Online Appendices to The Male-Female Gap in Post-Baccalaureate School Quality

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A Appendix

A.1 Data

My primary source of institutional data is the Integrated Postsecondary Education Data System (IPEDS), the census of institutions of higher education receiving federal financial aid in the U.S. I use IPEDS completions data between 1985 (when it began to count degrees earned by men and women separately) and 2006. The data includes the entire population of individuals earning a degree in a given year, including imputed data.[1]

For doctoral and master's program quality, I use the 1994 Study of Research Doctorate Programs (SRDP) data (Goldberger et al. 1995). For each institution offering a PhD in each of the 41 included fields, the SRDP surveyed faculty within that field to rank every program that they are familiar with on a scale from zero ("scholarly quality is insufficient for work at the graduate level") to five ("scholarly quality is distinguished beyond that of peer institutions"). This reputational measure covers 90% of students in the surveyed fields and 50% of all U.S. PhDs granted annually. I impute this ranking to master's degree programs in that field at that institution, if any.

For non-arts-and-sciences PB programs, I use a recent edition of the U.S. News and World Report's "America's Best Graduate Schools" survey (USNWR, 2005). The ranking system they use varies by field, generally using average student test scores for

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[1] In most years, imputed data accounts for less than 5% of observed degrees.

larger fields like law, medicine, business and education while using the reputational scale (which is for all intents and purposes identical to the SRDP's) in most other fields. Where available, I used the more objective test score measure of quality, and I used reputational scores for all other degree programs.

Most of the fields surveyed by USNWR have extensive coverage, ranging from 91% of law programs to 31% (274 of 884 programs) in education. In fields where coverage was large (more than half of the programs offering a degree are explicitly ranked) and published quality data was censored from the bottom, I imputed a quality quantile of one to programs with missing data, implying below-median selectivity.[2] In fields where the full range of the quality scale is observed, it was not reasonable to infer low quality from unreported data and I did not use any quality data for these programs. The resulting quality dataset has much broader breadth and depth than any used in previous work that I am aware of.[3]

For a small number of students, I impute PB school quality. Whenever possible, I assign students to the observed quality rank of their actual major. If this is not possible, I assign the student the average quality of ranked PB majors in their degree program within their institution. In a small number of vocational majors, the USNWR ranking data is truncated at the bottom to simply indicate low rank. For these students, I estimate program quality based on student demographics, undergraduate background and PB institution characteristics among students in the bottom half of PB quality, and then impute the prediction to the students with truncated data.

I obtain student-level data from the National Center for Educational Statistics' Baccalaureate and Beyond (B&B) survey. The B&B started as a representative sample of all individuals who earned a bachelor's degree from accredited U.S. institutions in 1993. Follow-up surveys were given in 1994, 1997, and 2003. The 1993 and 1994 surveys of the B&B contain detailed application and acceptance data. Students were asked the names of the two most-preferred institutions that they applied to, the highest award level to which they applied, and whether they were accepted into and enrolled in each.

[2]Fields in this group are master's in nursing, occupational therapy, physical therapy, public affairs, public health, social work and speech and language pathology. Doctorate programs in occupational therapy, physical therapy, and veterinary medicine are also included.

[3]Other papers in economics that have studies PB quality have used very coarse measurements of quality, like the Carnegie code, as in Spaeth (1968) and Zhang (2005)

The median number of applications for students who ever apply is one (the mean is 2.2), so for the typical student, even this limited reporting is very informative. Students do not report the degree program they applied to, so I use the (total-completions-weighted) average PB program quality within the institution as I follow individual student progress.[4] I match quality data to student information in the B&B using the IPEDS institutional and field identification number.

B&B students are more likely to persist on to a PhD program relative to other award levels, they are more likely to be in STEM fields, and they have parents with higher educational attainment and SES (Nevill & Chen, 2007). Based on my own tabulations, the ability of men applying to PB school by 1994 is 0.777 (s.e. = 0.030), compared to an ability of 0.563 (s.e. = 0.040) for men who apply after 1994. The gap is smaller for women, 0.410 (s.e. = 0.027) versus 0.299 (s.e. = 0.032).

