Trends in Gender Segregation in the Choice of Science and Engineering Majors*

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ABSTRACT

Numerous theories have been put forward for the high and continuing levels of gender segregation, but research has not systematically examined the extent to which these theories for the gender gap are consistent with actual trends. Using both administrative data and three education panel datasets, we evaluate several prominent explanations for the persisting gender gap in STEM fields, and find that none of them are empirically satisfactory. Instead, the persisting gender gap in STEM fields is plausibly attributable to a females' greater preference relative to males for elite occupational careers that are less "vocationally oriented" in the undergraduate years and that permit greater flexibility in undergraduate. This hypothesis is supported by an analysis of gendered pathways to medical and law school.

Introduction

Women now surpass men in college completion (Buchmann and DiPrete 2006) and attain bachelors, masters and doctoral degrees at rates that exceed those of men (Snyder and Dillow 2010). Yet horizontal gender segregation in fields of study, which had decreased somewhat in the 1970s and 1980s, has been stagnant for the past 20 years (Alon and Gelbsiger 2011; Charles and Bradley 2002). In particular, the literature has emphasized the slow gender integration in the pursuit of science, technology, engineering, and mathematics (STEM) majors (Turner and Bowen 1999; Xie and Shauman 2003). Given concerns about an undersupply of STEM graduates in this country, the female shortfall in the pursuit of science majors is an important social policy issue.

Recent evidence could support an impression that the gender gap in the attainment of science and engineering bachelor's degrees is narrowing. While only 37 percent of all STEM bachelor's degrees were awarded to women in 1977, women had surpassed men in the receipt of STEM bachelor's degrees as of 2000 and continue to receive STEM bachelor's degrees in increasing numbers (according to a National Center for Educational Statistics survey of colleges and universities that participate in the federal student financial aid programs, Figure 1).

[Figure 1 about here]

Aggregate data about share of STEM degrees by gender, however, conceal two related trends. First, more women than men enroll in higher education and receive bachelor's degrees, and the female lead has increased since women achieved parity in the number of bachelor's degrees in 1982. Yet, women continue to prefer non-science degrees to science degrees, so the increased share of science degrees awarded to women obscures a disproportionate female preference for non-science majors. Second, life science degrees became more popular in the early 1990s for both males and females. During the past two decades, women who choose science majors disproportionately pursue life science degrees. The combined consequence of these two trends is that the share of life science degrees awarded to women has increased from 50 to 70 percent over the last 30 years. At the same time, however, the share of physical sciences degrees awarded to women has fallen in the last decade to 30 percent, its lowest level since 1979. The gender disparity is sharpest in engineering, where the share of degrees awarded to women has never reached 25 percent. In other words, any female advantage in science degrees is confined to life sciences; the male advantage persists in every other STEM subfield (Figure 1).[1]

[1] In 2009, the life sciences subfield represented 60 percent of science majors. The life sciences generally include agricultural sciences, biological sciences, medical sciences, and other life sciences; at the

Numerous theories have been put forward for the high and continuing levels of gender segregation, but research has not systematically examined the extent to which these theories for the gender gap are consistent with actual trends. The question that motivates our study is how the gender gap in STEM fields of study has remained constant in the face of both broad trends in higher education and narrower trends in gender-specific factors that bear directly on the attractiveness of STEM fields of study, specifically concerning gender differences in test scores, life goals, expectations about work-family compatibility, and desires for extrinsic or intrinsic satisfaction. To do this, we revisit arguments from prior research to see how they hold up to different analytical strategies with better and more recent data. Turner and Bowen (1999) analyzed the College and Beyond data (which are drawn from 12 elite colleges and universities), and attributed between one-third and one-half of the gender gap in STEM majors in 1989 to a gender discrepancy in math scores, with even larger effects in preceding years. Using nationally representative data and a more inclusive set of test score measures to analyze the effects of test scores on major choice, we find that gender differences in test scores explain only a small fraction of the gap and play even less of a role in accounting for gender-specific trends in the pursuit of STEM majors. Second, we find that gender differences in life goals explain little of the disparity in fields of study (Hakim 2002; Shu and Marini 1998). We then use a set of counterfactual analyses to demonstrate the continuing role of preferences in predicting the major choices of women and men. Finally, we develop a relatively unexplored and potentially promising explanation for the continuing gender gap in STEM majors, namely, that women in

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bachelor's degree level, the medical sciences subfield is comprised primarily of premed majors and the other life sciences subfield is comprised primarily of nursing. The biological sciences subfield represents 37 percent of science majors (excluding other life sciences), and, when restricted to biological sciences, the female advantage is reduced, but females have comprised more than half of biological science majors since the late 1980s. In subsequent analyses, we focus on the biological sciences, treating other life sciences as non-sciences (akin to our treatment of engineering technologies, discussed in the Appendix).

four-year colleges favor majors that are less vocationally-oriented and that offer greater freedom of course choice during the undergraduate years. We find support for our hypothesis with data from medical and law school admissions that suggest that there are important consequences for choices of major by men and women in the constraints associated with majors that limit curricular flexibility.

1. Background.

The literature on gender and higher education has documented a substantial decline in gender segregation in fields of study through the 1970s, followed by a period in the 1980s in which the declines leveled off (Barone 2011; Bradley 2000; England and Li 2006; Jacobs 1989, 1995, 1996; Turner and Bowen 1999). Much of the decrease in gender segregation was attributed to progress during the 1960s and 1970s toward gender parity in the fields of education and business. The reasons for the stabilization at still-high levels of segregation are less settled, although it has been noted that few men have entered female-dominated fields (England 2010; England and Li 2006; Jacobs 1995) and that the arts and sciences have been particularly resistant to gender convergence (Turner and Bowen 1999).

Much of the earlier decrease in gender segregation has been attributed to improved opportunities for women in the labor market and consequent changes in the attractiveness of particular majors; as companies increased their efforts to recruit young women and as it became illegal for companies to discriminate in hiring personnel, women made steady progress in labor market participation. This growing opportunity story would suggest comparable progress in gender integration in fields of study. Even in engineering, which is the most segregated STEM field, women made steady progress until recently; the number of engineering degrees for women increased by a factor of six and raised the female share of engineering degrees from 4.5 in 1977 to a peak of 21 percent in 2002 (see Figure 1). Explanations for the persisting shortfall of women in engineering (and STEM fields overall) must take account of these broader trends in higher education and the labor market.

The growing share of four-year college students who are women would by itself enhance gender integration in male-dominated fields of study. However, the striking persistence of segregation in fields of study is difficult to reconcile with gender parity in access to higher education (Charles 2011); indeed, gender parity serves to intensify segregation in fields of study by increasing the numbers of female students who enter traditional female majors and occupations (Alon and Gelbgiser 2011).

It has been suggested that gender segregation in STEM fields of study is highly resistant to change, with the most prominent explanation being a discrepancy in math test scores between men and women (Ceci and Williams 2010; Ceci, Williams and Barnett 2009; Halpern et al. 2007; Hyde et al. 2008; Turner and Bowen 1999; Wai et al. 2010). However, most research concludes that gender differences in average math achievement, as measured by standardized tests, are now too small to explain gender segregation in STEM fields or occupations (Hyde 2005; Hyde et al. 2008; Spelke 2005; Xie and Shauman 2003). Other research has suggested that the relative shortage of females having very high math test scores explains part of the gender gap in STEM fields (Hyde and Mertz 2009; Machin and Pekkarinen 2008; Pope and Snyder 2010). Yet the fact that gender differences in test-score variance is variable across countries suggests that socio-cultural factors rather than biological ones explain the gap (Guiso et al. 2008; Niederle and Vesterlund 2010; Penner 2008). Clearly there is a residual gender gap in STEM fields of study that test scores do not explain (Halpern et al. 2007; Turner and Bowen 1999).

Other explanations have included a slowdown in the shift of women out of traditional educational choices (Bradley 2000; England and Li 2006). But what are these traditional choices, and how do they become reflected in preferences? Preferences have been conceptualized as different weights placed on career and family compatibility (England 2005; Frehill 1997; Hakim 2002), differences in intrinsic and extrinsic motivations that alter the attractiveness of particular careers (Beutel and Marini 1995; Bobbitt-Zeher 2007; Bridges 1989; Davies and Guppy 1997; Konrad et al. 2000; Johnson 2001; Marini et al. 1996), and different interests in working with people as opposed to physical objects and abstract concepts (Barone 2011; Eccles 2007; Hansen et al. 1993; Lippa 1998. Men are more likely than women to cluster in fields with higher economic returns (Davies and Guppy 1997; Wilson and Boldizar 1990), in part because they view work as their primary adult role (Eccles and Hoffman 1984). It is often suggested that these differences between the genders explain gender differences in choice of college majors and careers.

While values explanations linked with family/work conflicts have superficial appeal, they are undermined by the substantial gender integration that has occurred in medicine, law, and business professions, which all are demanding in the number of hours they require (England 2010; Wilson and Boldizar 1990). There is no obvious difference in the level of work flexibility between STEM careers and law, medicine or business. Boulis and Jacobs (2008) specifically consider the explanation that differences in work flexibility account for gender segregation in medical specialties and find it wanting. Growing opportunities for women in these fields may be related to the slower rates of women's progress in physical science and engineering, but prior research has not addressed this issue empirically. Indeed, no existing studies directly test the matrix of existing explanations against comprehensive trend data on the gender pattern in STEM fields. This limitation is significant: trend studies are necessary to investigate dynamic theories about changes in either the broader opportunity structure or in the gender-specific distribution of values and skills across cohorts.

In the sections that follow, we test existing theories to see how well they explain the trends in the gender gap in STEM fields of study, using more recent and comprehensive data than prior studies. We examine test scores to see how much of the gender gap they explain, and to determine whether there is evidence of a trend in female major choices when holding test scores constant. We also examine the life goals of male and female adolescents to see how well they explain the gender disparity in major choice.

We then develop an alternative theory that combines gender differences in preferences with structural differences in the organization of college majors. Studies that focus exclusively on the attractiveness of STEM fields to women without considering competing opportunities in other elite fields cannot address the broader environment in which women make choices about their college majors. To remedy this gap, we consider whether the slow rates of women's progress in the physical sciences and engineering is connected with women's growing opportunities for pursuing non-STEM degrees and careers that are equally prestigious and socially important. We suggest a complex relationship between college major and post-baccalaureate choices in which high-achieving women are more likely than high-achieving men to prefer elite careers that are flexible regarding the requisite undergraduate majors (particularly majors that are structured to be less vocational). In other words, women are more likely to prefer careers that permit multiple pathways or impose weaker constraints on choice of major.

2. Data.

This paper analyses administrative data from the CIRP (Cooperative Institutional Research Program) Freshman Survey for the years 1971-1999 as well as data from three NCES (National Center for Education Statistics) longitudinal surveys conducted since 1980. The administrative data comes from the WebCASPAR database maintained by the National Science Foundation.[2] The CIRP Freshman Survey (1971-1999) permits us to analyze self-reports of the probable majors of incoming first-year students over time. Collectively, the three longitudinal surveys permit us to analyze and compare the educational pathways of high school students who graduated in the spring of 1982, 1992, and 2004. The oldest, the High School and Beyond Longitudinal Study of 1980 (HSB), was first administered to a stratified, nationally representative sample of approximately 30,000 high school sophomores and 28,000 high school seniors nested within about 1120 high schools, with follow-ups in 1982, 1984, 1986, and 1992. We use the 1980 sophomore cohort sample. Of these students, 18,500 were selected for the high school transcript study; 15,000 of these students were followed every other year through 1986 and then again in 1992, when the respondents were 27-28 years old. The second of the three studies, the National Education Longitudinal Study of 1988 (NELS), began with a sample of 25,000 eighth grade students in 1988 within about 1000 schools, with follow-ups in 1990, 1992, 1994, and 2000. For each in-school follow-up, the student sample was freshened to obtain a representative, cross-sectional grade-cohort (i.e., 10th-graders in 1990 and 12th-graders in 1992).

