMAT score is strongly positively correlated with prestige of schooling (both on the undergraduate and MBA level), undergraduate GPA, the likelihood of majoring in science or engineering, and the likelihood of ultimately obtaining an MBA. Women also score substantially worse on the GMAT than do men. I observe that the father's education and dedication dummies have a similar correlation pattern with the aforementioned *s* variables, though the magnitudes of these relationships are much smaller. Due to clarity of results, I use GMAT scores as the *z* variable in my primary analysis.

To further motivate my decision to distinguish among men and women, and between MBA-holders and non-MBA holders for all of my subsequent tests, I note that respondents often differ considerably by gender and educational attainment in the characteristics described above. I present select summary statistics in the following tables:

[2] Note that the model does not require that firms know nothing about these *z* variables. Indeed, firms may have other information (*q* in the model) that is partially predictive of these variables. The key is that this knowledge is imperfect, as firms cannot observe *z* variables directly.

TABLE 1
Summary Statistics for Four Subsamples

	MBA		No MBA		P-Values	
	Men	Women	Men	Women	Post-MBA Men = Pre-MBA Men	Post-MBA Women = Pre-MBA Women
GMAT (standardized)	0.571	0.216	0.200	-0.218	0.000	0.000
	(0.881)	(0.894)	(0.958)	(0.919)		
Top-25 MBA (dummy)	0.147	0.122				
	(0.354)	(0.328)				
Undergraduate Competitiveness (1-9)	4.513	4.784	4.474	4.141	0.004	0.003
	(2.162)	(2.222)	(2.175)	(2.004)		
Undergraduate GPA (0.00-4.00)	3.032	3.174	2.965	3.050	0.001	0.000
	(0.401)	(0.377)	(0.418)	(0.425)		
STEM Major (dummy)	0.297	0.178	0.305	0.168	0.737	0.633
	(0.457)	(0.383)	(0.460)	(0.374)		
Social Science Major (dummy)	0.176	0.152	0.154	0.161	0.211	0.667
	(0.381)	(0.359)	(0.361)	(0.367)		
Humanities Major (dummy)	0.0623	0.112	0.0503	0.0909	0.268	0.209
	(0.242)	(0.316)	(0.219)	(0.288)		
Business Major (dummy)	0.465	0.557	0.492	0.580	0.267	0.425
	(0.499)	(0.497)	(0.500)	(0.494)		
Father Graduated College (dummy)	0.550	0.477	0.483	0.468	0.006	0.770
	(0.498)	(0.500)	(0.500)	(0.499)		
Black (dummy)	0.0591	0.134	0.0942	0.185	0.008	0.022
	(0.236)	(0.342)	(0.292)	(0.388)		
Hispanic (dummy)	0.149	0.171	0.147	0.129	0.941	0.039
	(0.356)	(0.377)	(0.355)	(0.336)		
Dedicated to Career (dummy)	0.163	0.142	0.222	0.167	0.002	0.234
	(0.370)	(0.349)	(0.416)	(0.373)		
Observations	626	409	1412	1089		

The sample consists of respondents who took the GMAT, and for whom the listed control variables are observed. “MBA” refers to those who eventually graduated from an MBA program, while “No MBA” refers to those who never attended, or never graduated from, an MBA program. Standard errors are given below the means in parentheses. In the last two columns, I provide p-values for whether pre- and post-MBA means are equal for each gender.

TABLE 2
Experience and Wage by Wave

	Wave 1	Wave 2	Wave 3	Wave 4 (MBA)	Wave 4 (No MBA)
Potential Experience	4.692	4.677	6.446	8.087	10.066
(Years) [3]	(4.428)	(4.358)	(4.321)	(5.077)	(4.220)
Log Wage	2.540	2.573	2.726	2.908	3.067
(Log Dollars/Week)	(0.496)	(0.425)	(0.436)	(0.503)	(0.487)
Observations	2870	2450	2950	3105	1144

The sample consists of wage observations for respondents who took the GMAT. I drop the upper 0.5th quantile for both experience and wage. “MBA” refers to those who had graduated from an MBA program by Wave 4, while “No MBA” refers to those who never attended, or never graduated from, an MBA program by Wave 4. All recorded wage observations prior to Wave 4 are prior to an individual’s matriculation into an MBA program. Standard errors are given below the means in parentheses.

There is evidently considerable variation in GMAT score by subsample. Men achieve a significantly higher score than women, and MBA-holders (predictably) achieve a significantly higher score than non-MBA holders. MBA-holders attended more competitive undergraduate institutions than non-MBA holders, though there is relatively little variation between gender (or indeed, overall). Undergraduate GPA is remarkably uniform among all subsamples, whereas men were much more likely to major in a STEM field than were women. Father’s education is also fairly uniform across subsamples, though MBA-holders, and especially male ones, were much more likely to have a college-educated father. Finally, men were more likely than women to express dedication to their careers, though curiously, non-MBA holders recorded higher levels of dedication than did MBA-holders.

[3] Note that the mean experience for Wave 2 declines slightly from the mean experience for Wave 1. This is because respondents that were enrolled in their undergraduate institutions during Wave 1 have now entered the labor market.