There is some concern that the SAT and ACT are downward-biased measures of ability for females. The average women's SAT score in 1988, when most of the B&B students would have taken the exam, was 0.26 standard deviations below the average man's (College Board, 2008). A similar gap exists among the students who take PB admissions tests like the GMAT or LSAT, but too few students report these scores in the B&B to perform any strong test of gender bias across tests. Without alternate and widespread measures of ability like subject test performance or high school coursework, we can't draw conclusions regarding whether the test score difference is caused by bias or selection (since females are more likely to earn bachelor's degrees and therefore B&B women are disproportionately selected from low-ability individuals).

[4]This aggregation is only problematic for my purposes if the programs that females apply to are systematically over- or under-ranked within institution. For example, if females are more likely to apply to education programs than to law programs, AND education programs are systematically ranked higher (relative to other education programs) than law programs (relative to other law programs) within an institution, then females will appear to be apply to lower-quality programs than is true. Among students who enroll in PB education, however, there is not a systematic or significant difference by gender in program quality within institution.

A.2 Within-Between Analysis of Degree Shares

We can describe the share of degrees granted to a gender group (as in equation (2) of the paper) by stating that

$$S^{st} = \frac{C^{s(t+\tau_d)}}{C^{(t+\tau_d)}} = \frac{\sum_{d,q} C_{dq}^{s(t+\tau_d)}}{\sum_{s,d,q} C_{dq}^{s(t+\tau_d)}} = \sum_{d,q} \varphi_{dq}^{t} S_{dq}^{st} \quad , \tag{A.1}$$

where φ_{dq}^{t} is the fraction of all PB degrees that were granted in programs in group dq,

$$\varphi_{dq}^{t} = \frac{\sum_{s} C_{dq}^{s(t+\tau_d)}}{\sum_{s,d,q} C_{dq}^{s(t+\tau_d)}} = \frac{C_{dq}^{(t+\tau_d)}}{C^{(t+\tau_d)}} \quad . \tag{A.2}$$

The value S_{dq}^{st} is weighted by φ_{dq}^{t}, the relative popularity of that PB program among all individuals who obtained PB degrees, and summed to recover S^{st}. Given equation (A.1), define the change in the total share of degrees earned for group s between cohorts 1 and 2 to be

$$S^{F2} - S^{F1} = \left(\sum_{d,q} \varphi_{dq}^{2} S_{dq}^{F2} - \sum_{d,q} \varphi_{dq}^{2} S_{dq}^{F1} \right) - \left(\sum_{d,q} \varphi_{dq}^{1} S_{dq}^{F1} - \sum_{d,q} \varphi_{dq}^{2} S_{dq}^{F1} \right) \quad . \tag{A.3}$$

Since shares φ_{dq}^{t} are gender invariant, the same decomposition can describe the change in the female-male degree share gap. The change from year 1 to 2 in the share gap between women and men is

$$\begin{aligned} (S^{F2} - S^{M2}) - (S^{F1} - S^{M1}) = & \left(\sum_{d,q} \varphi_{dq}^{2} \left(S_{dq}^{F2} - S_{dq}^{M2} \right) - \sum_{d,q} \varphi_{dq}^{2} \left(S_{dq}^{F1} - S_{dq}^{M1} \right) \right) \\ & + \left(\sum_{d,q} \varphi_{dq}^{2} \left(S_{dq}^{F1} - S_{dq}^{M1} \right) - \sum_{d,q} \varphi_{dq}^{1} \left(S_{dq}^{F1} - S_{dq}^{M1} \right) \right) \quad . \end{aligned} \tag{A.4}$$

In both equations (A.3) and (A.4), the left parenthesized term represents the "within" variation: the change in the share of degrees earned (or, the gap in the share), holding the proportion of individuals obtaining that degree constant. The right parenthesized term is the "between" variation: the degree to which programs became

relatively more or less popular, holding constant the share (or, gap in the share) of individuals of gender s in programs of that type. A positive value in equation (A.4) indicates a relative shift in the share of degrees granted to women. A positive within term implies that a greater fraction of degrees are going to F in time 2 than in time 1. A positive between term indicates that either a program where F tends to specialize has become more popular or a program where M tends to specialize has become less popular.

Table A1 presents the within and between decomposition, according to equation (A.4), of the difference-in-difference presented in the righthand column of Table 2 of the paper, by degree program and quality. Each award level row is the sum of its degree programs, and the award levels sum to the total at bottom right. As in the main text, this data only includes fields where I have quality data.

