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Bye bye Ms. American Sci: Women and the leaky STEM pipeline

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A B S T R A C T

More than two-thirds of STEM jobs are held by men. In this paper, I provide a detailed analysis of the STEM pipeline from high school to mid-career in the United States, decomposing the gender gap in STEM into six stages. Women are lost from STEM before college, during college, and after college. Men are more likely to be STEM-ready before college, scoring higher on science tests and having taken more advanced math and science courses. This accounts for 35% of the overall gender gap in STEM careers. During college, men are far more likely than women to start in a STEM major, accounting for 26% of the gap. After college, male STEM graduates are more likely to enter STEM jobs, accounting for 41%. Men's higher persistence in STEM majors is a smaller factor, while women attend college at higher rates than men, which works to reduce the final gender gap in STEM. The results show that there is no single stage to focus on in understanding the gender gap in STEM.

1. Introduction

Both policymakers and researchers acknowledge the importance of STEM (science, technology, engineering, and mathematics) education and jobs for economic growth and innovation (e.g., Jones, 2009). Yet women are underrepresented in these fields. Men make up about two-thirds of STEM college graduates and hold even higher share of STEM jobs. Because STEM fields typically pay well, women's underrepresentation contributes to the overall gender pay gap (Brown & Corcoran, 1997; Jiang, 2021).

In this paper, I trace the experiences of women in this STEM "pipeline" from high school to the labor market in the United States.[2] I investigate when women are lost from the pipeline, asking which stages of the pipeline are most important, and where these women go when they leave STEM.

Using two data sources – one for high school and college experiences and one for the labor market – I consider six stages of the STEM pipeline from high school to mid-career. These include STEM readiness in high school (based on courses taken and test scores), college attendance, initial college major choice, graduation with a STEM degree, and early- and mid-career jobs. By mid-career, men make up almost three-fourths of STEM employment. My main question of interest is what stages contribute the most to this gender gap. Knowing this allows policymakers to better target efforts to recruit and retain talented women in STEM.

The results show that women are lost from the STEM pipeline before college, during college, and after college. There is no single stage that stands out. Instead, there are three stages of the highest importance: STEM readiness before college, the initial major choice in college, and the transition to early-career employment after college.

Before entering college, women are, on average, less prepared for STEM majors than men are. They are less likely to have taken calculus, biology, and physics, and they also score lower on science tests. I define several criteria for STEM readiness and show that men meet more of them on average; importantly, men are overrepresented in the upper tail of readiness. This accounts for 35% of the overall gender gap in STEM careers.

In college, women are far less likely to choose a STEM major as their first major choice; this accounts for 26% of the overall gap. This is especially true among the most STEM-ready students entering college; of those who are highly prepared for STEM, 55% of men start in a STEM major, compared with about 35% of women. Women are also less likely to graduate with a STEM degree conditional on starting one, which accounts for a smaller share (13%) of the overall gap.

The gender gap in STEM continues to grow after college: among those who have persisted to complete a STEM college degree, women are far less likely to be found in STEM occupations at age 30 (48% of men vs. 32% of women). This transition to career accounts for 41% of the overall gap, the largest of any stage.

Women actually make up ground with their higher rates of college attendance, which works to reduce the final gender gap in STEM. But this is mediated by the fact that male attendees are more positively

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[2] The pipeline metaphor was popularized by the 1989 report of the National Science Foundation (NSF, 1989). It has been criticized as too simplistic for a complicated nonlinear process (Xie & Shauman, 2003), but it is still a useful metaphor for analyzing the choices of men and women who could potentially end up in STEM fields as they navigate educational and labor market choices.

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selected: both STEM-ready and less-STEM-ready women tend to go to college, while less-STEM-ready men attend at low rates. This means that among those who actually attend college, men are more STEM-ready on average than women, and in particular they dominate the upper tail of STEM readiness. Overall, college attendance narrows the gender gap in STEM by 6%. All of my main conclusions are qualitatively similar when I use very different definitions of STEM majors and occupations.