5. Primary Results

I now discuss in turn each of the aforementioned bases for discrimination. I break up my sample into two groups. The first includes any wage observations that occur after an individual's graduation from an MBA program (henceforth "post-MBA observations"); the second includes pre-matriculation wage observations for MBA graduates, as well as all wage observations for individuals who never attended an MBA program (henceforth "pre-MBA observations"). I then further subdivide each group by gender. For each regression, I represent an individual's experience profile as a quadratic in potential experience. Standardized GMAT scores are the unobserved *z* variable I use to test for employer learning, and I include control dummies for race (black and Hispanic), gender, major (for each of STEM, humanities, and social sciences, omitting business majors), whether the father attended college, and dedication to career. I further control for undergraduate GPA on a four-point scale, and I use a full range of year dummy variables (1975-1998) to account for inflation and wage trends. Finally, depending on the subsample, I control for either competitiveness of the undergraduate institution, or whether an individual attended a top-25 MBA program. I restrict my observations to full-time jobs (more than 35 hours per week) in which an individual earns more than four dollars per hour, and I report Huber-White standard errors, clustered at the individual level.

5a. Prestige of Schooling

School prestige is a natural basis for statistical discrimination. Admission to competitive universities requires considerable intelligence and work ethic, and more talented individuals tend to matriculate to more competitive universities. Competitive MBA programs go still further, judging individuals not just on their academic merits, but also on the quality of past work experience. It therefore seems plausible that firms will rely on universities' extensive screening of applicants to form judgements about their own potential hires. Indeed, not only are the names of prestigious universities well-known and respected in the labor market, firms also have ready access to this information on a prospective employee's resume.

i. MBA Programs

TABLE 3
The Effects of Standardized GMAT and MBA Prestige on Wages for post-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
Top-25 MBA	0.249***	0.258***	0.269***	0.260***	0.240	0.257
	(0.0625)	(0.0637)	(0.0722)	(0.0728)	(0.132)	(0.134)
Top-25 MBA * Pot. Exp.	-0.00326	-0.00426	-0.00388	-0.00275	-0.00628	-0.00842
	(0.00745)	(0.00762)	(0.00834)	(0.00840)	(0.0176)	(0.0178)
GMAT	0.0481***	0.0365	0.0423*	0.0568*	0.0536*	0.0312
	(0.0141)	(0.0210)	(0.0173)	(0.0252)	(0.0245)	(0.0398)
GMAT * Pot. Exp.		0.00143		-0.00174		0.00290
		(0.00218)		(0.00257)		(0.00441)
Female	-0.0705**	-0.0708**				
	(0.0233)	(0.0232)				
N	2680	2680	1623	1623	1057	1057
adj. R^2	0.436	0.436	0.467	0.467	0.373	0.373

The sample consists of post-MBA wage observations among respondents who took the GMAT and ultimately graduated from an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, undergraduate GPA, college major, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I begin by looking at the effect of MBA prestige, using as my sample all post-MBA wage observations. In the baseline regression for the aggregate sample (1), attending a top-25 MBA program has a significant effect on log wages, increasing them by .249 (corresponding to a 24.9% in actual wages). A one-standard-deviation increase in GMAT score corresponds to a

.0481 increase in log wages; although this coefficient is statistically significant, its magnitude is quite small. Furthermore, the baseline regression suggests that returns to a top MBA program hardly change over time, as a one-year increase in experience corresponds to only a .00326 decrease in log wage. I then add an interaction term between GMAT score and experience in (2). The coefficients do change in the manner predicted by the EL-SD hypothesis (the interaction between GMAT score and experience is positive, while the interaction between top MBA program and experience drops), but these changes are minuscule. Despite the strong correlation between GMAT score and attending a top program, none of the interaction term coefficients are statistically significant, and the magnitudes of the implied changes in wages over time are negligible. [4]

I then perform the same analysis separately for men and women. We first note that the coefficient estimates for men broadly follow those of the sample as a whole: model (3) shows that men benefit substantially from attending a top MBA program (corresponding to a wage increase of .269), and that the benefit of a higher score on the GMAT is comparable to the aggregate sample. That none of the interaction coefficients in (4) are significant suggests no evidence of employer learning, at least not regarding the skills about which the GMAT is informative.

A priori, one might imagine that statistical discrimination plays a larger role for women than it does for men: many women drop out of the labor force in order to raise a family, and so employers might see a degree from a top business school as evidence of a woman's commitment to her job. The results are not consistent with this hypothesis. Indeed, (6) suggests that the initial

[4] The results in this section are robust to how I define a "top" MBA program. If I repeat the analysis with a dummy variable for a top-10 MBA program, for example, I find that the coefficient on "top-10" is somewhat lower, though returns to "top-10" increase somewhat over time. Adding the GMAT-experience interaction term has an entirely negligible effect on the return profile to "top-10."

wage effect of attending a top MBA program is comparable between women and men, and once again, none of the interaction coefficients are statistically significant.