[2] WebCASPAR is maintained by the Division of Science Resources Statistics (SRS) within the NSF and is accessible at http://caspar.nsf.gov/. WebCASPAR includes information from a variety of surveys, including some of those conducted by the National Center for Education Statistics. The SRS harmonizes the data to produce multiyear information about individual fields of science and engineering at individual academic institutions. The source data that we use comes from the Higher Education General Information Survey and the Integrated Postsecondary Education Data System (IPEDS) that is conducted by NCES. IPEDS is a system of interrelated surveys conducted annually, which gathers information from every college, university, and technical and vocational institution that participates in the federal student financial aid programs.

We use the 1990 "freshened" sample, which was nationally representative of high school sophomores. The most recent panel survey is the Education Longitudinal Study of 2002 (ELS), which began with a sample of about 15,000 sophomores in 2002 that were followed up in 2004 and in 2006 when they were typically two years past high school graduation.

To measure "sophomore" status consistently, we focus on cohorts of standard enrollees; thus, we exclude late graduates (beyond July 31 of their graduating year), early graduates (before January 1 of their graduating year), and high school dropouts. We also exclude late postsecondary institution enrollees, and those who drop out before the spring of their second year in college. These restrictions ensure that we have a dataset of students of the same age and educational status.

The appendix explains the procedures we use to make the variables comparable across the three datasets.[3]

3. Examining Aggregate Evidence of Dissimilarity

3.1 Trends in Attendance at Four-Year Colleges and Selective Colleges

The most obvious trend in post-secondary education over the last 20 years is the increased rate of enrollment in higher education for women. To understand the effect of increased postsecondary education for women on the propensity to become a science major, we estimate changes in the marginal probabilities of being a science major and of being a female enrolled in four-year college across the three panel studies (see Table 1). Across the three cohorts, there was a statistically insignificant increase in the representation of women among students who choose scientific majors (from 33% in HSB to 36% in ELS). There was also a steady and

[3] All sample sizes are rounded to the nearest 10 pursuant to the NCES restrictive data use agreement.

statistically significant increase in the representation of women among attendees at four-year colleges: from 52 percent in HSB to 57 percent in ELS. If this five percentage-point increase in the share of college students who are female were evenly distributed across the majors, including science majors, it would have led to an increased share of science majors who were female. At the same time, Table 1 suggests that there have been uneven trends in the representation of college students in science majors: from 22 percent in HSB to 18 percent in NELS, back to 21 percent in ELS, with the differences between the NELS estimate and the estimates from both of the other surveys being statistically significant. It is thus not surprising that the propensity of women to major in the sciences follows a similarly uneven trend despite the growing share of students in four-year colleges who are female. In sum, these data suggest that the rising number of women in higher education has made a small but meaningful contribution to narrowing the gender gap in STEM fields overall.

[Table 1 about here]

Next, we address how the overall proportion of women within the sciences relates to female representation in particular subfields. Figure 2 shows bachelor's degrees awarded in selected science and engineering subfields from 1996 to 2009. The solid lines represent the female-male odds ratios (i.e., the female odds of majoring in the subfield relative to the male odds), while the dashed lines represent the proportion of the subfield that is female. Analysis of female participation in selected science subfields outside of the life sciences shows the complexity of the choices women have made over the last four decades. In the fields of physics, computer sciences and mathematics, the trends differ starkly despite the apparent similarity of the content. In physics, female representation has never reached 25 percent. In computer science, female participation grew rapidly during the 1970s and 1980s but fell sharply since then, so that current female representation is about as low as in physics. For mathematics and statistics, by contrast, female representation has remained near 50 percent for the last ten years; however, the female-male odds ratios are in steady decline given the rising number of women in higher education. In engineering, female representation has remained less than 25 percent in every year in the largest subfields, although female participation did grow somewhat starting in the late 1970s and 1980s and continuing through the 1990s. The only exceptions to this pattern are found in the smaller subfields of chemical engineering and materials engineering (also shown in Figure 2), where women have had slightly higher rates of participation. Finally, chemistry and earth sciences stand out along with mathematics as fields in which female participation has steadily risen to a current level of about 50 percent (of all Bachelor's degrees). While the female-male odds ratios are declining in mathematics, they are steadily increasing in chemistry, with women in 2009 being only 25 percent less likely to obtain a degree in chemistry (OR=0.75) and representing fully half of chemistry degree recipients.

[Figure 2 about here]

These data suggest that the gender differences in STEM subfields have been fluid, with women moving into and (in some cases) out of subfields at different rates. Thus, the slow convergence implied by Figure 1 obscures a complex pattern within the many distinct STEM subfields.

A related complexity is that the bachelor's degree field of study does not necessarily serve as an adequate proxy for initial college major. Students also will often have tentative preferences before actually declaring a major, and these considerations affect their course choices in the early college semesters. Consequently, even data on declared field of study may not reflect the actual distribution of initial choices. Engineering programs, however, are more likely than other academic programs to require students to declare a major in the first year in college, and therefore engineering enrollments arguably constitute an indicator of trends in first-year enrollments in science majors (National Science Board 2010).[4]

Administrative data show that full-time, first-year enrollment in engineering programs declined in the mid 1980s through 1997, when the trend reversed and enrollment in engineering programs increased (Figure 3a). Male enrollment followed the aggregate trend, while female enrollment increased from the late 1980s through the early 2000s, before declining. The combination of those trends produced a peak in the proportion of engineering students who are female at about 20 percent in the mid to late 1990s; this enrollment pattern is consistent with Figure 1, which shows a peak in female engineering degrees a few years later.

We can see from Figure 3b that the basic distributional patterns are present at the time of college entry, where women are least likely to select engineering fields of study and almost as unlikely to select physical sciences fields (presumably the slightly higher odds is influenced by the attractiveness of chemistry, demonstrated in Figure 2). For purposes of our study, it is useful to note the differential in the initial choice but to focus more systematically on the choice as of the sophomore year; this allows us to make comparisons over time for students at similar points in their educational careers.

[Figure 3 about here]

To quantify differences in major choices, we calculate an all-inclusive index of dissimilarity based on 20 broad field-of-study categories in the National Science Foundation's WebCASPAR database. The index, which uses all degree recipients at NCES institutions for

[4] This is not to say that engineering enrollments are fully representative of enrollments in other mathematic and scientific fields. As Figure 2 illustrates, they are not.

each year from 1977 to 2008,[5] is based on the sum of the absolute value of the differences between women and men majoring in each of the 20 fields. Dividing the sum by two produces a measure that captures the percentage of students who would need to change majors in order to produce a distribution that matches that of the other group. In 2008, for example, almost one-quarter of all women would have to change college majors for women to be distributed in the same manner as their male counterparts.

Figure 4 displays changes in the dissimilarity index over the past 30 years for bachelor's, master's, and doctoral degrees. The index shows a pronounced decline in gender segregation for bachelor degree recipients through the mid-1990s, at which point the declining segregation trend began to stagnate. This illustrates the slowdown in gender integration identified a decade ago by Turner and Bowen (1999).[6] The trends for master's and doctoral degrees in Figure 4 are less pronounced than are those for bachelor's degrees, suggesting that segregation is more resistant to change for those degree levels.

[Figure 4 about here]

A potentially important issue when measuring trends in STEM fields of study relates to the admission of foreign students, because research has shown that sex segregation in STEM fields across countries is not necessarily uniform (Barone 2011; Charles and Bradley 2002, 2009; Penner 2008).[7] The index for bachelor's degrees displays little difference between foreign and

[5] The 20 field of study categories used in the calculation of the dissimilarity index are architecture and environmental design, arts and music, business and management, communication and librarianship, education, engineering, geosciences, humanities, interdisciplinary or other sciences, law, life sciences, math and computer sciences, other non-sciences or unknown disciplines, physical sciences, psychology, religion and theology, science and engineering technologies, social sciences, social service professions, and vocational studies and home economics.

[6] Turner and Bowen (1999) observed a substantial reduction (a 10-percentage point drop) in the dissimilarity index from 1973 to 1983, followed by a cessation of the downward trend in the mid 1980s.

[7] Boulis and Jacobs (2008), for example, argue that foreign medical students contributed to the feminization of medicine.

U.S. students. For master's and doctoral students, however, the trends are strikingly different, with more consistent declines in gender segregation among foreign students than among domestic students. The impact of foreign students on post-secondary trends is especially large because foreign students make up a higher proportion of the master's and doctoral degree recipients than bachelor's degree recipients in science-related fields (National Science Board 2010). Figure 4 suggests that at least for bachelor's degrees the exclusion of foreign students from the education panel studies is unlikely to be problematic for understanding the gender composition of undergraduate majors.

We also computed trends in the index of association using WebCASPAR data (Charles and Grusky 1995). The index of association measures the factor by which women are underrepresented in the average field of study and is not affected by changes in the share of students in particular fields. Using the same 20 broad composite categories, the solid line in the first panel of Figure 5 represents the all-fields index; the dashed lines represent the indices for the subgroups education-business-other, arts and sciences, and sciences. The second panel magnifies the y-axis, showing the index for the years since 1980.

[Figure 5 about here]

The large decrease in the all-fields index before 1980 (dropping from more than 6 in the late 1960s to about 3 in 1980) is consistent with our previous findings. The trend in the education-business-other index demonstrates that gender segregation in those fields has continued to diminish, albeit at slower rates than it did before the 1980s. The arts and sciences (and especially the sciences), however, have actually experienced increasing levels of segregation in the past ten years.

Because the decomposition and regression analyses in the sections that follow rely on the three panel datasets, it is useful at the outset to compare the dissimilarity of fields of study in those panel datasets with the dissimilarity index reported above from the administrative data. The data in Appendix Table A1 suggest that the health professions and education are the most gender segregated non-science fields.[8] Consistent with Figure 1, engineering has remained the most gender segregated science field throughout the period of study (Appendix Table A1). Because the panel data necessarily uses more aggregated categories than does the WebCASPAR data, it is not surprising that the dissimilarity indices for those three years would be smaller than the indices reflected in Figure 4. Both the panel datasets and the WebCASPAR data show a slight increase in segregation since the 1980s.

4. Gender, Test Scores, and Trends in Field of Study

The most widely discussed determinant of major choice in the literature is math ability. The argument is that males might be more likely to pursue majors and careers that depend on math skills if they perform better on standardized math tests. While gender differences in average math tests have always been small and have converged in recent decades (Hyde et al. 2008), males at all relevant times have received a disproportionate share of the very best math scores. Turner and Bowen (1999) found that the gender disparity in SAT math scores explains nearly half of the disparity in choice of physical science majors for their sample of students drawn from largely selective colleges and universities.

Using tenth grade test scores from the panel datasets allow us to compare students from a representative sample of high school students, including those who do not take the SAT. We use

[8] The sample includes college sophomores in the three panel datasets that were enrolled in 16 composite categories in the fields of science, business, education, and the social sciences, with a large residual "Other" category.

standardized achievement measures, which provide an estimate of achievement relative to the population of tenth graders for that year.[9] The scores show a gender difference, with males more likely than females (by a ratio varying from about 1.4:1 to 1.8:1) to perform at 1.5 or more standard deviations above the mean (Table 2).

[Table 2 about here]

It is easy to overstate the importance of math scores in predicting the gender gap in STEM majors. If the relative rarity of women with high math achievement were the primary cause of the gender gap in the sciences, we would expect the propensity for high scoring students to major in the sciences to be nearly identical for men and women. But Table 3, which displays the distribution of men and women with math test scores above the mean in each respective survey, shows, as others have observed (Ceci and Williams 2010; Ceci et al. 2009; Hyde et al. 2008), that this expectation is not accurate. For each of the three surveys, males with high math scores have a higher propensity to major in science than females with high math scores. In 1982, about 45 percent of males with math test scores more than 1.5 standard deviations above the mean majored in science, compared to only 29 percent of females; in 2002, 38 percent of high-scoring males and 29 percent of high-scoring females chose science majors. The declining proportion of high-scoring students who major in the sciences may reflect both competitive opportunities in other fields and declining interest in science. Regardless of the explanation for this trend, the differential propensity of males and females to translate high math scores into science fields of study has remained roughly constant across the three surveys.

