Gender Differences in Field of Study Choice Set of STEM-bound Applicants

Sigal Alon, Tel-Aviv University Thomas DiPrete, Columbia University

Abstract

Sex segregation by field of study is currently the main axis of gender inequality in higher education. Female students' preferences for female-dominated majors are well documented as well as their low representation in STEM fields. The results of the current study demonstrate that horizontal sex segregation persists even within STEM majors. Using institutional administrative data on second as well as first choice major preferences from Israeli universities, we find that even among elite STEM-bound applicants females are more likely than their male counterparts to apply to more feminine STEM majors. The gender gap in preferences is larger in the first application choice than in the second and is most pronounced among academically weak applicants. The trend of rising gender diversity in STEM fields coupled with a changing selection of females into STEM result in a narrowing of the gender gap among academically weak applicants and a widening among strong applicants.

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Gender Differences in Field of Study Choice Set of STEM-bound Applicants

Extended Abstract

Theoretical Framework and Research Questions

Women now surpass men in overall rates of college graduation in many industrialized countries, and women attain master, professional, and doctoral degree at rates that approach, equal, or even exceed men's rates in some Western countries. Women also have made much progress in many high status occupational fields as well as in many branches of science. Despite this progress, sex segregation in fields of study persists at all levels of higher education. Men are more likely than women to major in science, particularly physical science and engineering. Why this level of segregation persists and the likely shape of future trends remain questions under active research by a large community of scholars.

Research on gender trends in STEM degrees frequently takes a "pathways" approach, and in particular examines the determinants of intent to major in STEM fields. The choice model that underlies this approach presumes that students form preferences for majors. These preferences are based on a student's field-specific aptitudes, on perceptions of opportunity, and also on idiosyncratic personal tastes, self-assessments, and values. The model hypotheses that opportunity, tastes, self-assessments, and values are influenced by both the local and global environment, which in particular may stereotype academic fields as more or less strongly "masculine" or "feminine." Changes in the environment are presumed to drive changes in sex segregation in STEM fields.

This theoretical perspective assumes implicitly that students consider multiple fields and make choices among a small set of favorites, and the actual major is a joint outcome of student choice and institutional constraints (e.g., when access to a particular major is competitive). However, data are almost never available about the fields that are given serious consideration in this choice process. Therefore, scholars can typically not observe the process of ranking and choosing among those candidate fields. Without this information, scholars also cannot assess the extent to which gender-specific change over time occurs in the fields given serious consideration as well as the one revealed in "intent to major" survey questions or revealed as the declared major in surveys or administrative data about the college experience. This omission is unfortunate, because it is possible that underlying trends in sex segregation are stronger in the broader set of candidate fields than in the actual major.

In this paper, we directly address the extent of gender segregation in the broader set of fields given serious consideration by students, and compare this to segregation in the actual major. We address the question of whether second choice STEM fields are as segregated as are first choice STEM fields or STEM majors, and we also ask whether gender differences in academic proficiency have the same effect on the broader set of candidate STEM fields as they do on the actual major. Finally we assess whether recent trends in sex segregation in STEM fields are stronger or weaker when the broader set of candidate STEM fields is examined. We specifically address these questions for students at elite universities. Elite universities are a strategically important research site because the students who enter elite STEM careers are disproportionately drawn from elite universities. We address these questions using recent trend data for two Israeli Universities: the Technion (the Israeli Institute of Technology), and Tel Aviv University.

Database, sample and Methods

To assess the gender differences in field of study choice set we use institutional administrative data that were obtained from chief Israeli universities for periods ranging from ten to twelve consecutive years (circa 1997 to 2008). The unique application and admission process in the Israeli universities makes this data attractive for the current investigation. This is because the application process and admissions for a bachelor's degree at the universities are major-institution specific; most professional degrees are offered at the undergraduate level; applicants need to rank their preferences in the application form; and, finally, the admission decision is based entirely on academic composite score so that all the applicants are ranked based on their academic preparation (and admissibility). The database, constructed by Alon, is especially suitable for the current analyses because of its large sample size; the ability to follow individuals' postsecondary experiences from the application stage through graduation; and the opportunity to study temporal patterns in the application behavior (for more details see Alon, 2011).