ii. Undergraduate Programs

TABLE 4
The Effects of Standardized GMAT and Undergraduate Competitiveness on Wages for pre-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
Competitive	0.0103^{*}	0.0126^{*}	0.00681	0.00835	0.0158^{*}	0.0187^{*}
	(0.00474)	(0.00492)	(0.00622)	(0.00630)	(0.00737)	(0.00759)
Competitive * Pot. Exp.	0.000594	0.000253	0.000595	0.000382	0.000594	0.000104
	(0.000640)	(0.000684)	(0.000930)	(0.000937)	(0.000804)	(0.000896)
GMAT	0.0315^{***}	0.0179	0.0278^{*}	0.0172	0.0406^{**}	0.0246
	(0.00866)	(0.0115)	(0.0112)	(0.0149)	(0.0135)	(0.0175)
GMAT * Pot. Exp.		0.00232		0.00174		0.00296
		(0.00146)		(0.00182)		(0.00225)
Female	-0.0650^{***}	-0.0660^{***}				
	(0.0131)	(0.0131)				
N	6880	6880	3861	3861	3019	3019
adj. R^2	0.397	0.397	0.406	0.406	0.364	0.365

The sample consists of all wage observations among respondents who took the GMAT, excluding jobs held after matriculation into an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, undergraduate GPA, college major, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I now examine the role of the competitiveness of respondents' undergraduate institutions, using pre-MBA observations as my sample. I note a pattern of results similar to that described above. I first observe that returns to attending more competitive undergraduate institutions are substantially lower than returns to attending top MBA programs. Model (1) suggests that, for the sample as a whole, attending a school that is one "competitiveness rank" higher results in a log wage increase of just .0103, which corresponds to a 1.03% increase in the wage.[5] We might interpret this result to indicate that undergraduate education is less reflective of a worker's productivity than is an MBA education; recall that the prestige of an MBA program reflects the quality of a student's prior work experience, whereas few undergraduates have substantial work experience prior to matriculating. The effect of GMAT scores on wages is somewhat smaller for pre-MBA jobs, with a one-standard-deviation increase in score corresponding to a .0315 increase in log wages, and there is a similar gender wage gap for both types of jobs.

Model (2) suggests that returns to undergraduate prestige and to GMAT scores, just as with post-MBA job observations, change little over time. Though the *z* interaction term is positive and the *s* interaction term has decreased, neither coefficient is statistically significant, and the magnitudes of both are inconsequential: the coefficient on the GMAT score grows by only one-tenth with every additional year of experience. Once again, we cannot conclude that employer learning takes place in any significant capacity.

Dividing the sample by gender leads to similar conclusions. Comparing (4) and (6), we observe that women initially receive a higher premium to attending a more competitive college, and that GMAT scores are a more important factor in determining female wages than male wages. Nonetheless, the insignificance of the interaction terms in both models suggest no evidence of employer learning or statistical discrimination.

[5] This result is robust to how "competitiveness" is coded. A dummy variable for the most competitive schools (top 10%) results in similarly low estimates of returns to a prestigious undergraduate institution.

5b. Undergraduate GPA and Major

Yet another basis for statistical discrimination is an indicator of performance in college. A student's GPA concisely summarizes four years of educational attainment and reflects an individual's problem-solving capacity in a variety of contexts. Previous analysis reveals that it is strongly linked with a higher wage, and employers have ready access to this information on an applicant's resume. Thus, it is reasonable to hypothesize that employers use undergraduate GPA to form expectations about less apparent correlates of productivity. Similarly, students may have substantially different experiences in college, depending on their choice of academic path. Some literature suggests that students may self-sort by ability into more or less difficult college majors, and there is a widespread perception that STEM (science, technology, engineering, and math) majors are more challenging than other courses of study.[6] It is on these grounds that I test for statistical discrimination by college major as well. I standardize all GPA measures to a 4-point scale, while I represent STEM majors with a dummy variable.

[6] Note that college graduates with different majors may differ not only in underlying ability, but may also obtain occupation-specific knowledge and skills through their course of study. I abstract from this detail and assume that employers understand choice of major purely as evidence of a worker's general skills and abilities.

TABLE 5
The Effects of Standardized GMAT and Undergraduate GPA on Wages for post-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
GPA	0.173***	0.179***	0.170**	0.162**	0.124	0.145
	(0.0468)	(0.0473)	(0.0570)	(0.0563)	(0.0759)	(0.0773)
GPA * Pot. Exp.	-0.00523	-0.00593	-0.000677	0.0000631	-0.00458	-0.00771
	(0.00508)	(0.00517)	(0.00596)	(0.00582)	(0.00793)	(0.00880)
GMAT	0.0479***	0.0344	0.0422*	0.0578*	0.0540*	0.0255
	(0.0141)	(0.0213)	(0.0173)	(0.0249)	(0.0246)	(0.0425)
GMAT * Pot. Exp.		0.00166		-0.00187		0.00373
		(0.00225)		(0.00253)		(0.00497)
Female	-0.0699**	-0.0701**				
	(0.0232)	(0.0232)				
N	2680	2680	1623	1623	1057	1057
adj. R^2	0.436	0.436	0.467	0.467	0.373	0.373

The sample consists of post-MBA wage observations among respondents who took the GMAT and ultimately graduated from an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, college major, stated dedication to career, and whether an individual's father attended college, whether the MBA program attended was ranked in the top 25, and year dummies. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Beginning with observations of post-MBA jobs, we immediately notice that undergraduate GPA plays a very large role in determining initial wages, even after controlling for the quality of the MBA program. For the aggregate sample, in (2), a one-point increase in GPA corresponds to a .173 increase in log wage – seventy percent of the increase associated with attending a top-25 business school – and this effect remains large even after many years of experience. We do not, however, observe evidence of statistical discrimination on this basis. Model (2) shows that returns to GPA remain essentially static over time, as the coefficients on the interaction terms are all statistically insignificant.