[Table 3 about here]

[9] The test scores come from cognitive test batteries given to the respondents of each survey during the spring of their tenth-grade year; by construction, it is normalized by cohort. The tests are similar but not identical across surveys.

Next, we decompose the contribution of tenth-grade test scores on the choice of a science major as of the sophomore year in college using the NCES panel datasets, which provide a representative sample of the entire college population.[10] To explore the sensitivity of the decomposition to sample selection, we also use subsamples of students who attend four-year colleges and those who attend selective institutions, based on the Barron's Selectivity Index for the applicable year.[11] We define science major to include the fields of computer science, math and statistics, engineering, biological and life sciences, and physical sciences.[12]

Table 4 summarizes the results of separate regressions for all male and female college students in the HSB, NELS and ELS, of science major on tenth grade math and reading test scores. Standardized test scores are categorized in .5 standard deviation increments above the mean, with less than the mean as the reference category. Because the test score distribution has longer tails in the ELS, there are more test score categories for that regression. We use these estimates to decompose the gender gap in field of study and consider the extent to which the gender gap would be reduced if the test scores were the same for boys and girls.[13]

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[10] We define college sophomores as those who graduate from high school on or before July 31 of their senior year, enroll in college before January 1 of their graduating year, and remain enrolled through the spring (interview date) of their sophomore year in college.

[11] The Barron's classification is based on SAT scores, grade point average, class rank required for admission, and overall admissions acceptance rate. Using the selectivity ratings for 1982, 1992, and 2004, Barron's is comparable across datasets. Barron's classifies the schools in the following categories: most competitive; highly competitive; very competitive; competitive; less competitive; and non-competitive. We use the first two categories for our selective subsample. In these categories, there are 90, 115, and 174 schools, in the three years, respectively; however, many of those institutions are not represented in the panel datasets. As a result, the samples of students in those categories for HSB and NELS are small, and the decomposition analysis did not produce significant results.

[12] The observed difference between the proportion of female and male science majors differs slightly from the data reported in Appendix Table A1 because of the treatment of undeclared majors (explained in the Appendix).

[13] High school course-taking patterns are also relevant. Gender variation in completion of advanced mathematics or science courses would be likely to influence college major. The data suggest that, in 1982, a higher percentage of males than females enrolled in advanced mathematics courses, but by 2004, there were no differences in enrollment between male and female twelfth graders (Ingels, Dalton, and LoGerfo 2008). Similarly, in 1982, there was no difference in the percentages of males and females enrolled in

[Table 4 about here]

The logistic regression coefficients are consistent with a relative female aversion to science majors net of test scores. The math test score coefficients suggest that test scores are more consequential for males at the lower levels (closer to the mean), but become equally or more consequential for females at the very highest levels. Yet test score differences account for only a small part of the observed difference between the distributions in science majors for women and men. Among HSB respondents, only 12 percent of the observed gender gap can be attributed to test scores when we use coefficients from the regression equation for males and the actual test scores of women. An even smaller portion of the gender gap is explained when we use coefficients for females and test scores for males. In ELS, the observed difference is about the same, and the percentage attributable to test scores is about 14 percent.

This finding (that achievement test scores explain less than 15 percent of the gender gap in STEM fields of study) on a representative sample of the entire sophomore college population (for three sophomore cohorts between 1984 and 2006) is in contrast to the finding of Turner and Bowen (1999), who attribute almost half of the gender gap in majoring in physical science to SAT test scores.[14]

One possible explanation for the difference between our results and those of Turner and Bowen is that the difference reflects the different scope of the two studies: Turner and Bowen (1999) using a narrower sample of graduates of highly selective schools, and our analysis using a nationally representative sample of college sophomores. To repeat, we find that up to 15 percent of the gap can be attributed to test scores for the subset of sophomores attending postsecondary

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advanced science courses, but by 2004, females enrolled in advanced science courses at higher rates than males.

[14] For the 1989 cohort, they find that 44 percent of the overall gap in fields of study, 45 percent of the gap in the physical sciences and math, and 33 percent of the gap in engineering were attributable to SAT test scores. For the 1976 cohort, the numbers are 52 percent, 100 percent, and 29 percent.

institutions. However, when we limit attention to sophomores attending selective colleges and universities, the fraction of the gender gap explained by test scores rises to roughly 22 percent.

A second possibility looks to their use of SAT scores rather than the NCES 10th grade math and verbal scores. The sample of SAT test takers is not representative of the applicable population of high school students; in particular, more females than males take the SAT (Buchmann, DiPrete, and McDaniel 2008; Halpern et al. 2007; Spelke 2005). Thus, it is likely that the set of female students who take the SAT dips farther into the female talent pool than does the set of male SAT test-takers. When we repeat our decomposition analysis for the subset of students whose SAT scores were reported in the NCES panel data,[15] and use the same set of cutpoints (mean, .5σ, 1σ, 1.5σ, 2σ, 2.5σ), we find some support for the conjecture that SAT scores have greater explanatory power; 20% of the gender gap in STEM majors can be explained using SAT scores for the ELS SAT test-taker sample as compared to 15 percent for the same sample using tenth-grade test scores

Third, we note that Turner and Bowen (1999: 305-06) used a categorical dependent variable for major rather than the binary variable we use here; however, this is unlikely to explain the divergent results because they report that the share of the differential attributed to test scores was larger when they used a binary variable for science and non-science fields (about 65 percent, compared to 44 percent using multiple categories).

A final possible explanation is that test scores explained more of the gap in 1976 and 1989, the period of their data analysis, than they do in the period from 1984 to 2006, which we analyze. To evaluate whether the relationship between math scores and the gender gap has

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[15] There is a continuing disparity in SAT math scores that favors men, particularly at the highest score levels; women have a slight advantage in verbal scores at the highest levels (Wai et al. 2010). Although male–female ratios in mathematical reasoning are substantially lower than 30 years ago, they apparently have been stable over the last 20 years and still favor males (Wai et al. 2010), thus providing some support for the theory that stagnation in gender segregation is attributable to test score differences.

changed in the past 30 years, we estimate a logistic regression of science major on gender, cohort (or survey), and math and reading scores, with two-way interactions involving gender, cohort, and test scores. Table 5 presents the results for the four-year college sample. Model 1 includes categorical variables for cohort (with HSB as the reference group), along with gender and two-way interactions involving cohort and gender. Model 2 adds the main effect of the standardized math and reading test scores to the regression. Model 3 includes the interactions between test scores and survey and between test scores and gender. The main effect of being female remains significant and of similar magnitude, and the effect of math scores continues to be significant, but these models provide no evidence that the translation of math test scores into science majors varies by gender. Nor do they uncover a female-specific trend in science majors in the three panel datasets. Finally, the interaction terms for test scores and survey suggest that the relation between test scores and major choice has also not changed significantly over time.[16]

[Table 5 about here]

Models 4, 5, and 6 use different STEM subfields as the dependent variable -- mathematics, statistics, or physical sciences (Model 4), biological sciences (Model 5), or engineering (Model 6), estimating the effects of the independent variables in Model 3 on those dependent variables. The female odds ratios are less than one for all three of the broad science fields, but the lowest and only statistically significant deviation from equal odds is for the engineering and computer sciences field. The trend variables suggest a reduction in the female/male odds ratio over time of majoring in engineering for women, and an increased odds ratio for majoring in the biological sciences. But these models do not find clear trends in the relationship between math or reading tests, gender, and choice of major.

[16] A likelihood-ratio test suggests that Model 2 shows a significant improvement from Model 1 (the chi-squared is significant at the .05 level). Model 3 does not show significant improvement from Model 2.

The conclusion drawn from these models is that men are more likely to choose a science major at every combination of math and reading levels. For example, the marginal effects in Model 2 suggest that men in the highest math and reading categories (more than 1.5 standard deviations above the mean) are twice as likely as women with scores in those same categories to select a science major (42 percent versus 21 percent). Conversely, for students in the lowest math and reading categories (below 0.5 standard deviations above the mean), men continue to be twice as likely as women to select a science major, but at lower probabilities (19 percent versus 8 percent. We find no significant gender difference in the translation of test scores into science majors, and we find that the relation between test scores and STEM fields of study has not changed significantly over the past 30 years. Women, in short, have a substantial preference for non-STEM majors. The nature of this preference, however, is ill defined. We turn to this topic in the next section.

5. The Relevance of Life Goals in Explaining the Gender Gap

The literature includes several explanations for the way in which gender differences in values and preferences relate to the female tendency to choose non-STEM majors. Hakim's (2002) theory argues that women and men frequently differ in the centrality of work-centered, home-centered, or adaptive lifestyles to the respondent's identity. Similarly, Bobbitt-Zeher (2007) suggests that gender differences in values influence decisions regarding higher education and occupation; she measures values through a single survey question about the importance of having lots of money. And using 23 job-values survey questions loading on seven different constructs, Marini et al. (1996) suggest that the sexes attach different values to extrinsic and intrinsic rewards associated with work (see also Frehill 1997). Although men once attached greater value to extrinsic rewards, women and men now do so to the same extent. Conversely, although both sexes attach importance to the intrinsic rewards of work, females consistently have attached greater value than males to intrinsic rewards.

However, this research has not established that aspirations, values, and identities have a strong influence on the gender gap in field of study, occupation, or pay (Frehill 1997; Hakim 2002, 2003; Polachek 1978). For example, Hakim finds that most men are work-centered, compared to only a minority of women; yet lifestyle preferences have little impact on women's choice of occupation (Hakim 2000, 2002, 2003). Similarly, Bobbitt-Zeher (2007) finds that aspirations for earning lots of money have only a modest effect on the gender income gap. Using HSB data, Frehill (1997) finds that gender differences in high school preparation and work-related values explain 30.2 and 2.4 percent of the gender gap in engineering, respectively.

We use survey questions about respondent life goals from the NCES panel studies (similar to those used in Marini et al. (1996) and Frehill (1997)) to consider whether males see their life goals as more compatible with STEM careers than do females. We estimated a multinomial logistic regression using college sophomore major choice as the dependent variable, with categories for biological sciences, physical sciences, mathematics and statistics, engineering and computer sciences, and a baseline "other" category. In the first model, the predictor variables are gender and standardized math and reading test scores (categorized in 0.5 standard deviation increments above the mean, with less than the mean as the reference category). In the second model, we add factors derived from 15 survey questions that capture respondent life goals as of twelfth grade.[17] The life goals variables are dichotomous indicators of whether the respondent selected the goal as being "extremely important". Using principal axis factor analysis

[17] These questions are based on a single survey stem that takes the form: "How important is each of the following to you in your life? (Not important; Somewhat important; Very important)": a. Being successful in my line of work b. Finding the right person to marry and having a happy family life c. Having lots of money d. Helping others in the community, etc.

with varimax rotation, we extracted 5 distinct factors. We refer to the factors as (1) importance of success; (2) importance of marriage and children; (3) importance of being a community leader; (4) importance of money and leisure time (correlation with the importance of success = .15); and (5) importance of being close to parents. We then interact those variables with gender to assess the extent to which men and women differ in the way that life goals influence their major choices.

Model 1 suggests that differences in math and reading scores largely explain the female preference for the biological sciences major; with test scores controlled, the relative risk ratio (RRR) on female does not differ significantly from one.[18] However, despite controls for test scores, the relative risk ratios on female for the other subfields are significantly below one (0.68 for mathematics, statistics, and physical sciences and 0.14 for engineering and computer sciences). This suggests a different explanation for female choices related to those fields, as we discussed above. In particular it is worth noting two things about the engineering majors compared to non-science majors. First, engineering majors tend to have lower reading and higher math scores than non-science majors (while other science majors tend to have higher math scores than non-science majors, but either the same or higher reading scores than non-science majors). Second, this model reaffirms the finding above that women are much less likely to choose engineering majors compared to non-science majors than they are physical science or biological science majors. These two factors suggest that engineering does not allow females to take advantage of a diversity of interests that they wish to pursue, a point the next section pursues at length.

[18] The RRR measures the relative risk, for a unit change in the predictor variable, of each STEM major relative to the referent group of non-science majors, assuming the other variables in the model are held constant.