For the current investigation we focus on the major choice set of first-time applicants. We focus on data from two institutions. As the main source we use the data from The Technion (TEC) which is Israel Institute of Technology.¹ We feature the TEC results because this institution offers degrees only in STEM fields; applicants can state only two preferences in their major choice set (and cannot choose a dual major); it is mandatory for applicants to have taken the highest level of math and physics in high school; and all students are ranked according to one academic index.

To substantiate the TEC results we have replicated the analyses with data from Tel-Aviv University. To focus on STEM-bound applicants we limit the analysis to the STEM fields in the applicants' major choice set. Applicants to TAU also state two choices but each choice can be a dual major (although this is not an option for several STEM majors). To deal with this complexity we devise a twofold strategy: 1) in cases where one of the majors in a choice is non-STEM we replace its information with missing data; 2) in cases where both majors are STEM we retain both information and uses averages to classify the characteristics of this choice (for example to classify choices by their gender composition and selectivity).

In both institutions we dropped from the analysis architecture and medicine because their unique admission process prevents comparing applicants on a single scale. Because these are the two most popular majors in females' major choice set our results provide conservative estimates for the gender gap in the gender composition of the field choice set.

The sample includes 36,274 applicants to TEC over a period of 11 years and 36,581 applicants to TAU-STEM over a period of 12 years.

Dependent variable: field of study's gender composition operationalized as the share of female students in a major. In cases of dual STEM majors (only in TAU) we calculated the average of the two majors in each choice.

¹ In the Shanghai ranking for 2011 the TEC was ranked in the 42nd place in engineering/technology and computer sciences and in the 15th place in computer sciences.

Independent variables: sex, academic composite score, ethnicity, age, immigration status, and year. The academic composite score is the only criterion used for admission by the Israeli universities. It is calculated by taking a weighted mean of an individual's matriculation diploma grades (similar to AP grades) and psychometric test score (similar to an SAT score). We use the score calculated by the TEC for all applicants, and the engineering composite score calculated by TAU for applicants to STEM majors. Both scores emphasize the level and achievements in math and physics courses taken in high school and the applicant's quantitative skills.

Analytical strategy: We fit regression models to the share of female students in the field of study. We run the analyses separately for the first and second application choices. The basic specifications controls for sex, academic composite score, and the product term between the two. Additional specification controls for year and a vector of background variables (ethnicity, age and immigration status). We also fit a year fixed-effects specification and year-specific models to assess temporal changes.

Preliminary Results

We present results for the TEC. Similar results were obtained for TAU.

- 1. The TEC is a male-dominated institution but the share of females is rising over time in the pools of its applicants, admits, and enrolled students (results not shown). The share of female students rose from 28 percent in 1998 to 35 percent in 2008.
- 2. Despite this increase in representation in STEM fields, we find that females, in all ability levels, enroll in more feminine majors than males (results not shown).
- 3. We track these differences in outcomes to gender differences in the major choice set. We find that among STEM-bound applicants there are gender differences in the gender composition of field of study choices. Females are more likely than males to apply to more feminine STEM majors even after taking into account academic preparation (see table 1). The gap is persistent over time and across academic levels.
- 4. The gender gap in the share of females in the major is larger in the first application choice than in the second (table 1).
- 5. The magnitude of the gender gap depends on the academic composite score (table 1). The results indicate that the gender differences in the share of females in a choice are most pronounced among academically weak applicants, yet they narrow with the rise of academic ability. Yet an unexplained gap exists even among those with the highest scores (table 1 and figure 1).
- 6. Among academically weak applicants females' second choice is less feminine than their first choice while males demonstrate stable preferences in terms of the gender composition in the majors they applied to. As a result, the gender gap among academically weak applicants is smaller in the second than in the first choice.
- 7. Temporal changes: we find little temporal change in the gender gap: in all years females apply to more feminine majors (gaps of 17-22 percent in the share of females in the major of choice). Results not shown. Yet, there is a change over time in the interplay between the gender gap and academic scores (table 6 and figure 2). Over time males of all