Comparing the male and female subsamples, my conclusions remain the same. GPA appears to play an equally important role in determining wages for both men and women (.162

and .145, respectively), but the introduction of the GMAT-experience interaction term in (4) and (6) does not cause returns GPA to fall over time to any significant degree.

TABLE 6
The Effects of Standardized GMAT and Undergraduate GPA on Wages for pre-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
GPA	0.164^{***}	0.184^{***}	0.151^{***}	0.163^{***}	0.151^{***}	0.180^{***}
	(0.0236)	(0.0247)	(0.0324)	(0.0342)	(0.0350)	(0.0354)
GPA * Pot. Exp.	-0.00632	-0.00955^{**}	-0.00103	-0.00289	-0.00796	-0.0134^{**}
	(0.00323)	(0.00344)	(0.00478)	(0.00513)	(0.00437)	(0.00425)
GMAT	0.0311^{***}	0.00812	0.0273^{*}	0.0131	0.0406^{**}	0.00994
	(0.00865)	(0.0116)	(0.0112)	(0.0155)	(0.0134)	(0.0168)
GMAT * Pot. Exp.		0.00396^{**}		0.00234		0.00572^{**}
		(0.00147)		(0.00195)		(0.00194)
Female	-0.0640^{***}	-0.0654^{***}				
	(0.0131)	(0.0131)				
N	6880	6880	3861	3861	3019	3019
adj. R^2	0.397	0.399	0.406	0.407	0.366	0.368

The sample consists of all wage observations among respondents who took the GMAT, excluding jobs held after matriculation into an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, competitiveness of undergraduate institution, college major, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

My results are much more interesting when we consider pre-MBA job observations. Again, we notice that GPA is a highly statistically significant determinant of log wage, with model (2) suggesting almost exactly the same effect (.184) as for MBA-holders. In this case, however, all of the interaction terms are significant. The coefficient on GMAT drops from .0311 in (1) (significant for a p-value of .001) to .00812 in (2) (statistically insignificant). On the other hand, the interaction between the GMAT score and experience comes in at .00396, which is significant at a p-value of .01. At the same time, the interaction between GPA and experience drops from -.00632 (statistically insignificant) to -.00955 (significant at p=.01). These observations are entirely consistent with the predictions of the EL-SD hypothesis. At zero experience, model (2) suggests that employers know nothing about the (unobserved) GMAT score, and so it plays no role in determining wage. Over time, however, employers learn about a worker's productivity in the dimension of his GMAT score, causing its coefficient to rise. The coefficient on undergraduate GPA simultaneously falls, indicating that employers placed undue initial weight on GPA in estimating productivity. Indeed, over a nine-year period (the total timeframe covered by this longitudinal survey), returns to undergraduate GPA should drop by almost half to .098.

Further subdividing the sample, we see that women account for almost the entirety of the statistical discrimination described above.[7] For men, the introduction of the GMAT interaction term in (4) causes the GPA interaction term to fall slightly, but neither interaction term is significant. For women, on the other hand, the effects of statistical discrimination are even more pronounced than they are for the whole sample. At zero experience, the coefficient on the GMAT score is insignificant, but it becomes increasingly important over time. Simultaneously, the GPA interaction coefficient of -.00796 in (5) drops to -.0134 in (6). This implies that, for women, returns to GPA should fall by 67% to .059 over a nine-year period.

[7] Note that sampling error may explain part, though likely not the entire, difference between genders.

TABLE 7
The Effects of Standardized GMAT and Major on Wages for pre-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
STEM Major	0.191***	0.200***	0.230***	0.237***	0.153***	0.166***
	(0.0222)	(0.0225)	(0.0269)	(0.0272)	(0.0366)	(0.0362)
STEM Major * Pot. Exp.	-0.00483	-0.00646	-0.0105**	-0.0118**	-0.00147	-0.00390
	(0.00321)	(0.00332)	(0.00393)	(0.00398)	(0.00491)	(0.00480)
GMAT	0.0315***	0.0134	0.0288*	0.0108	0.0404**	0.0217
	(0.00867)	(0.0113)	(0.0112)	(0.0149)	(0.0135)	(0.0169)
Soc. Sci. Major	-0.0432*	-0.0413*	-0.0588*	-0.0564*	-0.0268	-0.0252
	(0.0185)	(0.0185)	(0.0243)	(0.0244)	(0.0284)	(0.0284)
Humanities Major	-0.0540*	-0.0545*	-0.0636	-0.0612	-0.0426	-0.0453
	(0.0250)	(0.0250)	(0.0417)	(0.0416)	(0.0306)	(0.0304)
GMAT * Pot. Exp.		0.00314*		0.00303		0.00345
		(0.00143)		(0.00183)		(0.00207)
Female	-0.0647***	-0.0662***				
	(0.0131)	(0.0131)				
N	6880	6880	3861	3861	3019	3019
adj. R^2	0.397	0.398	0.409	0.409	0.364	0.365

The sample consists of all wage observations among respondents who took the GMAT, excluding jobs held after matriculation into an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, competitiveness of undergraduate institution, undergraduate GPA, stated dedication to career, whether an individual's father attended college, and year dummies. The omitted undergraduate major category is business. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

With regard to choice of major, we observe that STEM fields have a strongly positive association with wages for pre-MBA jobs[8], but we do not find evidence of statistical discrimination on this basis. Indeed, we observe that STEM majors command a log wage premium of .200 for the sample as a whole, about the same effect as a one-point increase in

[8] I omit discussion of undergraduate major for post-MBA jobs, as both the STEM dummy and its interaction are insignificant for this sample and its subdivisions by gender.