Model (2) suggests that life goals have an important relation to major choice (see Table 6). Students who said that success is important have significantly higher odds of entering any of the science subfields relative to the non-science fields. However, these effects are not gendered, and hence are consistent with other reports in the literature that extrinsic motivations have become more important to both females and males (Marini et al. 1996). Model (2) also suggests that students who think it is important to make money have significantly lower odds of majoring in the biological sciences, but the point estimate for the gender-values interaction implies that these attitudes are more characteristic of men than women. Students who said that marriage and children are important have significantly lower odds of majoring in engineering or computer sciences, but the interaction terms suggest this preference is more consequential for women than for men. Females who said that marriage and children are important are also less likely to choose biological science majors. These findings are consistent with the idea that females are more likely to see any type of science major as leading to a career that is incompatible with their aspirations regarding family.

[Table 6 about here]

The closest measure of intrinsic rewards in the panel datasets is the community outreach factor, which predicts a higher likelihood of a biological science major relative to a non-science major. There is some evidence in the literature that students who aspire to medical careers are likely to have extrinsic and intrinsic or altruistic goals that they expect to satisfy by pursuing a medical career (Boulis and Jacobs 2008). If biology is a pathway to medical school, then this finding makes sense and is consistent with previous findings in the literature. However, there is no evidence in our data of an interaction with gender, which suggests that the aspiration affects major choice the same for students of either gender.

Taken together, the various gender-related variations documented by the life goal questions explain little of the female preference for the non-sciences. A comparison of Models 1 and 2 illustrates this point. The addition of the life goals variables in Model 2 move the RRR for females only slightly closer to 1 for mathematics and physical sciences when compared to non-science fields, and they have essentially no impact on the RRR for females in the engineering and computer sciences fields (see Table 6). In short, females and males with similar test scores seem to resemble each other more than they differ in terms of the translation of life goals into majors. The somewhat greater tendency for females to experience family-related goals as a deterrent to entering science majors explains little of the gender gap in science majors. Importantly, and contrary to the preferences literature, life goals do not appear to be a driving force behind major choice, at least when separated from the broader opportunity structure that influences competition among majors.

6. Competition Among Majors and the Gender Gap

As mentioned previously, the apparent reduction of the overall gender gap conceals both a relative increase in the female choice of biological science majors and a continuing scarcity of women in physical science and engineering majors. The multivariate analyses document the limited extent to which differences in life goals and in mathematics ability can explain these trends. With the multivariate analyses in hand, we can illustrate better (Figure 6) the nature of trends by comparing observed and counterfactual trend lines that we constructed using WebCASPAR data. The "Observed" line in Figure 6 shows the actual trends in the female-to-male odds of majoring in the physical sciences, engineering, or math (the hard sciences). The "Equated Science/Non-Science Distribution" line is a counterfactual trend line constructed by assigning the male propensity to major in the sciences to females, but retaining the actual female preference for life sciences, conditional on majoring in the sciences. The "Equated Science Subfield Distribution" counterfactual line was constructed by assigning the male propensity to major in the physical sciences and engineering, conditional on majoring in science, to females but retaining the actual female propensity to major in the sciences.

[Figure 6 about here]

The final two lines explore the importance of the gender difference in math test scores. We estimated a logistic regression estimated with HSB data in which the dependent variable was whether the student majored in the physical sciences or engineering, and where gender and math scores are the only independent variables. We use the model to construct two counterfactual scenarios: (1) a monotonic convergence in male and female math scores to zero over a thirty year period, assuming residual female preferences (as measured by the coefficient for female) remain constant; and (2) a monotonic convergence in residual male and female preferences to zero over thirty years, assuming math score differentials remain constant

Figure 6 shows that the observed trend in the female-male odds ratios peaked at about 0.25 in the late 1980s, but fell back to early 1970s levels (about 0.20) around 2007. In the counterfactual trend that equates the gender preferences for science vs. non-science distributions, the female-male odds ratio approached 0.75 before 1980 but dropped to below 0.50 in more recent years. Conversely, in the past 30 years, the counterfactual trend that equates the gender preference for physical sciences and engineering, conditional on a science major, increases from less than 0.25 to nearly 0.50. This implies that the choice of subfields within the sciences—and specifically, the choice of biological science as opposed to physical science, mathematics or statistics, or engineering—has become increasingly important to understanding the gender gap in the physical sciences and engineering. Still, under either of those counterfactuals, the physical sciences odds ratios in 2009 would be slightly less than 0.50 as compared to the observed odds ratio of less than 0.25.

The counterfactuals in which we alternately converge math scores and female preferences illustrate the greater importance of preferences compared with test scores in contributing to the gender gap. If females had developed the same preferences over time as males, we would see the gender gap narrowing, with the odds ratio rising above 0.75 by 2009. Conversely, if average male and female math scores converged over time from the level found in HSB, there would have been no substantial effect on the gender gap. Again, the data document the importance of a female preference apart from math scores or other variables in the regressions.

Taken together, the preceding analyses establish that preferences are important – both in the form of preference for biological sciences compared with physical sciences and engineering, and preferences for science majors compared to non-science majors. However, Section 5 suggests that we cannot explain preferences simply as a set of aspirations that relate to one's choice of major. We need a better understanding of the role those majors play in the pathway toward an eventual career. Gendered socialization may well be a substantial factor predicting major choice, but the mechanism through which it operates may be a choice process directed not by gender differences in long-term life goals, but rather by gender differences in relative preferences for specific majors, and for their implications for general education as well as for pathways leading to particular occupations. Just as some young people choose a particular post-secondary educational strategy because it leads to a desired occupation, others may make their occupational decisions because of the freedom or constraint those decisions imply for the undergraduate courses they would prefer to take. College-oriented females clearly differ from males in their preference for careers in education, nursing, and many health therapist fields. Moreover, females and males may differ in their preference for specific educational courses even net of gender differences in occupational preferences. To the extent that a specific occupational choice allows females and males to exercise their gendered curriculum preferences, then gender differences in that occupational pathway may be smaller. To the extent that a specific occupational choice differentially frustrates females or males from satisfying curricular preferences, then gender differences in that occupational pathway may be larger. In particular, occupational pathways that allow relative freedom in curricular choices at the undergraduate level may thereby reduce gender differences relative to occupational pathways that reduce freedom in curricular choice at the undergraduate level in a way that differentially disadvantages one gender relative to the other.

The contrast between engineering and law or medicine is a prime example of differently structured curriculums differentially relate to gendered preferences. Upon completion of a bachelor's degree in engineering, a graduate might have choices to take a job in the engineering field (making the time spent in postsecondary education shorter than that for other professions), to pursue graduate studies in many STEM disciplines, or to enter professional school (law school, medical school, or business school). This degree field thus would appear to open multiple career pathways. However, the engineering degree is associated with vocationally oriented coursework and involves a relatively large number of required undergraduate courses (Frehill 1997). Engineering is also unusual in typically requiring a commitment in the first or second semester of college (Frehill 1997). Students who do not select engineering in the first few semesters but decide to move into engineering later in their college career will spend more time before graduation than those that committed earlier. At the same time, the structure of most engineering degree programs requires that engineering majors be relatively restricted in their ability to pursue coursework in other fields of interest. The engineering major thus comes at the expense of a broad undergraduate education.

In contrast to engineering, a humanities student might be able to select a major late in the undergraduate career and pursue a broad range of coursework, but upon graduation will have a more limited set of post-baccalaureate options: entering graduate school (with a long path to a PhD, see Menand (2010)), attending professional school, or possibly obtaining a job teaching in primary or secondary schools. Because women generally prefer education fields to a substantial extent (see Appendix Table A1), it is easy to see that a humanities student's second or (even) third choice of teaching following a terminal bachelor's degree might be preferable to women (Barone 2011). But it is also the case that women can readily indulge a preference for humanities courses or even a humanities major while then enrolling in a professional program in law, medicine, or business. It is much more difficult to indulge this preference if one adopts the goal of being a professional engineer.

If women have a disproportionate desire to maintain flexibility in coursework and career choices later into their college career, and a consequent distaste for professional undergraduate majors organized around physical science or engineering, this gender difference might explain part of the gender gap in STEM fields of study. Because the choice of majors is a "zero sum" constraint, gender equality in the physical sciences and engineering must be seen as a competition between those more constraining major choices and disciplines that structure their undergraduate curricula in a more flexible way. Post-baccalaureate professional schools (medicine, law, business) typically require little or no specialization in undergraduate field of study. If women are disproportionately likely to expect careers that do not require undergraduate specialization, then they have relatively little affirmative reason to select into a constraining field.[19]

One way to investigate this conjecture is to examine the post-baccalaureate aspirations of college sophomores. If males and females have different aspirations and if these aspirations relate to their major choices, we can gain better insight into the pathways that might guide major choices. Table 7 displays a cross-tabulation of aspirations for elite post-baccalaureate careers by gender from the NCES panel studies.[20] Table 7 documents a substantial shift in aspirations for elite careers. In 1984, males were more likely to aspire to elite careers than females (39 percent versus 37 percent); by 2006, the balance had shifted to females (69 percent versus 63 percent). Breaking this down, in 2006 females were nearly 40 percent more likely to aspire to an elite career with a non-science major than were males (58 percent versus 42 percent), and they were about equally likely to aspire to a non-elite career with a non-science major (28 percent versus 25 percent). Finally, of the relatively small number of women that choose science majors, in 2006 about 86 percent aspire to elite careers, compared to only 69 percent of men that choose science majors.

[Table 7 about here]

Another important test of this conjecture involves the different choices that women and men make in college, conditional on their enrolling in professional school. We obtained data on medical school matriculants from the American Association of Medical Schools. The data

[19] Because of changes in the last 30 years, females now receive professional degrees at approximately the same rates as males, but they are not yet more likely to pursue those degrees than are males. As of 2008, females received 47 percent of law degrees and 49 percent of medical degrees (Digest of Education Statistics 2009, Table 300).

[20] Table 7 aggregates survey data regarding anticipated level of degree as of the senior year in high school, along with field of study (science or non-science) as of the sophomore year in college. "Elite" careers involve graduate school or professional school (unfortunately the data do not differentiate). "Non-elite" careers terminate with an undergraduate degree.

include the number of matriculants coming from each undergraduate major by year and sex. The data suggest that women are less likely than men to enroll in medical school with a primary undergraduate degree in a STEM field: in 2009, 40 percent of women matriculated into medical schools with a non-science undergraduate degree, but only one-third of males did so. This difference suggests that women are able to attend medical school and reach a high-status profession without compromising their gendered preferences for a more humanistic undergraduate education.[21] Female enrollees had about the same odds as males of coming from the biological sciences fields, lower odds of coming from the physical sciences (0.61) and mathematics (0.90), and higher odds of coming from the humanities (1.36) or the social sciences (1.12).[22] Further, the data suggest that a science undergraduate education has become less important to medical school entry during the last 30 years: in 1981, 75 percent of matriculates had undergraduate degrees in the sciences, compared to only 63 percent in 2009. This coincides with the dramatic increase in female enrollment in medical schools during that time.[23]

Because of medicine's close connection to the sciences, medical school entrants are probably the most interesting case for understanding the implications that constraints on

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[21] We might assume that more women are majoring in the biological sciences so that they can enter medical school more easily, by performing better on the MCAT or appearing more attractive to admissions committees. However, even though we find that male and female medical students have roughly equivalent odds of coming from the biological sciences, the larger number of females majoring in biological sciences means that a lesser percent of female biological sciences majors applied to medical school. Using data from 1974-1995, Hall et al. (2001) find that 61% of female biological sciences majors compared to 97% of male biological sciences majors entered medical school. Similarly, Sax (2001) finds that male biological science majors are more likely than female biological science majors to enter medical school.

[22] AAMC data for 2009 matriculates suggest that 51% come from biological sciences, 12% from physical sciences, 1% from math, 5% from humanities, 12% from social sciences, 2% from specialized health sciences, and 16% from other majors. Females on average had lower MCAT scores and lower science GPAs, but higher non-science GPAs.