For example, we might ask why women increased their share of degrees earned in low-quality professional programs by 1.27%, relative to men. The answer is that the growth is almost all "within". Within-cell growth in women's attainment accounts for 1.2 percentage points of growth, while only 0.07 points are between. In fact, among professional degrees and doctoral degrees taken as a whole, the increased proportion of degrees going to women is largely within-cell growth. At every award level, both the within and between terms are positive, favoring women, but professional and doctoral within terms swamp the between effects, accounting for 83% of women's share growth. The bottom rows sum effect over quality. Within and between effects are roughly the same size (with within effects typically slightly larger) for ranked programs, across quality. This reflects the fact that low-quality programs tend to be fast-growing and female-intensive.

Among unranked programs, with within effect is almost twenty times larger than the between effect. Unranked programs are the driving force behind the within variation. Almost half of women's increased degree share due to within variation comes from unranked programs. If I omit unranked programs from Table A1 (that is, if I focus only on ranked programs), the increase women's relative master's degree share would be due in equal parts to within and between variation. Among ranked master's degree programs, women's gains are roughly in equal parts due to the secular increase in

attainment likelihood and the fact that female-intensive fields like social work, education, and nursing are the fastest growing. The master's degree within variation among unranked programs dominates the between effects of all quality levels. Unranked and low-quality programs account for 86% of within-degree-program growth at the master's level. These unranked and low-quality programs are an enormous contributor to the gains in women's PB attainment in the past two decades.

A.3 Selection-Corrected Continuation Model

Take the application choices, modeled by a mixed logit in the paper, as given. Given that the student applied, an admissions committee decides whether to accept or reject the applicant. Suppose that the applicant is admitted whenever the latent variable $y_i^j = f^j(Z_i, X_i^j) + \varepsilon_i^j > 0$.[5] There is reason to believe that ε_i^2 will be correlated with η_i^{aq} from equation (3), and therefore the likelihood of acceptance is correlated with the likelihood of being observed as an applicant. For example, high-ability students are presumably more likely to sort into more difficult or more selective programs. But these programs are also the least likely to accept any given applicant. This correlation will bias our estimates of the relationship between ability and admissions outcomes. Bourguignon et al. (2007) show that in the case of an error process with type-II extreme value distribution over H options in the first step (here, selection into applicant pools), and normally distributed errors in the second step (here, the admissions decision), assuming a linear relationship between the error processes of the form

$$E(\varepsilon_i^j | \eta_i^1 \dots \eta_i^H) = \frac{\sqrt{6}}{\pi} \sum_{h=1\dots H} \rho^h (\eta_i^h - E(\eta_i^h)) \tag{A.5}$$

where ρ^h is the correlation coefficient between ε_i^j and η_i^h then the contribution of each option to the bias in ν_i conditioning on the observed choice c

$$\lambda_i^h = E\left(\eta_i^h - E(\eta_i^h)\right) = \begin{cases} -\ln(P_i^c) & \text{if } \ h = c \\ \frac{P_i^h \ln(P_i^h)}{1 - P_i^h} & \text{if } \ h \neq c \end{cases} \tag{A.6}$$

[5] Since I model admissions, enrollment, and persistence each with a probit model, this general equation applies for all steps $j \geq 2$.

where P_i^h is the predicted likelihood of choosing option h. We can control for selection into applicant pools at the aq level by introducing the thirteen λ_i^h terms linearly into the admissions equation (Dubin & McFadden, 1984).

Once the admissions equation is estimated (along with the likelihood of acceptance), we proceed to the enrollment step. Given an acceptance offer, does the student enroll in that program? Bias due to selection occurs in much the same way as between the application and enrollment step. We may expect that low-ability students are more hesitant to accept offers from selective programs, but they are also presumably less likely to draw an offer to begin with. Greene (1998) shows that controlling for selection in this situation - with a probit in both steps 1 and 2 - can be done by a simple two-step process. It is simply a matter of taking the predicted probability of a positive outcome in the step-1 equation and including it as a simple linear parameter in step 2. Thus, both in the enrollment and the persistence choice, I control for selection by including the predicted probability from the previous step.

With a simple probit in both the choice of interest and the selection equation, the estimation problem reduces to a "recursive bivariate probit" (Greene, 1998). The parameters can be consistently estimated by including the estimated probability of a positive outcome in the previous step P_i^{j-1} in the equation for the latent variable. In both the enrollment and persistence decisions (choices $j = \{3, 4\}$), I estimate the equation $y_i^j = \delta_Z^j Z_i + \delta_X^j X_i^j + \delta^j \widehat{P}_i^{j-1} + \varepsilon_i^j$, as well as its counterpart with no correction for selection.