GPA. Men, interestingly, receive a much higher return on choosing a STEM major than do women; compare the male coefficient of .237 in (4) with the female coefficient of .166 in (6). Men are also the only group for which the STEM interaction term is statistically significant, and over nine years, returns to the STEM major fall by nearly half. For all three groupings, however, we cannot conclude that statistical discrimination exists in this dimension. With the addition of the GMAT interaction term, the STEM interaction terms either hardly change (implying that the decline in the STEM coefficient for men is due to other causes) or remain statistically insignificant, and none of the GMAT interaction terms are significant.

5c. Gender

Yet another potential means of employer discrimination is on the basis of gender. My previous regressions record a small, but statistically significant, gap between male and female wages. There exists an extensive literature analyzing this gender gap, and an EL-SD test allows one to examine the role of statistical discrimination in causing it. An EL-SD hypothesis asserts that firms initially use gender as a proxy for unobserved negative correlates of productivity; perhaps firms perceive that women are less dedicated than men to their careers, or that women are more inclined to drop out of the labor market in the interests of raising a family. If this is true, then as firms learn more about a woman's true productivity the coefficient on "female" should become less negative, and unobserved correlates of productivity should play a larger role in determining the wage.

TABLE 8
The Effects of Standardized GMAT and Gender on Wages
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Post-MBA	(2) Post-MBA	(3) Pre-MBA	(4) Pre-MBA
Female	0.0287	0.0295	-0.0116	-0.0149
	(0.0375)	(0.0386)	(0.0188)	(0.0187)
Female * Pot. Exp.	-0.0130**	-0.0131**	-0.00986***	-0.00944***
	(0.00440)	(0.00461)	(0.00272)	(0.00271)
GMAT	0.0474***	0.0493*	0.0313***	0.0196
	(0.0140)	(0.0211)	(0.00866)	(0.0112)
GMAT * Pot. Exp.		-0.000234		0.00202
		(0.00220)		(0.00133)
N	2680	2680	6880	6880
adj. R^2	0.440	0.440	0.399	0.399

The sample consists of all wage observations among respondents who took the GMAT. Potential experience is modeled with a quadratic polynomial. All equations control for race, major, undergraduate GPA, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze post-MBA job observations among those who graduated from an MBA program, while columns (3) and (4) analyze job observations prior to matriculation into an MBA program. Accordingly, models (1) and (2) also control for whether the a respondent's MBA program is ranked in the top 25, while models (3) and (4) control for competitiveness of a respondent's undergraduate institution. Standard errors are Huber-White standard errors, clustered at the individual level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For both pre- and post-MBA jobs observations, my results are inconsistent with the EL-SD hypothesis for gender. Examining (1) and (3), we observe that by adding an interaction term between female and experience, the starting gender gap disappears: at zero experience, the coefficients on female are not statistically different from zero. On the other hand, the female interaction term is highly significant. Model (1) predicts that returns to female should decline by .117 in nine years, while (3) estimates a decline of .0887 in the same period. Adding the GMAT interaction in (2) and (4) does not significantly affect the female interaction terms, and the coefficients on the GMAT interactions are statistically insignificant.

Recall from Section 4 that women score nearly half a standard deviation worse on the GMAT than do men. Given this strongly negative correlation, in the presence of employer learning, we should expect a large positive coefficient on the GMAT interaction, and the female interaction coefficient should become considerably less negative when the GMAT interaction is added. That the GMAT interaction is insignificant and the female interaction does not appreciably change suggests little evidence of employer learning, at least in the dimensions measured by the GMAT. Moreover, the profile of returns to female (starting at zero and sharply declining over time) is clearly not consistent with a story whereby firms discriminate by gender at the time of hiring, but rather suggest that a difference in productivity emerges over time. A further analysis of this dataset may be well-suited to investigating the cause of this evolution.

5d. Presence of MBA

TABLE 9
The Effects of Standardized GMAT and MBA on Wages
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Men	(4) Men	(5) Women	(6) Women
Graduated	0.0180	0.0213	0.00802	0.0107	0.0438	0.0450
	(0.0211)	(0.0211)	(0.0277)	(0.0277)	(0.0316)	(0.0315)
Graduated * Pot. Exp.	0.000829	0.000366	-0.0000517	-0.000474	0.000304	0.000241
	(0.00285)	(0.00286)	(0.00355)	(0.00357)	(0.00423)	(0.00425)
GMAT	0.0380^{***}	0.0235	0.0308^{**}	0.0217	0.0504^{***}	0.0371^{*}
	(0.00943)	(0.0124)	(0.0118)	(0.0162)	(0.0151)	(0.0184)
GMAT * Pot. Exp.		0.00216		0.00134		0.00207
		(0.00134)		(0.00171)		(0.00185)
Female	-0.0699^{***}	-0.0707^{***}				
	(0.0143)	(0.0143)				
N	7760	7760	4369	4369	3391	3391
adj. R^2	0.440	0.440	0.450	0.450	0.408	0.409

The sample consists of all wage observations among respondents who took the GMAT. Potential experience is modeled with a quadratic polynomial. All equations control for race, major, undergraduate GPA, competitiveness of

undergraduate institution, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Lastly, I analyze the entire collective sample to investigate statistical discrimination on the basis of having an MBA ("Graduated"). The baseline characteristics of this aggregate group are comparable to the subgroups I previously considered: the effect of a one-standard-deviation increase in GMAT score corresponds to a significant .0380 increase in log wage, and there is a sizable gender gap of -.0699. For all subdivisions of the sample, when both Graduated and its interaction with experience are included in the regression, neither term is significant. We also note that women gain considerably more from an MBA than do men.