[23] This is not entirely related to a shift in female preferences. The MCAT was restructured in the early 1990s to broaden the types of knowledge tested; the restructuring was intended to, and did, lead to an increase in the percentage of medical school students with social science majors (Boulis and Jacobs 2008; Cooper 2003; Singer 2001).

undergraduate curricular choices have for the gender gap in STEM fields of study. Nonetheless, an examination of pathways to law school is also illuminating for our conjecture. We obtained data from the Law School Admissions Council on the undergraduate majors of law school applicants during the past 5 years. These data suggest that in 2009 female law school applicants had higher odds of coming from the humanities and arts (1.25), the social sciences (1.05), and other non-science fields (1.37), but lower odds of coming from the natural sciences (0.83), engineering and computer sciences (0.26), and business (0.67). Law school applicant data also suggest that women pursue a broader set of pathways to law school than males. Looking to some of the largest "feeder" majors, 19 percent of men major in political science, 17 percent in business, and 7 percent of men major in history (collectively 43 percent). For women, by contrast, those numbers are 17 percent, 11 percent, and 4 percent, respectively (collectively 32 percent). Women also are much more likely to major in fields that are not traditional pathways to law school; thus, 7 percent of women major in English, and 7 percent of women major in psychology (compared to 5 percent and 4 percent, respectively, for males).

The data on law school and medical school applicants affirm that a substantial group of women follow the traditional pathways both to law school (political science) and to medical school (biology). Nonetheless, it is more common for women to pursue nontraditional pathways than it is for men. Women are more likely than men to apply or enter medical school or law school from non-science majors, and, although it is less clear what the expected feeder routes might be for law school applicants, women tend to pursue a broader set of pathways. Thus, these data support the hypothesis that females contemplating a professional career are more attracted to degree fields where there are "weak" constraints on majors (multiple pathways) than when there are "strong" constraints (few and male-gendered pathways).

Conclusion

Although women have closed much of the gender gap in the pursuit of STEM majors in the last 30 years, their progress has been uneven outside of the biological sciences. Despite some moderate success in chemistry and mathematics, the share of women obtaining math and physical science degrees is not markedly higher than it was 30 years ago. Moreover, women have made virtually no progress in engineering fields since the mid 1990s, and they earn fewer degrees in engineering than they do in the physical sciences, math, and computer sciences. Indeed, the gender gap in subfields other than life sciences is wider now than it was ten years ago.

Conventional narratives explain little of the continuing (and, in some ways, worsening) gender gap. Although a gender differential in top mathematics test scores remains, this gap has been narrowing and thus would not explain a widening gender gap in quantitative-based fields like computer science and engineering. Further, the success of women in some strongly quantitative science fields (such as chemistry) undercuts the math score rationale.[24] Our decomposition analysis buttresses those points; contrary to earlier work, we show that (at least since the 1980s) the math score gap explains at most a small fraction of the variation in field of study choices. The same is true for reading: while engineering majors are most likely to fall within the high math/low reading group even net of gender, our multivariate analyses suggest that the relatively greater reading skills of women do not directly or indirectly account for the continuing large gender gap in engineering majors.[25] The increasing female representation in

[24] It is difficult to measure either the demands on math ability for particular majors or the rigor of required coursework. It is possible, therefore, that the subfields selected by women are less quantitatively challenging.

[25] In any event, the effect of reading scores seems somewhat circular. High reading scores might suggest a proficiency that incentivizes students to choose non-science majors, or high scores might stem from a

four-year and selective institutions is consequential for the absolute numbers of female students majoring in STEM fields, but is not closing the gender gap in *rates* of majoring in STEM fields; the increased numbers of women in postsecondary education are equally if not more likely to pursue non-science fields of study. Finally, although research into life goals appears to be a relevant and important line of inquiry for future research into how males and females choose majors, our analyses suggest that values or life goals alone will contribute little to understanding gender disparities in undergraduate major choice, because they do not account for the different ways that majors fit into life plans.

Recognizing the limitations of the dominant existing explanations, we instead suggest a greater focus on curriculum and the vertical as well as horizontal structure of the educational pathways to alternative elite careers. Although it has become more likely for women to follow what have been traditionally "male" pathways into higher education, they have not altered their underlying preferences for science majors to a significant extent. At the same time, with more choices among elite occupations, women also tend disproportionately to enter new fields that permit greater diversification in undergraduate majors. We cannot be sure why women enter these fields, but we observe that the women that do so come from a broader set of undergraduate majors than the males that do so. Men, in contrast, appear more bound to traditional, less flexible, more vocationally oriented pathways. Our results suggest the possibility that if engineering professions were organized like medicine with some training in the undergraduate years followed by intensive training in graduate school, the fraction of engineers who were women would be higher than is currently the case.

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breadth of knowledge derived from reading (that signals an interest in non-science fields). The latter perspective, emphasizing the failure of engineering to tap into this diversity of interests, resonates with our emphasis in Section 6 on vocationally constraining major choices.

The data we use about professional school applicants offer an interesting glimpse of a much larger puzzle and provide a strong indication that the gender gap in STEM fields cannot be explained by focusing on individual-level determinants such as test scores, or job values and life goals as expressed in current survey data. We need a better way to model competition among majors and between science careers and other elite professional careers including especially law, medicine, and business. Such a model also needs to incorporate the gendered nature of selection into these schools; thus, future trends in the gender gap in STEM fields could be affected if professional schools enforce a gender-parity policy and increasingly become more selective for female students than they are for male students.

In sum, the analyses in this paper suggest that the contribution to the gender gap of competition among majors is a promising avenue for further research. They imply that the curricular structure of undergraduate and professional education and the differing constraints they place on curricular choice may play a role in gender segregation in STEM fields that is as important as the factors implicated in the major existing theories. This is a conjecture that merits additional investigation.

Appendix

Field of Study

All three studies asked in slightly different ways about students' field of study. Field of study generally is reported using a standard taxonomy known as the Classification of Instructional Programs, or CIP. The CIP originally was developed by the NCES in 1980 and was revised in 1985 and 1990. The 2000 edition (CIP-2000) is the third and current revision of the taxonomy and has 53 general categories and more than 2000 specific categories. The CIP categorizes fields at the most granular level under six-digit codes of the form xx.yyzz. Fields of study can be further aggregated according to two- and four-digit prefixes of the code. For example, "Organic Chemistry" has the six-digit code 40.0504, which places it in "Chemistry" (40.05) and "Physical Sciences" (40).

Beginning in the second follow-up, HSB classified field of study information using six-digit CIP codes (High School and Beyond Fourth Follow-up Methodology Report p.78), a list of which can be found in High School and Beyond, 1980: Sophomore Cohort Second Follow-up (1984) (ICPSR 8443). This is the most detailed information we have about field of study in any of the datasets. Consistent with the CIP taxonomy, "Organic Chemistry" has the code 40.0504 in the HSB.

NELS uses a 3-digit field of study coding system. The first two digits and associated titles seem to follow the CIP coding system. The third digit provides additional detail, but not necessarily in a way that is parallel to the specific categories in CIP. For example, NELS 400 represents chemistry, but the final digit does not map in any way to the CIP coding system. Moreover, we are not able to distinguish organic chemistry from other chemistry subfields.

ELS uses a classification system that is "largely" based on CIP-2000, but with 33 general categories and 192 specific categories (ELS: 2002 Base-Year to Second Follow-up Data File Documentation, p. 117). In the restricted dataset, F2MAJOR4 is a four-digit code, with the first two digits (equivalent to F2MAJOR2 in the public dataset) indicating one of the 33 general categories, and the last two digits indicating a specific category. Unfortunately, the numerical designations do not track the CIP coding system; thus, we were compelled to rely on the titles of the major groups to construct our major variables. For example, in the two-digit codes, physical sciences are categorized with the code 25; in the four-digit codes, the chemistry subfield is separately designated as code 2503. However, based on our examination of the major group titles, it appears that ELS merely aggregated CIP general categories in a few cases (presumably those with small enrollment) and then renumbered the resulting categories. For this paper, the more granular general categories in HSB and NELS were collapsed into the 2-digit codes found in ELS.

A related issue is the source of the field of study information. The field-of-study variables for college sophomores are all based on self-report, but the treatment of undecided or undeclared majors varies across datasets. This produces substantial variation in the proportion that report a particular field of study across datasets; thus, in ELS, about 22 percent of college enrollees have undeclared majors, but the proportion declining to identify a field of study is much lower in the other datasets.

The data are consistent with an increase in college sophomores with undecided majors over time. However, the form of the survey question might influence the apparent trend. In HSB, college sophomores are asked: "(During the last month enrolled), what was your actual or intended field of study or training (for example...)?" Similarly, in NELS: "(During your last month of attendance,) what is(was) your actual or intended major field of study at `INSTNAME'?" However, in ELS, students first were asked: "Now in 2006, have you declared a major yet at [spring 2006 school]?" Then, students who answered yes were asked, "What is your major or field of study?"

To account for the disparate number of students without declared majors in ELS, we use students' expectations in cases where students have not declared a major. The expected major variable was collected in the spring of 2006 and asks, "When you began at [first attended postsecondary institution], what field of study did you think you would most likely pursue? (Please choose one)."

Weights

We use panel weights to tabulate findings for the population of base-year 10th graders (or first follow-up for NELS). These weights allow us to adjust for unequal selection probabilities and to more accurately represent the sophomore field of study decisions of a national population of tenth graders.

[Appendix Table A1 about here]

References

Alon, Sigal, and Dafna Gelbgiser. 2011. “The Female Advantage in College Academic Achievements and Horizontal Sex Segregation.” *Social Science Research* 40:107-119.

Barone, Carlo. 2011. “Some Things Never Change: Gender Segregation in Higher Education across Eight Nations and Three Decades.” *Sociology of Education* 84(2):157-176.

Beutel, Ann M., and Margaret Mooney Marini. 1995. “Gender and Values.” *American Sociological Review* 60(3):436–448.

Bobbitt-Zeher, Donna. 2007. “The Gender Income Gap and the Role of Education.” *Sociology of Education* 80(1):1-22.

Boulis, Ann K., and Jerry A. Jacobs. 2008. *The Changing Face of Medicine: Women Doctors and the Evolution of Health Care in America*. Ithaca, NY: Cornell University Press.

Bradley, Karen. 2000. “The Incorporation of Women Into Higher Education: Paradoxical Outcomes?” *Sociology of Education* 73(1):1-18.

Bridges, Judith S. 1989. “Sex Differences in Occupational Values.” *Sex Roles* 20(3):205–211.

Buchmann, Claudia, and Thomas A. DiPrete. 2006. “The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement.” *American Sociological Review* 71(4):515-541.

Buchmann, Claudia, Thomas A. DiPrete, and Anne McDaniel. 2008. “Gender Inequalities in Education.” *Annual Review of Sociology* 34:319-337.

Ceci, Stephen J., and Wendy M. Williams. 2010. “Sex Differences in Math-Intensive Fields.” *Current Directions in Psychological Science* 19: 275-279.

Ceci, Stephen J., Wendy M. Williams, and Susan M. Barnett. 2009. “Women's Underrepresentation in Science: Sociocultural and Biological Considerations.” *Psychological Bulletin* 135(2):218-261.

Charles, Maria. 2011. “A World of Difference: International Trends in Women’s Economic Status.” *Annual Review of Sociology* 37: 355-371.

Charles, Maria, and Karen Bradley. 2002. “Equal but Separate? A Cross-National Study of Sex Segregation in Higher Education.” *American Sociological Review* 67(4):573-599.

Charles, Maria, and Karen Bradley. 2009. “Indulging our Gendered Selves? Sex Segregation by Field of Study in 44 Countries.’’ *American Journal of Sociology* 114(4): 924–76.

Charles, Maria, and David B. Grusky. 1995. “Models for Describing the Underlying Structure of Sex Segregation.” *American Journal of Sociology* 100:931-971.

Cooper, Richard A. 2003. “Impact Of Trends In Primary, Secondary, And Postsecondary Education On Applications To Medical School. I: Gender Considerations.” *Academic Medicine* 78:855-63.