This structure assumes that selection bias only comes from one-step adjacent choices, rather than a full unrestricted multivariate correlation matrix. This is equivalent to assuming that the only influence of further-removed choices comes through their influence on the selection mechanism, and thus the estimated probability, in the previous step. While a full multivariate model may be theoretically preferable, it is not feasible given the relatively small sample sizes at hand. Since each step uses generated regressors, I estimate all standard errors by bootstrap.

It is also interesting to track the evolution of ability gaps and the gender-quality gap along the path to a degree. In Table A2, I describe average student ability and program quality, broken down by award level and gender, along the path to a PB

degree. This allows us to see how these variables evolve as students progress. Table A1 also shows the results of a t-test of differences between the genders for each step and award level. Among students who apply to master's programs, women consistently have lower measured ability, but apply to schools that on average are only marginally lower-ranked. The average ability of applicants to professional and doctoral programs do not differ across gender. While men and women apply to professional degree programs of equal average quality, women apply to and enroll in doctoral programs of significantly lower quality.

Table A2 shows us that among professional degree applicants, men and women are virtually identical in terms of ability and the average quality of the programs they apply to. Among master's and doctoral degree applicants, men are more ambitious applicants, applying to significantly higher-ranked programs than the women. This is true even as the men and women who apply to doctoral programs are not otherwise observably different at the mean. The men who apply to master's degree programs have a mean ability score 0.3 standard deviations above the women. Men are, however, less distinguished than the women in terms of undergraduate GPA and honors received.

In all panels of Tables A3, I present two types of results. One is from regressions that condition on observables and on progression past the previous step. In admissions, I estimate the latent variable $y_i^2 = \beta_Z^2 Z_i + \beta_X^2 X_i^2 + \varepsilon_i^2$ for all students who applied to a program in at the given award level. The other type of results also control for selection-on-observables in the previous step. In admissions, where the application choice is multinomial, I control for selection by including the λ_i^h terms of equation (A.6), represented by vector Λ_i. This equation is $y_i^2 = \delta_Z^2 Z_i + \delta_X^2 X_i^2 + \delta^2 \Lambda_i + \varepsilon_i^2$.

I am interested in the interaction between gender, ability and quality along the process to a PB degree, and so these variables are included in every step. As such, the X^j variables serve an important role as exclusion restrictions in terms of the selection process along the path of educational continuation. I report the coefficients associated with X_i^j for both the results reported in the paper (where X_i^j coefficients were left unreported) as well as for the selection-corrected specifications.

I test the overidentification of the model (and the strength of the implicit identifying variation) by performing a likelihood ratio test on each specification. This involves

taking the difference in the log likelihood of the full model and the log likelihood of another regression where the X^j variables are excluded. The resulting statistic (times two) has a chi-squared distribution with the degrees of freedom equal to the number of excluded variables. The more independent explanatory power that the X^j variables have, the larger the test statistic will be. This test is analogous to the F test that is standard in the "weak instruments" literature, and a threshold value of around 10 is applicable here to provide evidence in support of the strength of the exclusion restrictions.

These exclusion restrictions are strongly supported in every master's degree regression, and in most professional degree regressions. The identifying variation tends to be weaker among doctoral degree applicants. For this reason, as stated in the paper, we need to be cautious in interpreting the coefficients causally.

As discussed in the paper, the selection correction in admissions, panel a of Table A3, does affect the results. The significant coefficient on the interaction between ability and gender among master's degree applicants disappears once we introduce the selection terms. The results of the admissions decisions at other award levels, and in both the enrollment and persistence decisions (shown in panels b and c of Table A3), are not significantly impacted by the selection correction, and it has no effect on the qualitative results. In unreported regressions, I look for gender differences in sensitivity to undergraduate debt. As in Weiler (1994), I find no evidence of such.

The X_i^3 variable that most substantially and significantly impacts willingness-to-enroll is the presence of a financial aid offer. The impact of the variable is very large, at around 0.6 standard deviations of the latent variable across all award levels. Marriage is a strong negative predictor of enrollment in professional and doctoral programs. There is no evidence that the amount of undergraduate debt has a significant impact on enrollment decisions. This is consistent with Millet (2003), who finds no impact on enrollment conditional on having already applied. In the persistence equations (shown in panel c), I am not able to estimate the impact of divorce among in doctoral students, nor part time enrollment for doctoral or professional students, because they happen so infrequently in the dataset.