Once again, the tests provide little evidence of statistical discrimination. The addition of the GMAT interaction term in (2), (4), and (6) hardly changes the graduated interaction term, and all interactions are not statistically significant. Although one might expect the test to be successful for women alone – it seems plausible that firms favorably estimate the career-dedication of women who have obtained an MBA – the results offer no evidence in favor of the EL-SD hypothesis, regardless of sample subdivision.

5e. General Remarks

With few exceptions, I observe little overall evidence of employer learning or statistical discrimination, regardless of the combination of *s* variable and subsample that I analyze. Though past literature suggests that the role of statistical discrimination varies considerably within a particular country, my results are similar across various subdivisions of the sample. This outcome is consistent with a story whereby employers are very well-informed about most members of my sample. Recall that the survey on which my results are based tracks registrants for the GMAT; these are highly educated individuals that have already graduated from an undergraduate institution, or who graduate from such an institution within the first two years of the survey. These are also likely to be highly career-driven individuals, having expressed an implicit interest in obtaining a career-focused advanced degree. Employers likely have a wealth of information by which to assess productivity of this sample. Even beyond college ranking, GPA, and major, they can observe undergraduate internships, extracurricular activities, and any number of other factors that are informative about productivity. It seems reasonable that employers know much more about this sample than they would about, for example, the less educated samples analyzed in AP and much of the rest of the existing literature.

These results are consistent with Arcidiacono et al.'s lack of evidence for the EL-SD hypothesis among university graduates, as well as with Bauer and Haisken-DeNew's similar conclusions regarding German white-collar workers. The latter two authors suggest that employers screen prospective white-collar workers much more thoroughly than prospective blue-collar workers, leaving less room for subsequent employer learning. An alternative explanation advanced by Bauer and Haisken-DeNew is that white-collar work is "noisy" and difficult to learn from. Whereas it is relatively easy to associate the tangible products of blue-collar labor with underlying skills, the input and output of white-collar workers involve less tangible "ideas" that are difficult to relate to inherent productivity. Bordón and Braga's findings do suggest the existence of statistical discrimination among college-educated workers, though as Broecke's analysis suggests, there is little reason to believe that the authors' conclusions about Chilean workers should hold true in other countries.

6. Secondary Results

In this section, I assess the robustness of my findings in Section 5 using alternative measures of experience. I also present various secondary results, including a discussion of alternative *z* variables and the relative magnitudes of interaction coefficients in the above models.

6a. Actual Cumulative Experience versus Potential Experience

As a first robustness check, following the example of AP, I recalculate the regressions in Section 5 using actual experience, rather than potential experience, as my experience measure. Note that actual experience is endogenous insofar as it conveys information about a worker's productivity in and of itself—more productive workers are likely to have more actual work experience. Consequently, I instrument actual experience and all of its interactions with potential experience and its corresponding interactions.

For almost all bases of discrimination, my results differ little using this alternative measure of experience. The interaction between GMAT and actual experience is invariably insignificant, and the introduction of this interaction term has little to no impact on the return profile of the *s* variable. These results (not reported) further suggest the absence of statistical discrimination on the basis of university prestige, undergraduate major, gender, and presence of an MBA.

The one noticeable difference between this set of results and that reported in Section 5 involved discrimination by GPA for pre-MBA observations. In contrast to my primary results, where I found strong evidence in favor of the EL-SD hypothesis among the aggregate pre-MBA sample and among pre-MBA women, I find little evidence of statistical discrimination using this alternative experience measure. The baseline profile of returns to GPA is very similar across the two sets of results: the coefficient at zero experience is .164 for the aggregate sample and .153 for women (cf. .184 and .180 in the original specification), while the GPA interaction coefficients are -.00712 for the aggregate sample and -.0104 for women (cf. -.00955 and -.0134 in the original specification). Crucially, however, the GMAT interaction coefficient is statistically insignificant in both samples. Adding this interaction in models (2) and (4) does not significantly affect the GPA interaction coefficient, contradicting the evidence for statistical discrimination observed in Section 5b.