Davies, Scott, and Neil Guppy. 1997. “Fields of Study, College Selectivity, and Student Inequalities in Higher Education.” *Social Forces* 75(4): 1417-1438.

Dickson, Lisa. 2010. “Race and Gender Differences in College Major Choice.” *ANNALS of the American Academy of Political and Social Science* 627:108-124.

Eccles, Jacquelyn S. 2007. “Where Are All the Women? Gender Differences in Participation in Physical Science and Engineering.” Pp. 199-210 in *Why Aren’t More Women in Science? Top Researchers Debate the Evidence,* edited by S. J. Ceci, and W. M. Williams. Washington, D.C.: American Psychological Association.

Eccles, J. and L. Hoffman. 1984. “Sex Roles, Socialization, and Occupational Behavior.” Pp. 367-420 in *Child Development Research and Social Policy*, edited by H. Stevenson and A. Siegel. Chicago, IL: University of Chicago Press.

England, Paula. 2005. “Gender Inequality in Labor Markets: The Role of Motherhood and Segregation.” *Social Politics: International Studies in Gender, State & Society* 12(2):264-288.

------. 2010. “The Gender Revolution: Uneven and Stalled.” *Gender and Society* 24(2): 149-166.

England, P., and Su Li. 2006. “Desegregation Stalled: The Changing Gender Composition Of College Majors, 1971-2002.” *Gender and Society* 20(5):657–677.

Frehill, Lisa M. 1997. “Education and Occupational Sex Segregation: The Decision to Major in Engineering.” *Sociological Quarterly* 38(2): 225-249.

Guiso, Luigi, Ferdinando Monte, Paola Sapienza, and Luigi Zingales. 2008. “Culture, Gender, and Math.” *Science* 320(5880):1164-1165.

Hakim, Catherine. 2000. *Work-Lifestyle Choices in the 21st Century: Preference Theory*. Oxford: Oxford University Press.

------. 2002. “Lifestyle Preferences as Determinants of Women’s Differentiated Labor Market Careers.” *Work and Occupations* 29:428-459.

------. 2003. “A New Approach to Explaining Fertility Patterns: Preference Theory.” *Population and Development Review* 29:349-74.

Hall, Frances R., Collins Mikesell, Pamela Cranston, Ellen Julian, and Carol Elam. 2001. “Longitudinal Trends in the Applicant Pool for U.S. Medical Schools, 1974-1999.”

Academic Medicine 76(8): 829-34.

Halpern, Diane F., Camilla P. Benbow, David C. Geary, Ruben C. Gur, Janet Shibley Hyde, and Morton Ann Gernsbacher. et al. 2007. "The Science of Sex Differences in Science and Mathematics." *Psychological Science in the Public Interest* 8(1):1-51.

Hansen, Jo-Ida C., Rose C. Collins, Jane L. Swanson, and Nadya A. Fouad. 1993. "Gender Differences in the Structure of Interests." *Journal of Vocational Behavior* 42(2):200–11.

Hyde, Janet Shibley. 2005. "The Gender Similarities Hypothesis." *American Psychologist* 60(6): 581–592.

Hyde, Janet S., Sara M. Lindberg, Marcia C. Linn, Amy B. Ellis, and Caroline C. Williams. 2008. "Gender Similarities Characterize Math Performance." *Science* 321:494-495.

Hyde, J. S, and Janet E Mertz. 2009. "Gender, Culture, and Mathematics Performance." *Proceedings of the National Academy of Sciences* 106(22):8801-8807.

Ingels, Steven J., Ben W. Dalton, and Laura LoGerfo. 2008. *Trends Among High School Seniors 1972-2004*. National Center for Education Statistics, Institute of Education Sciences. Washington, DC: U.S. Department of Education.

Jacobs, Jerry A. 1989. "Long-Term Trends In Occupational Segregation By Sex." *American Journal of Sociology* 95(1):160–173.

------. 1995. 'Gender and Academic Specialties: Trends among College Degree Recipients during the 1980s.'' *Sociology of Education* 68:81–98.

------. 1996. "Gender Inequality and Higher Education." *Annual Review of Sociology* 22:153–185.

Johnson, Monica K. 2001. "Social Origins, Adolescent Experiences, and Work Value Trajectories during the Transition to Adulthood." *Social Forces* 80(4):1307–1341.

Konrad, Allison M., J. Edgar Ritchie, Pamela Lieb, and Elizabeth Corrigall. 2000. "Sex Differences And Similarities In Job Attribute Preferences: A Meta-Analysis." *Psychological Bulletin* 126(4):593–641.

Lippa, Richard. 1998. "Gender-Related Individual Differences And The Structure Of Vocational Interests: The Importance Of The People-Things Dimension." *Journal of Personality and Social Psychology* 74(4):996–1009.

Machin, Stephen, and Tuomas Pekkarinen. 2008. "Global Sex Differences in Test Score Variability." *Science* 322(5906):1331-1332.

Marini, Margaret M., Pi-Ling Fan, Erica Finley, and Ann M. Beutel. 1996. "Gender and Job Values." *Sociology of Education* 69(1): 49-65.

Menand, Louis. 2010. *The Marketplace of Ideas: Reform and Resistance in the American University*. New York, NY: W.W. Norton & Company.

National Science Board. 2010. *Science and Engineering Indicators 2010*. Arlington, VA: National Science Foundation (NSB 10-01).

Niederle, Muriel, and Lise Vesterlund,. 2010. “Explaining the Gender Gap in Math Test Scores: The Role of Competition.” *The Journal of Economic Perspectives* 24(2):129–144.

Penner, Andrew M. 2008. “Gender Differences In Extreme Mathematical Achievement: An International Perspective On Biological And Social Factors.” *American Journal of Sociology* 114(S1):S138-170.

Polachek, Solomon W. 1978. “Sex Difference in College Major.” *Industrial and Labor Relations Review* 31(4): 498-508.

Pope, Devin G, and Justin R Sydnor. 2010. “Geographic Variation in the Gender Differences in Test Scores.” *Journal of Economic Perspectives,* 24(2): 95-108.

Sax, Linda J. 2001. “Undergraduate Science Majors: Gender Differences In Who Goes To Graduate School.” *Review of Higher Education, 24*(2):153-172.

Shu, Xiaoling, and Margaret Mooney Marini. 1998. “Gender-Related Change In Occupational Aspirations: A Magazine Of Theory And Practice.” *Sociology of Education* 71(1):43-67.

Singer, Allen M. 2001. “The Ups and Downs of Medical School Applicants.” *Journal of the American Osteopathic Association* 101(12): 706-10.

Snyder, Thomas D. and Sally A. Dillow. 2010. *Digest of Education Statistics 2009.* National Center for Education Statistics, Institute of Education Sciences. Washington, D.C.: U.S. Department of Education.

Spelke, Elizabeth S. 2005. “Sex Differences in Intrinsic Aptitude for Mathematics and Science?: A Critical Review.” *American Psychologist* 60:950-958.

Turner, Sarah E., and William G. Bowen. 1999. “Choice of Major: The Changing (Unchanging) Gender Gap.” *Industrial and Labor Relations Review* 52(2):289-313.

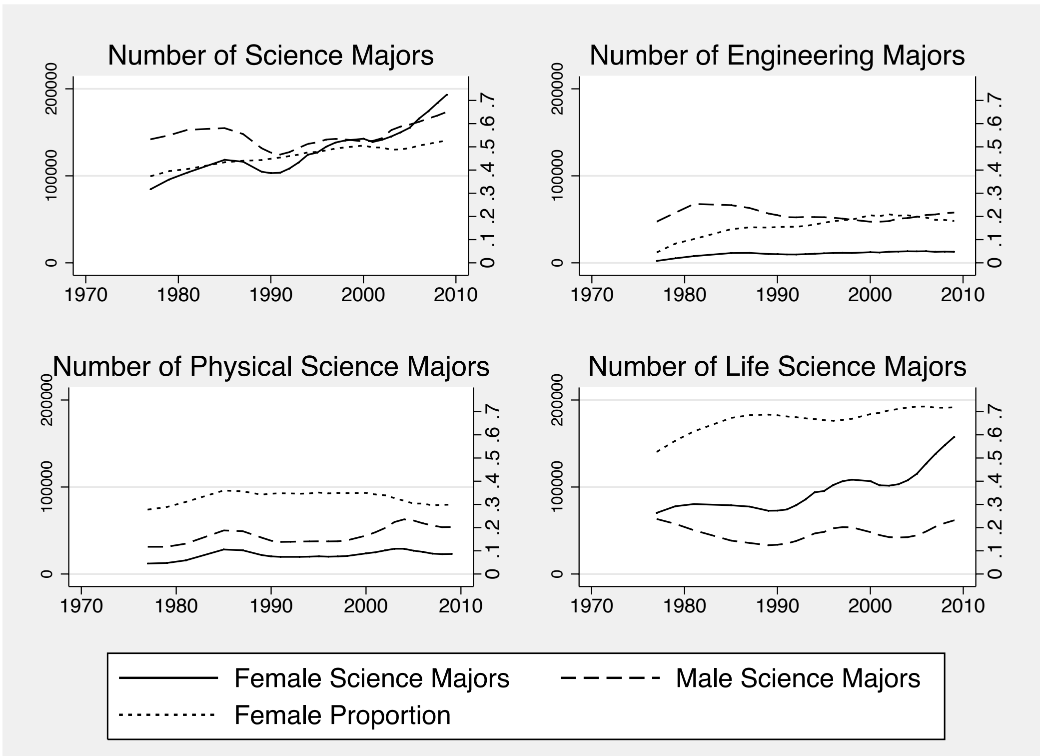
Wai, Jonathan, Megan Cacchio, Martha Putallaz, and Matthew C. Makel. 2010. “Sex Differences In The Right Tail Of Cognitive Abilities: A 30-Year Examination.” *Intelligence* 38(4):412-423.

Wilson, Kenneth L. and Janet P. Boldizar. 1990. “Gender Segregation In Higher Education: Effects Of Aspirations, Mathematics Achievement, And Income.” *Sociology of Education,* 63(1):), 62-74.

Xie, Yu, and Kimberlee A. Shauman. 2003. *Women in Science: Career Processes and Outcome*. Cambridge, MA: Harvard University Press.

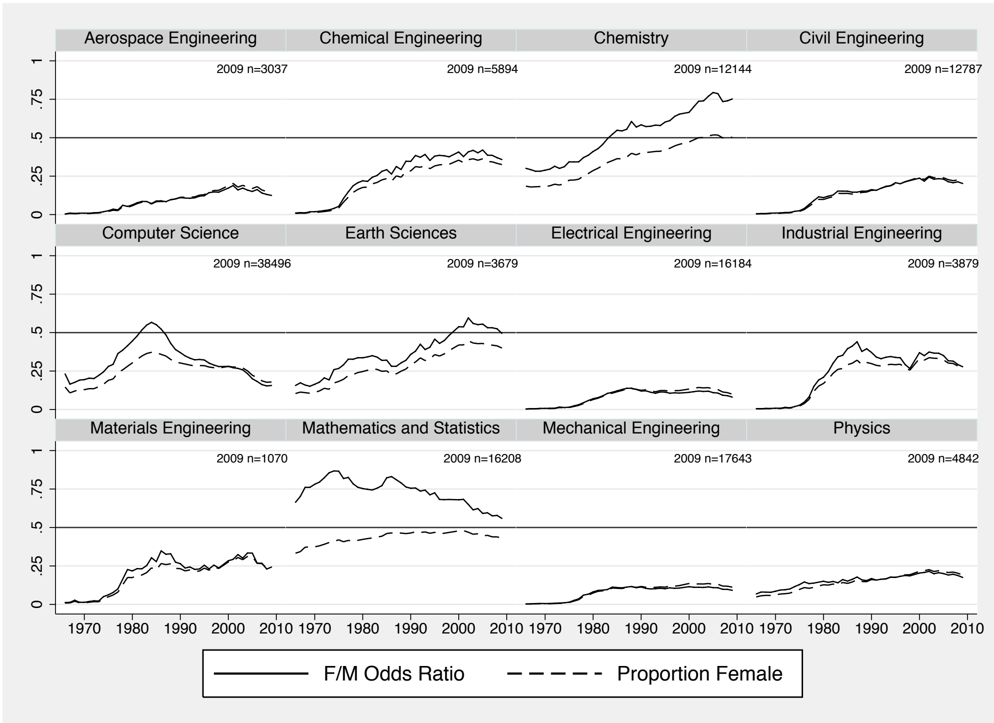
Figures and Tables

Figure 1: Bachelor's Degrees Awarded to Men and Women in Science and Engineering Fields of Study, 1977-2009