A.4 Mean income across PB quality

Table A4 presents mean income by award level, program quality category, and gender. Education is measured by the highest degree attained by 2003 (for all students in the B&B). Importantly, this is not conditioned on ability, unemployment status, or experience. The average male graduate from a master's program in the bottom 75% of the rankings earns as much as the typical male without a PB degree. Male graduates of bottom-50% doctoral programs in this cohort earn significantly less than men without a PB degree in 2003, and at higher PhD quality ranks, average earnings are equivalent to those of non-degree-holders. This contrasts with men from all qualities of professional degree programs, and from top master's programs.

Among women, the same qualitative story holds at the master's level. There is no significant difference between women's average income with only a bachelor's and the income among those holding a master's degree from a school in the bottom 75%. As with men, the earnings among women with a degree from a top master's degree program is significantly higher than among women with no PB degree. The size of the boost is similar across gender. Men from top master's programs earn 56% more than men with no PB degree, while women from the same programs earn 66% more than women with no PB degree. On the other hand, while the men who graduate from top professional degrees earn more than any other group in Table A6, the income of women from the top 10-50% professional degree programs is not significantly different than the income of women from the top 10%. The reverse is true among doctoral degrees: men's average income appears flat across quality, while women's (while measured imprecisely) rises.

B Degree Programs

Below is the list of the degree programs I define, with their most popular component majors. Within broad academic discipline I group "applied" master's programs, "academic" master's programs, and all doctoral programs. The parenthesized numbers next to degree program titles are the fraction of all B&B enrollees in that group. The italicized and parenthesized numbers (which may not sum to 100 due to rounding

or omitted majors) indicate the proportion of that degree program's students in each listed major.

- Humanities
  1. Master's in liberal arts (4.8%): religion & pastoral (*34%*), english (*33%*), languages (*12.8%*), etc.
  2. Master's in communications and media (4.6%): library science (*45%*) fine and performing arts (*32%*), communications (*17%*) , etc.
  3. Doctorate in humanities and education (2.6%).
- Social Sciences
  4. Master's in social sciences (5.3%): psychology (*46%*), history (*16%*), sociology (*12%*), etc.
  5. Master's in public service (4.6%): social work (*31%*), public administration (*26%*), leisure and recreational studies (*11%*), etc.
  6. Doctorate in social science (3.0%).
- Hard Sciences
  7. Master's in physical sciences (1.7%): mathematics (*34%*), geoscience (*26%*), chemistry (*17%*), physics (*10%*), etc.
  8. Master's in engineering and technology (5.0%)
  9. Doctorate in hard science (2.0%).
- Biomedical Sciences
  10. Master's in biological science (2.7%): biology (*73%*), environmental science (*14%*), agricultural science (*13%*), .
  11. Master's in health sciences (7.4%): nursing (*75%*), community and public health (*25%*).
  12. Doctorate in biomedical science (2.4%).
- Professional and vocational fields
  13. Master's in business (16.4%).
  14. Master's in education (25.6%).
  15. Law (JD) (6.4%).
  16. Medicine (MD) (3.6%).

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Table A1: Within-between decomoposition of the change in degree share gaps