academic levels increased their inclination toward more feminine majors - this may represent a change in males' preferences and/or a structural change (the temporal trend of rising gender diversity in STEM fields). Conversely, over the period of the investigation academically weak females moved away from feminine majors while those with high scores showed the opposite pattern. These results plausibly capture the abovementioned structural change but also represent a temporal change in the selection of females into STEM fields. Among strong applicants, females had similar choices to their male counterparts in 1998 (in terms of gender diversity) but over time a gender gap emerged. Thus, the gender gap narrowed overtime among academically weak applicants whereas it widened among strong applicants.

Taken together, the results of this study contribute to the rich literature on gender inequality in higher education by demonstrating that horizontal sex segregation persists even *within* STEM majors. Using institutional administrative data from Israeli universities we have a unique opportunity to show how gendered-choices in application formulate these differences. We reveal that even among STEM-bound applicants, females are more likely than their male counterparts to apply to more feminine STEM majors. This gender gap in preferences is larger in the first application choice than in the second and is most pronounced among academically weak applicants (although it exists even among the strongest applicants). The trend of rising gender diversity in STEM fields coupled with a changing selection of females into STEM result in a narrowing of the gender gap among academically weak applicants.

Future Analyses

We will augment these findings by using McFadden's choice model. This framework is especially appropriate for assessing gender differences in the major choice set because it allows the value of the independent variables to differ for each alternative and over time. Alternativespecific variables include the characteristics of the major (gender composition and selectivity), and these effects can be modeled along with the characteristics of the applicant (gender, the composite score, and the number of majors applied to). The model will be also fitted separately for males and females.

References

- Alon, Sigal. *Forthcoming*. "The Diversity Dividends of a Need-blind and Color-blind Affirmative Action Policy." *Social Science Research*.
- Alon, Sigal and Dafna Galbgiser. 2011. "The Female Advantage in College Academic Achievements and Horizontal Sex Segregation." Social Science Research, 40(1):107– 119.
- Buchmann, Claudia and Thomas A. DiPrete. 2006. "The Growing Female Advantage in College Completion: The Role of Parental Resources and Academic Achievement." *American Sociological Review* 71:515-541.
- Charles, Maria and Bradley Karen. 2002. "Equal but Separate? A Cross-National Study of Sex Segregation in Higher Education." *American Sociological Review*, 67(4):573-599.