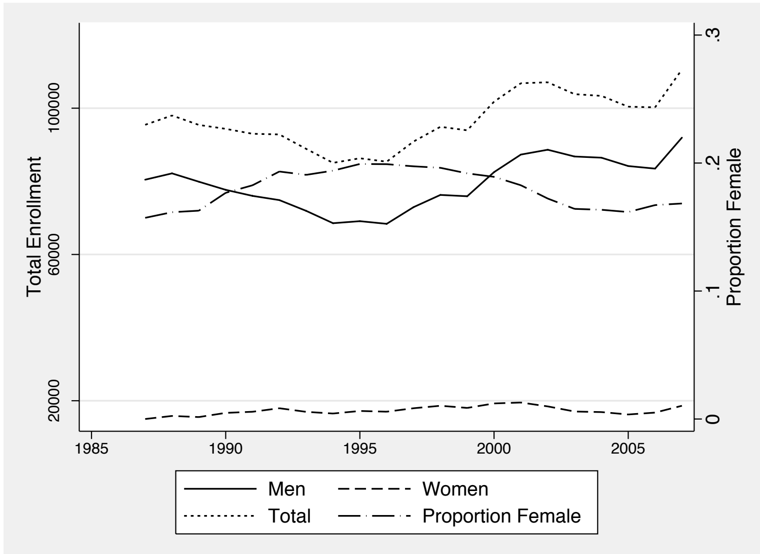
Source: National Science Foundation WebCASPAR Database

Figure 2: Bachelor's Degrees Awarded to Men and Women in Selected Science and Engineering Subfields, 1966-2009



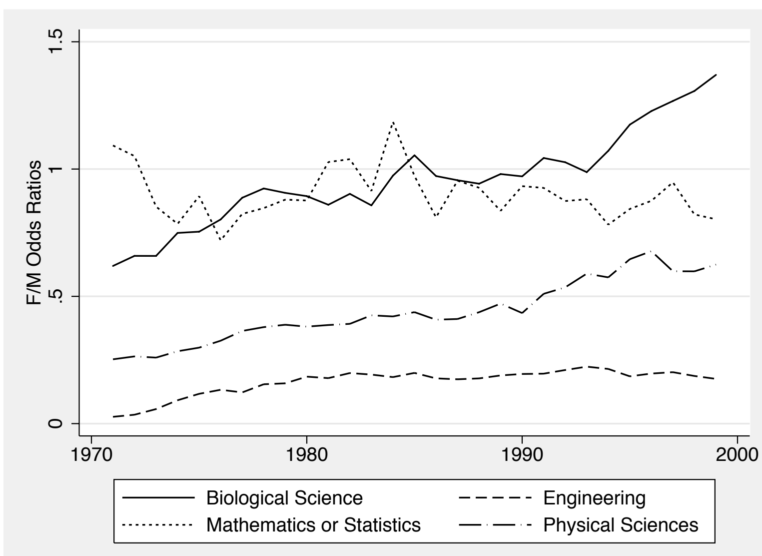
Source: National Science Foundation WebCASPAR Database

Figure 3a: First-Year Enrollment in Engineering Major



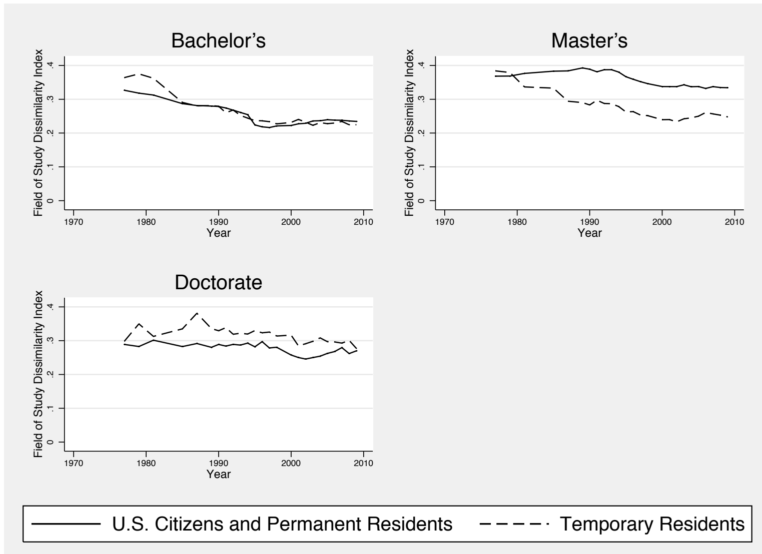
Source: NSF Women, Minorities, and Persons with Disabilities in Science and Engineering

Figure 3b: Trends in the F/M Odds of Selecting Science Subfield as a Probable Field of Study During Freshman Year



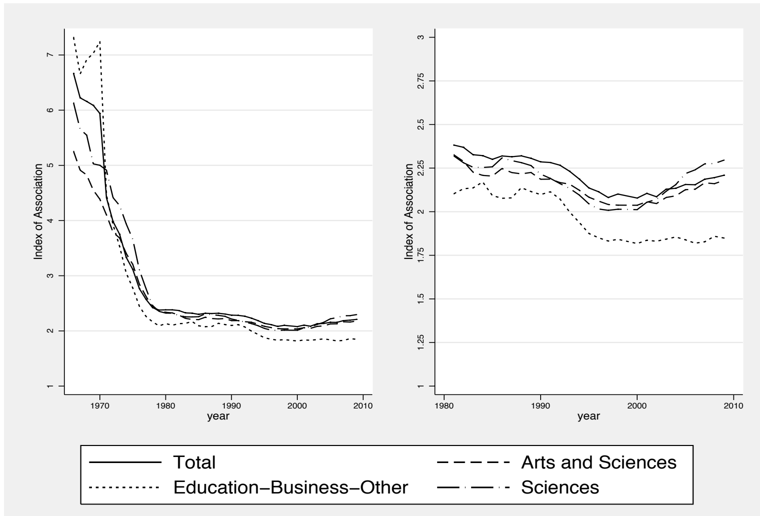
Source: CIRP Freshman Survey (1971-1999).

Figure 4: Total Dissimilarity Index by Degree Level and Citizenship Status



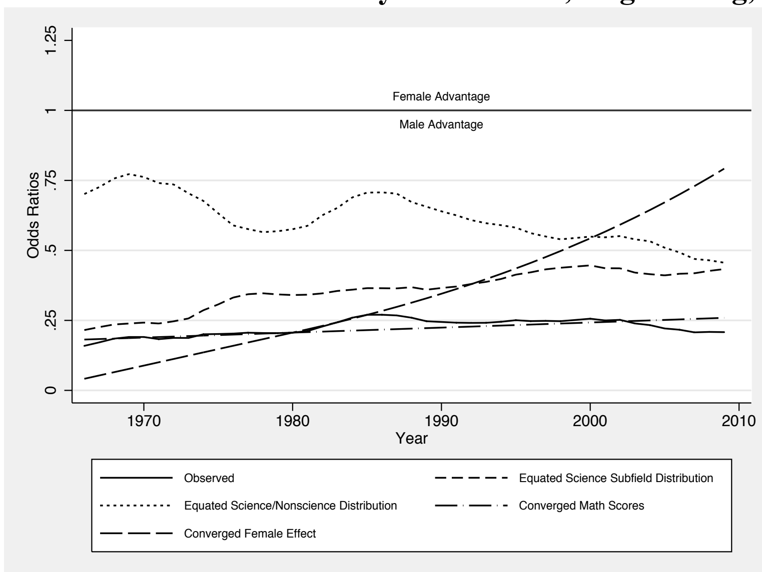
Source: National Science Foundation WebCASPAR Database

Figure 5: Index of Association, B.A. Recipients, by Components



Source: National Science Foundation WebCASPAR Database

Figure 6: Counterfactual Odds Ratios for Physical Science, Engineering, and Math Majors



Source: WebCASPAR Database (data excludes nursing and therapy subfields).
Explanatory Note: The solid line represents a trend line for the observed female to male odds of majoring in the physical science, engineering, or mathematics subfields from the late 1960s through the present date. The broken lines each represent a different counterfactual trend line, as described in the text.

Table 1: Probability of Being Female if a Science Major (Four-Year College Sophomores: 1982, 1992, 2004)

	HSB		NELS		ELS	
	Mean	S.Err.	Mean	S.Err.	Mean	S.Err.
P (F|S)	0.327	0.022	0.347	0.018	0.361	0.016
% Science	0.218	0.009	0.166	0.006	0.202	0.006
% Female	0.519	0.011	0.542	0.008	0.563	0.007
P (S|F)	0.136	0.011	0.106	0.007	0.130	0.003

Table 2: Cross-Tabulation of Tenth-Grade Math Test Scores (Standardized) for College Sophomores, by Gender and Survey

	HSB (1980)		NELS (1990)		ELS (2002)	
	Male	Female	Male	Female	Male	Female
Below mean	28.1	34.7	23.1	25.8	23.1	31.5
Mean to .49σ above	17.3	17.5	16.2	19.8	18.9	22.1
.5σ to .99σ	23.8	22.7	20.2	19.9	23.5	22.0
1σ to 1.49σ	19.2	17.5	22.1	21.3	19.6	16.3
1.5σ and above	11.6	7.6	18.4	13.2	14.9	8.1

Table 3: Cross-Tabulation of Combined Science Majors and High Math Test Score Categories

	HSB		NELS		ELS	
	Male %	Female %	Male %	Female %	Male %	Female %
1.5 standard deviations above mean or higher	45.2	28.7	38.0	19.1	37.6	29.4
1-1.49 standard deviations above mean	42.1	18.0	26.4	13.7	32.6	13.2
0.50-0.99 standard deviations above mean	27.6	13.2	16.4	6.3	24.1	8.7
0-0.49 standard deviations above mean	17.8	9.0	12.9	6.0	18.4	7.9

Table 4: Regression and Decomposition of Science Major on High School Test Scores

	Regression				Decomposition	
	Female		Male			
	Coef.	Std. Err.	Coef.	Std. Err.	Observed Diff. (%W-%M)	Due to Scores (M. Coef.)
HSB					-.153	12.67%
Math2	-0.26	0.40	0.43	0.29		
Math3	0.30	0.34	0.78**	0.29		
Math4	0.60	0.34	1.34**	0.28		
Math5	1.22**	0.42	1.54**	0.33		
Read2	0.23	0.33	0.31	0.25		
Read3	-0.01	0.31	-0.20	0.28		
Read4	0.33	0.35	0.07	0.28		
Read5	0.26	0.47	0.45	0.35		
Constant	-2.30**	0.23	-1.78**	0.22		
NELS					-.113	15.00%
Math2	0.29	0.25	0.07	0.24		
Math3	0.23	0.29	0.41	0.22		
Math4	1.05**	0.24	0.98**	0.23		
Math5	1.45**	0.31	1.60**	0.25		
Math6	1.99**	0.52	2.17**	0.42		
Read2	-0.30	0.25	0.05	0.22		
Read3	-0.11	0.27	0.09	0.22		
Read4	0.10	0.28	0.01	0.21		
Read5	-0.26	0.32	-0.33	0.27		
Constant	-2.84**	0.20	-2.05**	0.16		
ELS					-.147	14.57%
Math2	0.31	0.25	0.11	0.20		
Math3	0.29	0.27	0.42*	0.18		
Math4	0.75**	0.28	0.90**	0.20		
Math5	1.43**	0.32	1.04**	0.23		
Math6	2.58**	0.44	1.48**	0.29		
Math7	2.62**	0.78	1.53**	0.44		
Read2	-0.20	0.22	-0.12	0.18		
Read3	-0.14	0.25	0.11	0.18		
Read4	-0.11	0.28	-0.09	0.19		
Read5	-0.08	0.31	-0.61*	0.25		
Read6	-0.53	0.37	-0.02	0.32		
Read7	-.59	0.68	-0.95	0.56		
Constant	-2.50**	0.16	-1.52**	0.15		