I interpret the exact percentage contributions with caution due to the fact that there are many pathways into and out of STEM in the U.S. One can "skip" a stage, for example – say, not starting in a STEM major – and still rejoin the STEM pipeline at a later stage. But the particular importance of STEM readiness, initial major choice, and early-career job choice holds up across different approaches I have used.

These results show clearly that there is no single stage at which women are being lost from STEM, meaning there are no easy remedies for closing the gender gap. There are fewer STEM-ready women by the time college begins, fewer of them choose STEM majors, and fewer of those choose STEM careers. Even when narrowing in on the highly qualified, well-educated women with STEM degrees, gender gaps in outcomes remain. I do not evaluate specific mechanisms or policy options in this paper, but my results suggest that multiple policy levers would be needed to meaningfully close the gender gap in STEM careers.

The gender gap in STEM fields has been studied extensively by researchers in economics, education, and other fields (see Kahn & Ginther, 2017, for a survey). Descriptive studies have established gender gaps in STEM that are larger even than racial gaps (Bettinger, 2010; Dickson, 2010). Potential explanations for these gaps are many, including differences in pre-college preparation (Speer, 2017), the gender makeup of faculty (Carrell, Page, & West, 2010; Hoffmann & Oreopoulos, 2009), the influence of peers (Fischer, 2017), and differences in taste for competition (Niederle & Vesterlund, 2011). Qualitative evidence from the education literature often highlights the culture of STEM fields that is male-dominated, highly competitive, and unfriendly to women (Brainard & Carlin, 1998; Seymour & Hewitt, 2000).

The primary contribution of this paper is providing a comprehensive analysis of the STEM pipeline from high school to mid-career. My results speak indirectly to the reasons women leave STEM by looking at who leaves at each stage and where they go. While other researchers have studied parts of the pipeline (discussed in the next section), their focus has been narrower than mine. I show that several stages of the pipeline contribute to the end result. Even those women who make it over some significant hurdles may leave later on. Focusing only on the college experience, for example, misses the important roles of labor market and high school choices, and focusing only on the labor market misses the critical choices made before and during college. The gender gap in STEM appears prior to college, expands significantly in college, and continues to grow after college.

The paper proceeds as follows. Section 2 defines the six stages of the STEM pipeline that I will consider and reviews the substantial literature on this topic. Section 3 describes the data, Section 4 provides the results by stage, and Section 5 decomposes the overall gender gap into the contribution of each stage. Section 6 concludes.

2. The stages of the STEM pipeline

I define a STEM career as having a four-year STEM college degree and working in a STEM occupation.[3] It is not possible to analyze every event in a person's life that impacts career outcomes, so instead I break the STEM pipeline into six important stages. For my main analysis, I will use common definitions of STEM: the Department of Homeland Security list for college majors (which excludes social sciences) and two different definitions of STEM occupations. One is the Bureau of Labor Statistics list (which excludes social sciences and medical jobs) as well as a modified version that includes some medical jobs. I also explore how my conclusions change if alternative definitions are used.

The first stage is pre-college "STEM readiness". The question is how prepared students are for a STEM major as they reach the age at which they can choose such a path. This stage reflects everything that happens up to the time the person reaches the end of high school. I will measure STEM readiness using information on test scores and courses taken prior to college.

Many papers document differences in pre-college test scores between boys and girls, including in STEM-related subjects like math and science (e.g., Bedard & Cho, 2010; Fryer & Levitt, 2010). Teachers' biases and stereotypes likely contribute to these gaps (Lavy & Megalokonomou, 2019; Lavy & Sand, 2018). On the other hand, girls generally perform better in school than boys, even in STEM subjects (O'Dea, Lagisz, Jennions, & Nakagawa, 2018).

The second stage is college attendance, where I look specifically at four-year colleges. On average, women are more likely to attend college than men (Goldin, Katz, & Kuziemko, 2006), but there could be differential selection in attendance for men and women by STEM readiness, which would make the impact of attendance on the gender gap in STEM ambiguous. Some of the attendance gap is likely due to differing non-college job options for men and women (Chuan & Zhang, 2021).