	Top 5%		Top 5-10%		Top 10-25%		Top 25-50%		Bottom 50%		Unranked		Sum over qualities		Total change in share difference
	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	
Masters	0.09	0.16	0.14	-0.01	0.37	0.44	0.56	0.66	2.02	2.47	5.47	0.55	8.66	4.26	12.93
Liberal Arts	0.001	0.003	0.001	0.002	-0.003	-0.010	-0.020	-0.034	0.018	-0.021	0.008	0.014	0.01	-0.05	-0.04
Comm. & Media	0.002	-0.002	-0.004	-0.011	0.006	-0.031	0.028	-0.041	0.020	-0.046	-0.057	-0.105	-0.01	-0.24	-0.24
Social Science	0.016	0.006	0.016	0.006	0.064	0.012	0.084	0.004	0.240	0.003	0.909	0.043	1.33	0.07	1.40
Public Service	0.061	-0.001	0.080	0.003	0.073	0.031	0.145	0.037	0.367	0.011	0.184	0.110	0.91	0.19	1.10
Engineering	0.017	0.047	0.016	0.078	0.064	0.195	0.107	0.285	0.158	0.398	0.312	-0.069	0.67	0.93	1.61
Physical Science	0.008	0.012	0.002	0.027	0.047	0.072	0.051	0.090	0.076	0.121	0.091	0.069	0.27	0.39	0.67
Biology	0.007	0.001	-0.002	0.000	-0.002	-0.003	0.011	0.000	0.034	0.006	0.206	-0.001	0.25	0.00	0.26
Health Science	0.012	0.039	0.020	-0.015	-0.035	0.220	-0.090	0.470	0.111	0.895	0.103	0.361	0.12	1.97	2.09
Education	0.021	-0.085	-0.002	-0.100	0.077	-0.111	0.083	-0.169	0.373	0.818	0.999	1.006	1.55	1.36	2.91
Business	-0.050	0.139	0.019	-0.002	0.077	0.061	0.166	0.016	0.624	0.284	2.717	-0.876	3.55	-0.38	3.17
Professional	0.15	0.07	0.18	0.09	0.36	0.14	0.67	0.17	1.50	0.33	1.20	0.07	4.06	0.87	4.93
Law	0.102	0.040	0.117	0.064	0.146	0.096	0.192	0.090	0.618	0.251	0.116	0.019	1.29	0.56	1.85
Medicine	0.048	0.029	0.066	0.029	0.214	0.041	0.478	0.080	0.883	0.084	1.079	0.051	2.77	0.31	3.08
Doctoral	0.07	0.03	0.08	0.04	0.21	0.06	0.27	0.09	0.26	0.07	0.61	0.04	1.50	0.33	1.83
Hum. and Educ.	0.001	-0.017	0.023	-0.015	0.016	-0.035	0.019	-0.018	0.057	-0.001	0.077	0.012	0.19	-0.07	0.12
Social Science	0.016	0.002	0.016	0.005	0.033	-0.001	0.038	-0.004	0.104	-0.013	0.147	-0.002	0.35	-0.01	0.34
"Hard" Science	0.018	0.048	0.017	0.051	0.079	0.099	0.072	0.106	0.028	0.078	0.019	-0.018	0.23	0.36	0.60
Biomed. Science	0.036	-0.006	0.024	0.000	0.079	-0.003	0.141	0.003	0.074	0.003	0.371	0.052	0.72	0.05	0.77
Sum over degrees	0.31	0.25	0.41	0.12	0.93	0.63	1.51	0.91	3.78	2.87	7.28	0.67	14.23	5.46	
Total change in share difference	0.57		0.53		1.57		2.42		6.65		7.95				19.69

Note : see text for details of the calculation. Categories may not sum due to rounding.

Table A2: Average student ability and program quality, by award level, gender, and progress to a PB degree

Panel a: Bachelor's degree holders

	Bachelors		
	Male	Female	p(Male = Female)
Ability	0.505	0.202	0.000
	(0.017)	(0.015)	
N	2902	3570	

Panel b: Applicants

	Masters			Professional			Doctoral		
	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)
Ability (if applied)	0.617	0.295	0.000	1.066	0.917	0.150	1.253	1.022	0.097
	(0.055)	(0.042)		(0.068)	(0.078)		(0.104)	(0.094)	
Quality applied	55.5	51.8	0.050	59.4	60.6	0.745	72.1	66.2	0.034
	(1.5)	(1.2)		(2.2)	(2.8)		(2.0)	(2.6)	
N	504	651		177	138		101	85	

Panel c: Students offered admissions

	Masters			Professional			Doctoral		
	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)
Ability (if admitted)	0.645	0.372	0.001	1.134	1.077	0.694	1.419	1.088	0.054
	(0.068)	(0.052)		(0.093)	(0.118)		(0.112)	(0.131)	
Quality admitted	52.2	49.1	0.148	54.0	58.5	0.379	73.0	64.3	0.025
	(1.7)	(1.5)		(2.7)	(4.1)		(2.5)	(3.7)	
N	411	543		123	106		80	66	

Panel d: Enrolled students

	Masters			Professional			Doctoral		
	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)	Male	Female	p(Male = Female)
Ability (if enrolled)	0.712	0.435	0.001	1.108	1.052	0.709	1.460	1.128	0.063
	(0.066)	(0.055)		(0.114)	(0.125)		(0.102)	(0.158)	
Quality enrolled	54.4	49.7	0.063	52.2	61.6	0.114	70.0	65.0	0.197
	(1.9)	(1.8)		(3.1)	(4.9)		(2.9)	(4.1)	
N	285	374		90	63		62	54	

Note: Summary statistics for ability and quality, by award level and gender, along the path to a PB degree. Statistics are weighted to account for sample structure, and are taken conditional on reaching that step in the path to attainment of a PB degree. Standard errors are in parenthesis.