Notes: Calculations are based on logistic regression estimations that include binary variables for high math and high reading scores on the sophomore achievement tests. Test scores are categorized in .5 increments from 0 to 2.5 standard deviations above the mean (Math 2-Math7, for example, with Math7 representing 2.5 standard deviations or more above the mean), with less than the mean as the reference category. The decomposition columns show the observed difference in the share of women in science and the share of men in science and the percentage of the difference attributable to test scores using the coefficients from the estimation for men. Standard errors are adjusted for school clusters. * p ≤ .05; ** p ≤ .01 (two-tailed tests)

Table 5: Logistic Regression of Science Major on Covariates and Interaction Terms (Clustered on School)

	1		2		3		4 (Phys. Sci.)		5 (Life Sci.)		6 (Engin.)	
Female	0.325***	(0.039)	0.349***	(0.043)	0.373***	(0.056)	0.651	(0.236)	0.725	(0.204)	0.325***	(0.066)
NELS	0.701***	(0.068)	0.603***	(0.06)	0.751	(0.123)	0.686	(0.298)	1.971*	(0.601)	0.514**	(0.110)
ELS	0.810*	(0.075)	0.762**	(0.073)	0.963	(0.143)	0.827	(0.320)	1.484	(0.441)	0.671*	(0.129)
Female x NELS	1.129	(0.169)	1.141	(0.174)	1.096	(0.173)	1.058	(0.357)	0.894	(0.254)	0.819	(0.180)
Female x ELS	1.175	(0.168)	1.233	(0.179)	1.205	(0.178)	1.458	(0.473)	1.502	(0.415)	0.528**	(0.113)
Test Scores (Base:<.5σ above mean)												
1.Math .5σ - .99σ			1.371***	(0.107)	2.071***	(0.356)	1.883	(0.379)	1.879	(0.638)	1.863**	(0.392)
2.Math 1σ – 1.49σ			2.211***	(0.175)	2.811***	(0.496)	2.394*	(0.575)	1.237	(0.478)	2.794***	(0.594)
3.Math 1.5σ and above			3.865***	(0.339)	4.149***	(0.86)	3.091**	(0.818)	2.825**	1.085)	3.241***	(0.807)
1.Read .5σ - .99σ			0.923	(0.068)	0.893	(0.151)	0.973	(0.382)	0.910	(0.309)	1.081	(0.218)
2.Read 1σ – 1.49σ			0.888	(0.069)	0.882	(0.163)	1.944	(0.717)	1.400	(0.467)	0.667	(0.153)
3.Read 1.5σ and above			0.752**	(0.069)	1.104	(0.27)	3.095**	(1.340)	0.610	(0.352)	0.977	(0.282)
Test Score Interactions												
NELS x 1.Math					0.596*	(0.13)	1.114	(0.613)	0.519	(0.199)	0.709	(0.208)
NELS x 2.Math					0.841	(0.182)	1.152	(0.603)	1.060	(0.443)	1.101	(0.310)
NELS x 3.Math					0.929	(0.229)	1.701	(0.925)	0.463	(0.195)	1.712	(0.547)
ELS x 1.Math					0.694	(0.135)	0.763	(0.379)	0.904	(0.327)	0.722	(0.188)
ELS x 2.Math					0.704	(0.142)	0.914	(0.433)	1.267	(0.521)	0.693	(0.185)
ELS x 3.Math					0.853	(0.201)	1.020	(0.515)	0.743	(0.309)	1.025	(0.313)
Female x 1.Math					0.795	(0.126)	0.764	(0.318)	0.639	(0.157)	1.037	(0.261)
Female x 2.Math					0.927	(0.148)	1.378	(0.538)	0.815	(0.206)	1.177	(0.290)
Female x 3.Math					1.052	(0.185)	2.459*	(0.990)	1.039	(0.278)	0.935	(0.269)
NELS x 1.Read					1.06	(0.219)	0.821	(0.392)	1.423	(0.536)	0.707	(0.188)
NELS x 2.Read					1.017	(0.223)	0.551	(0.251)	0.995	(0.371)	0.899	(0.257)
NELS x 3.Read					0.584	(0.163)	0.420	(0.219)	2.12	1.285)	0.317**	(0.113)
ELS x 1.Read					1.081	(0.206)	0.847	(0.380)	1.149	(0.414)	0.727	(0.183)
ELS x 2.Read					0.992	(0.208)	0.527	(0.237)	0.727	(0.265)	1.310	(0.364)
ELS x 3.Read					0.658	(0.176)	0.515	(0.260)	1.389	(0.831)	0.546	(0.186)
Female x 1.Read					0.963	(0.144)	0.850	(0.303)	1.358	(0.317)	0.523**	(0.130)
Female x 2.Read					1.014	(0.162)	0.500	(0.179)	1.367	(0.334	0.797	(0.198)
Female x 3.Read					1.105	(0.206)	0.358**	(0.137)	1.392	(0.404	1.029	(0.306)
Observations	10190		10190		10190		10190		10190		10190	

Table 6: Multinomial Logistic Regression of Major Choice on Female, Test Scores, a Life Goals

	Model 1		Model 2	
Life Sciences	RRR	Std. Err.	RRR	Std. Err.
Female	0.929	0.111	0.871	0.119
Test Scores (Base:<.5σ above mean)				
1.Math 0.5σ - 0.99σ	1.417**	0.246	1.520**	0.267
2.Math 1σ – 1.49σ	1.687***	0.321	1.866***	0.365
3.Math 1.5σ and above	2.868***	0.585	3.437***	0.727
1.Read 0.5σ - 0.99σ	1.300*	0.198	1.349*	0.208
2.Read 1σ – 1.49σ	1.329	0.247	1.397*	0.271
3.Read 1.5σ and above	1.077	0.230	1.140	0.257
Life Goal Factors				
Success			1.530***	0.218
Family			1.024	0.159
Community outreach			1.567**	0.284
Money			0.621**	0.118
Close to parents			1.435	0.473
Interactions				
Success x female			0.955	0.205
Family x female			0.596***	0.111
Community outreach x female			1.107	0.252
Money x female			1.456	0.389
Close to parents x female			0.705	0.281
Math & Physical Sciences				
Female	0.682**	0.125	0.737	0.147
Test Scores (Base:<.5σ above mean)				
1.Math 0.5σ - 0.99σ	1.706*	0.506	1.793**	0.525
2.Math 1σ – 1.49σ	3.350***	0.949	3.529***	0.999
3.Math 1.5σ and above	6.916***	2.097	7.864***	2.407
1.Read 0.5σ - 0.99σ	0.866	0.236	0.916	0.252
2.Read 1σ – 1.49σ	0.774	0.223	0.832	0.239
3.Read 1.5σ and above	0.914	0.265	0.999	0.289
Life Goal Factors				
Success			1.733**	0.425
Family			0.806	0.144
Community outreach			0.993	0.209
Money			1.024	0.288
Close to parents			1.050	0.525
Interactions				
Success x female			0.633	0.200
Family x female			1.221	0.316
Community outreach x female			1.330	0.371
Money x female			1.066	0.415
Close to parents x female			1.905	1.208
Engineering and Computer Sciences				
Female	0.143***	0.019	0.142***	0.022

Test Scores (Base:<.5σ above mean)				
1.Math 0.5σ - 0.99σ	1.493**	0.237	1.519***	0.241
2.Math 1σ – 1.49σ	2.183***	0.391	2.196***	0.397
3.Math 1.5σ and above	3.892***	0.737	4.023***	0.760
1.Read 0.5σ - 0.99σ	0.817	0.125	0.817	0.124
2.Read 1σ – 1.49σ	0.947	0.155	0.943	0.156
3.Read 1.5σ and above	0.661**	0.130	0.635**	0.127
Life Goal Factors				
Success			1.249***	0.100
Family			0.853*	0.080
Community outreach			1.089	0.114
Money			1.057	0.142
Close to parents			0.706*	0.146
Interactions				
Success x female			0.914	0.208
Family x female			0.596***	0.113
Community outreach x female			0.757	0.209
Money x female			1.451	0.453
Close to parents x female			0.980	0.465
Observations	4700		4700	

Source: Education Longitudinal Study of 2002. Note: The base category for the dependent variable is “other” major. * p<0.10, ** p<0.05, *** p<.01. Standard errors are clustered on schools.

Table 7: Elite Aspirations and Major Choice, by Gender

	HSB		NELS		ELS	
	Male (%)	Female (%)	Male (%)	Female (%)	Male (%)	Female (%)
Elite Non-science	24.5	29.7	52.9	66.3	41.8	57.9
Elite Science	14.7	7.2	20.1	9.6	21.6	11.2
Non-elite Non-science	41.2	50.5	21.2	22.0	24.5	27.7
Non-elite Science	16.0	6.6	5.2	1.5	9.6	1.8
Does not expect to complete college	3.6	6.0	0.6	0.6	2.5	1.4

Source: HSB, NELS, ELS. Note: Elite aspirations refer to the expectation of receiving an advanced degree as of the sophomore year in college. The analysis is restricted to sophomores in four-year colleges.

Appendix Table A1: Trends in Enrollments by Gender and Field of Study

	HSB			NELS			ELS		
	F%	M%	Diff.	F%	M%	Diff.	F%	M%	Diff.
Agriculture	1.3	3.2	-1.9	0.8	1.2	-0.4	0.7	1.2	-0.5
Architecture	0.5	0.9	-0.4	0.5	1.1	-0.6	0.7	1.2	-0.5
Business	27.8	24.8	3.0	15.5	18.6	3.1	11.9	16.4	-4.5
Communications	4.7	4.8	-0.1	3.5	3.6	-0.1	4.7	2.7	2.0
Education	11.0	4.6	6.4	16.2	5.8	10.4	10.3	4.5	5.8
Engineering Techn.	0.3	3.4	-3.1	0.2	2.3	-2.1	0.0	0.2	-0.2
Fine Arts	2.6	3.8	-1.2	4.4	4.0	0.4	5.1	4.7	0.4
Health Professions	13.7	3.5	10.2	15.9	6.9	9.0	16.1	4.0	12.1
Law	0.9	0.6	0.3	1.3	0.8	0.5	0.5	0.3	0.2
Psychology	3.4	1.8	1.6	5.2	2.3	2.9	5.7	2.1	3.6
Social Sciences	5.3	6.2	-0.9	5.4	6.9	-1.5	5.1	6.1	-1.0
Other, unknown or undecided	15.1	14.2	0.9	21.6	25.6	-4.0	30	35.7	-5.7
Nonscience subtotal	*86.6*	*71.8*		*90.5*	*79.1*		*90.8*	*79.1*	
Biological Sciences	3.3	2.8	0.5	4.3	5.2	-0.9	5.1	5.0	0.1
Computer Science	5.9	7.8	-1.9	1.4	3.7	-2.3	0.8	3.6	-2.8
Engineering	2.4	13.8	-11.4	1.5	9.3	-7.8	1.3	9.4	-8.1
Math and Statistics	0.8	0.9	-0.1	1.4	0.9	0.5	0.6	1.1	-0.5
Physical Sciences	1.0	2.9	-1.9	0.9	1.8	-0.9	1.4	1.8	-0.4
Science subtotal	*13.4*	*28.2*		*9.5*	*20.9*		*9.2*	*20.9*	
Gender Gap			**-14.8**			**-11.4**			**-11.7**
Index of Dissimilarity			**22.9**			**23.7**			**24.2**

Note: **We treat agriculture, engineering technologies, and health professions as non-science fields of study; if those fields were consolidated with the core science fields, there would be a considerable reduction in the gender gap.** Source: ***High School and Beyond Longitudinal Study of 1980 (HSB); National Education Longitudinal Study of 1988 (NELS); Education Longitudinal Study of 2002 (ELS).***