TABLE 10
The Effects of Standardized GMAT and Undergraduate GPA on Wages for pre-MBA Jobs
Dependent Variable: Log Wage; IV estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Women	(4) Women
GPA	0.154***	0.164***	0.132**	0.153**
	(0.0307)	(0.0337)	(0.0470)	(0.0549)
GPA * Pot. Exp.	-0.00583	-0.00712	-0.00756	-0.0104
	(0.00409)	(0.00449)	(0.00632)	(0.00743)
GMAT	0.0430***	0.0330*	0.0634***	0.0469
	(0.00934)	(0.0158)	(0.0150)	(0.0254)
GMAT * Pot. Exp.		0.00150		0.00260
		(0.00205)		(0.00305)
Female	-0.0519***	-0.0528***		
	(0.0139)	(0.0140)		
N	6586	6586	2881	2881
adj. R^2	0.358	0.359	0.310	0.309

The sample consists of all wage observations among respondents who took the GMAT, excluding jobs held after matriculation into an MBA program. Potential experience is modeled with a quadratic polynomial. All equations control for race, competitiveness of undergraduate institution, college major, stated dedication to career, whether an individual's father attended college, and year dummies. Columns (1) and (2) analyze the aggregate sample, while columns (3) and (4) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6b. Start MBA Experience at Zero

In response to literature suggesting more educated individuals face less statistical discrimination, Light and McGee (2013) demonstrate that EL-SD conclusions are sensitive to how the econometrician defines the start date of an individual's career. Light and McGee show that, if the period over which employers learn is overstated, then the EL-SD model underestimates the extent of employer learning. The authors first reproduce Arcidiacono et al.'s evidence that high school graduates, but not college graduates, face discrimination on the basis of years of education. They then re-estimate their model for college graduates, redefining the beginning of these individuals' careers as the date of graduation from an undergraduate institution. From this, Light and McGee conclude that high school and college graduates face comparable levels of discrimination.

The jobs one secures after graduating from an MBA program often differ substantially from pre-MBA jobs. Indeed, obtaining an MBA is often a key step in transitioning from a purely analytic role to a managerial position. If the nature of one's employment is, in fact, considerably different upon graduation, then firms may find pre-MBA work experience relatively uninformative with regard to assessing an MBA-graduate's productivity. My analysis of post-MBA observations may therefore underestimate the true extent of employer learning for that subsample. To correct for this, I perform Light and McGee's analysis with respect to post-MBA jobs. In re-estimating each of the models in Tables 3 and 5, as well as models (1) and (2) in Table 7, I once again use potential experience as my experience measure. This time, however, I allow work experience to accumulate only upon graduation from an MBA program. My results for post-MBA observations become somewhat sharper when I use this alternative measure of experience: the magnitudes of the *s* and *z* interaction coefficients increase, and these interactions become more statistically significant.

Overall, restarting MBA experience from zero causes my post-MBA results to align more closely with my pre-MBA results. Despite the increased statistical significance of the interactions terms, most of them remain insignificant at the 5%-level. My new results do broadly follow the predictions of AP's model (the GMAT interaction term is positive, while the *s* interaction changes appropriately from its baseline specification); nevertheless, the small magnitudes of these effects do not provide evidence of statistical discrimination on the basis of school prestige, major, or gender for MBA graduates. On the other hand, I do now find evidence for the EL-SD hypothesis among MBA graduates on the basis of undergraduate GPA. As with the pre-MBA sample, this evidence manifests itself among the among post-MBA women, but not among post-MBA men.

TABLE 11
The Effects of Standardized GMAT and Undergraduate GPA on Wages for post-MBA Jobs
Dependent Variable: Log Wage; OLS estimates (standard errors).

	(1) Aggregate	(2) Aggregate	(3) Male	(4) Male	(5) Female	(6) Female
GPA	0.189^{***}	0.202^{***}	0.181^{**}	0.177^{**}	0.187^{**}	0.228^{**}
	(0.0465)	(0.0470)	(0.0620)	(0.0625)	(0.0680)	(0.0706)
GPA * Pot. Exp. (MBA)	-0.0257^{*}	-0.0306^{*}	-0.0177	-0.0162	-0.0373	-0.0522^{*}
	(0.0128)	(0.0132)	(0.0171)	(0.0176)	(0.0196)	(0.0215)
GMAT	0.0589^{***}	0.0442^{*}	0.0495^{*}	0.0534	0.0772^{**}	0.0291
	(0.0171)	(0.0222)	(0.0225)	(0.0312)	(0.0277)	(0.0335)
GMAT * Pot. Exp. (MBA)		0.00570		-0.00147		0.0192^{*}
		(0.00507)		(0.00709)		(0.00923)
Female	-0.0942^{***}	-0.0952^{***}				
	(0.0278)	(0.0278)				
N	2089	2089	1261	1261	828	828
adj. R^2	0.327	0.327	0.330	0.330	0.290	0.293

The sample consists of post-MBA wage observations among respondents who took the GMAT and ultimately graduated from an MBA program. Potential experience is modeled with a quadratic polynomial. All equations

control for race, college major, stated dedication to career, whether an individual's father attended college, whether the MBA program attended was ranked in the top 25, and year dummies. Potential experience equals zero upon graduation from an MBA program. Columns (1) and (2) analyze the aggregate sample, columns (3) and (4) analyze males, and columns (5) and (6) analyze females. Standard errors are Huber-White standard errors, clustered at the individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Comparing Table 11 with Table 5, I note that undergraduate GPA now plays a much more significant role in determining post-MBA wages, especially for women: a one-point increase in GPA corresponds to a .177 increase in initial log wage for men, a .228 increase in initial log wage for women, and a .202 increase in initial log wage for the aggregate sample. In model (6) (the female sample), returns to the GMAT at zero experience are no different from zero. However, the GMAT interaction terms is statistically significant, with a one-standard-deviation increase in score corresponding to a 1.92% yearly wage increase. Finally, the GPA interaction term in model (6) noticeably drops from its baseline value in model (5), becoming significant at the 5% level. Model (6) predicts returns to GPA for women will decline to zero in only 4.4 years. This is a much faster rate of learning than what I observe for the pre-MBA sample, where GPA remains an important determinant of wage with even nine years of experience.