Table A3: Progress through post-baccalaureate education, by award level

Panel a: Admissions offer to top choice

	Master's		Professional		Doctoral	
	(1)	(2)	(3)	(4)	(5)	(6)
female	-0.027	0.308	-0.145	-0.096	0.927	1.084
	(0.216)	(0.414)	(0.386)	(0.878)	(0.701)	(1.624)
ability	0.118	-0.397	0.221	-1.316	0.282	-1.717
	(0.080)	(0.484)	(0.161)	(1.373)	(0.174)	(2.265)
ability x Female	0.199*	0.163	-0.063	-0.489	0.000	0.347
	(0.101)	(0.214)	(0.205)	(0.459)	(0.236)	(0.891)
program quality	-0.015**	-0.016**	-0.012**	-0.014**	-0.001	-0.005
	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.011)
quality x female	0.001	0.001	0.004	0.003	-0.008	-0.006
	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.016)
UG GPA	0.15	0.207	0.044	0.613	1.658	1.952
	(0.226)	(0.238)	(0.633)	(0.772)	(0.979)	(1.396)
UG school quality	0.001	0.004	-0.012	0.01	0.072	0.084
	(0.011)	(0.012)	(0.027)	(0.033)	(0.042)	(0.062)
UG GPA x UG quality	0.001	0	0.005	-0.001	-0.021	-0.025
	(0.003)	(0.004)	(0.008)	(0.010)	(0.012)	(0.018)
UG honors	0.350**	0.357**	0.201	0.128	0.242	0.291
	(0.129)	(0.132)	(0.191)	(0.227)	(0.243)	(0.329)
Selection correction?	No	Yes	No	Yes	No	Yes
Field-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1155	1155	315	315	186	186
Pseudo-R^2	0.108	0.116	0.079	0.119	0.087	0.147
Likelihood ratio χ^2	23.66	23.2	7.94	10.94	4.64	4.01

Panel b: Enrollment, given admissions

	Master's		Professional		Doctoral	
	(1)	(2)	(3)	(4)	(5)	(6)
female	0.283	0.279	-0.521	-0.513	1.259	1.223
	(0.190)	(0.195)	(0.421)	(0.496)	(0.850)	(3.467)
ability	0.016	-0.006	0.298	0.279	0.444*	0.435
	(0.082)	(0.091)	(0.197)	(0.224)	(0.224)	(2.334)
ability x Female	0.057	0.033	-0.081	-0.081	-0.403	-0.399
	(0.107)	(0.113)	(0.258)	(0.297)	(0.305)	(1.258)
program quality	0.002	0.003	-0.006	-0.006	0.005	0.005
	(0.003)	(0.003)	(0.005)	(0.006)	(0.008)	(0.061)
quality x female	-0.005	-0.005	0.004	0.004	-0.01	-0.01
	(0.003)	(0.004)	(0.007)	(0.008)	(0.012)	(0.092)
Any aid offer	0.722**	0.715**	0.601**	0.594**	0.911**	0.911
	(0.095)	(0.097)	(0.186)	(0.219)	(0.306)	(6.630)
UG debt	-0.004	-0.003	-0.012	-0.012	-0.037	-0.037
	(0.007)	(0.007)	(0.011)	(0.013)	(0.025)	(0.402)
Parent HH income	0	0	0.008	0.008	-0.03	-0.031
	(0.007)	(0.007)	(0.017)	(0.021)	(0.033)	(0.581)
Married	-0.222	-0.227	-0.619*	-0.616	-0.934*	-0.932
	(0.118)	(0.124)	(0.297)	(0.363)	(0.369)	(12.521)
Selection correction?	No	Yes	No	Yes	No	Yes
Field-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	954	954	229	229	146	146
Pseudo-R^2	0.072	0.073	0.118	0.118	0.241	0.241
Likelihood ratio χ^2	23.54	24.05	8.63	8.74	9.34	9.45

Table A3, continued: Progress through post-baccalaureate education, by award level