T1 % Female	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
/ARIABLES	(1) app1_1	(2) app1_2	app1_3		app1yearFE	app2_1	app2_2	app2_3		app2yearFE
ANIADLES	app1_1	app1_z	app1_3	app 1_4	appryearre	appz_1	appz_z	appz_3	appz_4	appzyearre
sex	20.721**	20.448**	53.901**	56.694**	57.129**	18.117**	17.846**	40.908**	43.404**	43.719**
	[0.215]	[0.212]	[2.348]	[2.324]	[2.314]	[0.245]	[0.242]	[2.686]	[2.667]	[2.661]
composite_basic		-0.460**	-0.339**	-0.319**	-0.320**		-0.415**	-0.331**	-0.300**	-0.302**
		[0.013]	[0.015]	[0.016]	[0.016]		[0.015]	[0.018]	[0.019]	[0.019]
_lsexXcompo_1			-0.406**	-0.438**	-0.443**			-0.280**	-0.307**	-0.311**
			[0.028]	[0.028]	[0.028]			[0.032]	[0.032]	[0.032]
appyear				0.589**					0.463**	
				[0.032]					[0.037]	
controls				yes	yes				yes	yes
Constant	26.211**	64.277**	54.288**	1,140.350*		28.289**	62.693**	55.692**	-888.332**	
	[0.120]	[1.083]	[1.286]	[63.459]	[1.700]	[0.137]	[1.244]	[1.484]	[73.242]	[1.995]
Observations	26.274	- 26 274	5 26 274	- 26 274	5 0C 074	5 20 120	5 20 120	5 20 120	5 20 120	5 20 129
R-squared	36,274 0.204	36,274 0.230	36,274	36,274	36,274	30,128	30,128 0.175	30,128 0.177	30,128 0.190	30,128 0.195
80	0.204		0.234 : % Fem: /	0.252	0.259 2 (model3,8)	0.153		0.177		
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80 70 60 50 40 80 40 40 80 20 20		Figure 1	: % Fem: <i>I</i>	Арр1 Арр	·		0.175	App1 M App1 F App2 M		
80 70 60 50 30 80 60 50 30 80 60 50 50 50 50 50 50 50 50 50 50 50 50 50		Figure 1	: % Fem: <i>I</i>	Арр1 Арр	·			App1 M App1 F App2 M		
80 70 60 50 10		Figure 1	: % Fem: <i>I</i>	Арр1 Арр	·			App1 M App1 F App2 M		
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Constant Observations R-squared VARIABLES	(1) app1_98 90.956** [6.257] -0.229** [0.044] -0.902** [0.078] 42.129** [4.885] 4.022 0.256 (12) app2_98 74.960** [7.846]	(2) app1_99 93.159** [6.614] -0.335** [0.044] -0.942** [0.081] 45.071** [4.342] 3,381 0.268 (13) app2_99	(3) app1_00 71.649** [6.662] -0.424** [0.047] -0.667** [0.082] 41.694** [5.140] 3,512 0.264 (14)	(4) app1_01 70.796** [7.231] -0.439** [0.049] -0.649** [0.088] 52.998** [5.376] 3,616 0.240	(5) app1_02 71.038** [7.505] -0.327** [0.052] -0.595** [0.091] 32.289** [5.566] 3,555 0.296	(6) app1_03 58.480** [8.502] -0.354** [0.053] -0.434** [0.102] 43.739** [5.858] 3,387	(7) app1_04 27.058** [9.671] -0.363** [0.066] -0.052 [0.116] 32.362** [7.131]	(8) app1_05 53.574** [9.142] -0.261** [0.067] -0.337** [0.109] 21.667** [7.214]	(9) app1_06 45.153** [8.767] -0.151** [0.059] -0.300** [0.104] 25.167** [6.182]	(10) app1_07 15.889 [8.381] -0.368** [0.057] 0.074 [0.100] 36.308** [6.000]	(11) app1_08 42.404** [7.748] -0.163** [0.053] -0.277** [0.092] 29.099** [5.273]
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composite_bas		[8.282]	[7.821]	[7.993]	[8.149]	[9.451]	[10.750]	[10.228]	[10.224]	[9.337]	[9.363]
	-0.186**	-0.277**	-0.435**	-0.508**	-0.290**	-0.303**	-0.362**	-0.302**	-0.179**	-0.268**	-0.109
	[0.055]	[0.057]	[0.055]	[0.054]	[0.057]	[0.060]	[0.073]	[0.075]	[0.068]	[0.064]	[0.065]
_lsexXcompo_1	-0.716**	-0.656**	-0.538**	-0.337**	-0.270**	-0.149	-0.194	-0.325**	-0.026	-0.013	-0.327**
	[0.097]	[0.102]	[0.096]	[0.097]	[0.099]	[0.113]	[0.129]	[0.122]	[0.121]	[0.111]	[0.111]
Constant	37.231**	48.677**	51.919**	57.757**	28.677**	40.789**	30.272**	19.967*	29.830**	35.051**	27.115**
	[6.237]	[5.625]	[6.133]	[6.053]	[6.217]	[6.733]	[8.068]	[8.169]	[7.284]	[6.771]	[6.481]
Observations	3,368	2,785	2,916	3,099	2,943	2,781	2,084	2,580	2,477	2,575	2,520
R-squared	0.177	0.170	0.206	0.192	0.230	0.182	0.208	0.236	0.193	0.215	0.188
90 80 70 50 50 50 50 30 20 20 10											
0 52 52	54 56 58 60			9 8 0 8 V 2 8 8		92 94 96	100 102 104				
				omposite st	010						