6c. Other *z* Variables

Most papers in the EL-SD literature use some form of aptitude test as their *z* variable, though others have used parental education or sibling wage rate as alternative unobserved correlates of productivity. My dataset offers sufficient data to repeat the above analysis using both parental education and a variety of subjective measures of dedication to one's job. As a proxy for parental education, I construct a dummy variable for whether an individual's father attended college, and I construct a "dedication" dummy for those that, in a series of opinion questions in the Wave 1 survey, ranked "career" and "wealth" as "very important."[9] As discussed briefly in Section 4, the father's education dummy is positively correlated with schooling prestige, undergraduate GPA, majoring in a STEM field, and graduating from an MBA program, but negatively correlated with the "female" dummy. The dedication dummy is negatively correlated with graduating from an MBA program, but otherwise follows the same correlation pattern as the father's education dummy. Even so, regressions of the various *s* variables on these alternative *z* variables reveal much weaker relationships than those that emerge when I use standardized GMAT scores as the *z* variable.

When I use these alternative *z* variables in the regressions of Section 5, their baseline coefficients (i.e., before I add the *z* interaction terms) are generally, though not always, significant. The *z* interaction coefficients, on the other hand, are invariably insignificant, and their inclusion in the regression has no significant effect on the *s* interactions. These results broadly support my earlier findings regarding the absence of employer learning, though I state this conclusion with some reservations. First, AP's model predicts that a weak correlation between the *z* and *s* variables will cause only a small change in the *s*-interaction coefficient. Thus, with these variables especially, I cannot immediately associate the small effect on the return profile to *s* with an absence of statistical discrimination. It is also unclear that father's education and this dedication dummy measure the same underlying elements of productivity as does an individual's GMAT scores. Though I attribute the insignificance of these new *z* interactions to an absence of employer learning, I caution that they may measure a different dimension of employer learning than the one detailed in Section 5.

[9] Alternative ways of constructing an individual's level of dedication to his career did not substantially affect my results.

6d. Relative Magnitude of Effects

AP's model offers a second testable prediction of the EL-SD hypothesis, concerning the relative magnitudes of the interaction coefficients. Intuitively, the extent to which the *s* variable declines in importance should be proportional to the extent to which employers learn about the *z* variable. AP show that this is indeed the case, and that the constant of proportionality is actually the regression coefficient of *z* on *s*. Using the notation in Equation (5), AP predict that $-\frac{cov(s,z)}{var(s)}\beta_{zt} = \beta'_{st}$, which I attempt to verify for the models in Section 5 in which I found evidence of statistical discrimination. Allowing GPA to be the *s* variable, I first test this proposition for the aggregate sample of pre-MBA observations. The GPA interaction coefficient is -.00955, while the GMAT interaction coefficient is .00396; multiplying the GMAT interaction with the negative of the regression coefficient (0.7566) results in a value of –.00300. A Wald test rejects that this is the same as the GPA interaction coefficient (p=.0418). Restricting my test to female pre-MBA observations yields a similar result. The GMAT interaction coefficient (.00571) times the negative of the regression coefficient (.860) yields a value of –.00492. Comparing this to the GPA interaction coefficient (-.0134), a Wald test rejects equality (p= .0430).

In both cases, the magnitude of the change in returns to GPA is greater than the (appropriately scaled) change in returns to GMAT score. This is unsurprising: the baseline models for these samples reveal an exogenous decline in returns to GPA over time, independent of employer learning about the GMAT. It is possible that employers learn about other unobserved correlates of productivity, leading to the decline in the GPA coefficient over time. Alternatively, this observation may be consistent with a model in which individuals with a low GPA receive remedial training.

7. Conclusion

This paper tests whether employers statistically discriminate on the basis of school prestige, undergraduate GPA, undergraduate major, gender, and whether an individuals has an MBA. Using a test developed in Altonji and Pierret (2001), I find evidence that employers do discriminate on the basis of undergraduate GPA, especially among women, but there is little evidence to suggest discrimination by school prestige, undergraduate major, gender, or presence of an MBA degree. My results are fairly uniform across MBA-graduates and college graduates: they suggest that women in both groups face discrimination by GPA, while neither group appears to face discrimination on the basis of other factors. My results also differ little by gender, with neither men nor women facing extensive overall discrimination.

I interpret my results to suggest that for well-educated samples, such as the one this paper investigates, firms are relatively well informed about the productivity of their employees at time of hire. Consequently, employer learning and statistical discrimination play at most a small role in determining employees’ wages. Few other studies have evaluated the EL-SD hypothesis for such a highly educated sample, though my results support the existing literature in affirming that highly educated individuals face relatively little statistical discrimination. A further study might investigate the extent to which these conclusions hold for a variety of career paths, assessing the importance of employer learning in a variety of industries. It would also be worthwhile to examine whether my conclusions regarding gender discrimination are applicable to a more representative sample of the US labor force.

8. References

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