	Panel c: Completion, given enrollment					
	Master's		Professional		Doctoral	
	(1)	(2)	(3)	(4)	(5)	(6)
female	0.593**	0.568*	-0.05	0.034	1.199	0.847
	(0.227)	(0.234)	(0.539)	(0.662)	(0.977)	(1.274)
ability	0.190*	0.187	-0.383	-0.436	0.111	-0.007
	(0.094)	(0.097)	(0.269)	(0.300)	(0.231)	(0.409)
ability x Female	-0.072	-0.077	0.405	0.398	-0.136	-0.026
	(0.123)	(0.123)	(0.386)	(0.443)	(0.330)	(0.518)
program quality	0.004	0.003	0.007	0.008	0.006	0.006
	(0.003)	(0.003)	(0.006)	(0.008)	(0.009)	(0.011)
quality x female	-0.006	-0.006	-0.005	-0.005	-0.016	-0.014
	(0.004)	(0.004)	(0.009)	(0.011)	(0.013)	(0.017)
Total PB financial aid	0.015	0.013	0.015	0.013	0.02	0.018
	(0.010)	(0.011)	(0.014)	(0.016)	(0.017)	(0.025)
Employed while enrolled	0.627**	0.634**	1.054**	1.097**	0.573	0.613
	(0.123)	(0.128)	(0.277)	(0.358)	(0.323)	(0.404)
Enrolled part time	-0.289*	-0.283	.	.	.	.
	(0.147)	(0.154)				
Newly married	0.268*	0.262*	-0.021	-0.049	0.219	0.177
	(0.116)	(0.122)	(0.298)	(0.349)	(0.314)	(0.393)
Newly divorced	-0.114	-0.104	-0.888*	-0.825	.	.
	(0.208)	(0.244)	(0.432)	(0.503)		
Birth of first child	-0.084	-0.075	0.102	0.086	0.715	0.719
	(0.121)	(0.134)	(0.298)	(0.364)	(0.404)	(0.449)
Selection correction?	No	Yes	No	Yes	No	Yes
Field-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	659	659	153	153	116	116
Pseudo-R^2	0.087	0.087	0.124	0.128	0.124	0.132
Likelihood ratio χ^2	24.91	24.94	19.31	20.41	8.41	7.49

Note: Each column is a separate probit regression. Acceptance regressions model an admissions offer in 1994 into the student's first-choice program, given application. Enrollment regressions model enrollment by 1994, given any acceptance. Completions regressions model completion of some PB degree by 2003, given any enrollment by 1994. Admissions shifters include the applicant's undergraduate GPA, undergraduate school quality, an interaction between the GPA and undergraduate quality, and an indicator for the presence of honors on the student's undergrautate transcript. Enrollment shifters include the presence of a financial aid offer, the quantity of undergraduate debt, parent's income, whether the student is married, and whether the student has children. Completions shifters are the size of the student's financial aid package,whether the student was working or enrolled part time while in school, and indicators for whether the student married, divorced, or had their first child after enrollment. All regressions control for field-of-study. Standard errors are in parenthesis. * indicates p<0.05, ** indicates p<0.01.

Table A4: Average income by gender, educational attainment, and post-baccalaureate program quality.

	No Post-baccalaureate degree		
	Men	Women	M - F difference
.	67,030	36,979	30,051
	(1780)	(732)	(1925)
	Master's		
	Men	Women	M - F difference
Top 10%	99,349	60,580	38,770
	(10427)	(6143)	(12102)
Top 10-25%	68,967	41,656	27,311
	(5401)	(4753)	(7195)
Top 25-50%	64,956	38,802	26,154
	(5125)	(3330)	(6112)
Bottom 50%	66,565	42,443	24,122
	(4392)	(2739)	(5176)
	Professional		
	Men	Women	M - F difference
Top 10%	93,499	73,688	19,811
	(14417)	(18753)	(23654)
Top 10-25%	91,823	74,853	16,969
	(12179)	(8489)	(14846)
Top 25-50%	75,635	79,872	-4,237
	(9566)	(7436)	(12117)
Bottom 50%	91,189	57,099	34,089
	(10875)	(5924)	(12384)
	Doctoral		
	Men	Women	M - F difference
Top 10%	63,637	49,314	14,323
	(6540)	(16960)	(18178)
Top 10-25%	72,922	69,800	3,123
	(9097)	(6630)	(11257)
Top 25-50%	68,612	53,831	14,781
	(7525)	(7582)	(10682)
Bottom 50%	52,628	41,551	11,077
	(7539)	(8530)	(11384)

Note: Simple means of labor market income in 2003, according to PB degree attainment, program quality, and gender.