The third stage is the initial major choice. Once a student has chosen to attend college, he or she must choose a field of study. In the United States, the initial major choice is typically not binding, but it represents a declaration of intent and interest, and there are costs involved in changing majors later. While there is surely a relationship between major choice and academic preparedness, major choice also depends on many other factors, including preferences (Wiswall & Zafar, 2015), peer effects (Fischer, 2017; Zölitz & Feld, 2021), and factors as seemingly unimportant as the order in which college courses are taken (Patterson, Pope, & Feudo, 2019). Preferences for majors have been found to differ on average by gender (Arcidiacono, 2004; Zafar, 2013).

The fourth stage is persisting to graduation with a STEM degree. Prior research shows that women are more likely to switch out of STEM majors (Astorne-Figari & Speer, 2019), while men are more likely to drop out of college entirely (Astorne-Figari & Speer, 2018). Hsu, Libassi, and Stange (2019) look at differences across universities in STEM graduation rates. Here, I look at how these patterns differ by the level of readiness of the student. It could be that this attrition from STEM is only weeding out less able students, but this is an empirical question.

The fifth stage is the transition from college to early-career occupation. Men and women are found in different types of occupations on average (e.g., Altonji & Blank, 1999; Blau & Kahn, 2007), but here I focus on STEM graduates. These graduates have demonstrated readiness, interest, and enough persistence to finish the major. I ask whether there are significant differences in occupational choices among this selected group, and if so, where STEM graduates are going if not to STEM jobs. While some studies have looked at the path to graduate programs or academic positions in STEM (Bostwick & Weinberg, 2022; Miller & Wai, 2015), my focus is broader.

The final stage is career progression, from early-career job to mid-career job. Some research and press attention on gender gaps in STEM focuses on the male-dominated culture of STEM fields, as well as their lack of flexibility and family-friendliness (Frome, Alfeld, Eccles, & Barber, 2006; Wiesgram & Diekman, 2015). Delaney and Devereux (2021) find a steady exodus of women from STEM careers in the UK during the first 15 years after college. I cannot say anything causal about the reasons women may leave STEM jobs, but I can compare

[3] The main results are similar when focusing only on the job outcome and not requiring the degree. I focus on this outcome because of the policy and research interest in gender gaps in college major and because a college degree provides access to the higher-paying STEM jobs.

labor market outcomes for younger women and older women to ask how their choices change over time.

There are a few other papers that decompose narrower portions of the STEM pipeline, most of which focus on time in and prior to college. Key and Sass (2019) look at the determinants of the college major gender gap in Florida, while Delaney and Devereux (2019) decompose the gap in initial major preferences in Ireland. Levenstein, Morar, and Owen-Smith (2019) study the STEM pipeline at a large university, looking at initial major choice and graduation with STEM degrees. Card and Payne (2021) study the gap in STEM major entry in Canada, finding an important role for a gender gap in STEM readiness. Looking later in the pipeline, Cech and Blair-Loy (2019) and Wiesgram and Diekman (2015) study gender differences in job choices, and Delaney and Devereux (2021) follow college graduates 15 years into their careers. Ceci, Ginther, Kahn, and Williams (2014) focus on academic science careers specifically, while Bostwick and Weinberg (2022) look at persistence in STEM graduate programs. My contribution is to look at the entire pipeline in a comprehensive way and identify the stages that contribute the most to the overall gap.

Kahn and Ginther (2017) summarize much of this literature, and they also highlight a potential weakness of my paper: later-life choices such as college major and occupation choice may be linked to traits developed early in life, such as competitiveness and risk-aversion. If these affect major or career choices, but not grades and test scores, then my approach will wrongly attribute the gap to those later stages rather than to early-life factors.

3. Data

To trace the STEM pipeline from high school to the labor market, I need information on school experiences, grades, test scores, college major choices, and job outcomes. Because STEM majors and occupations are relatively small as a percentage of the entire labor force, the data must be large to effectively characterize the STEM pipeline.[4] There is no data set I am aware of that allows this, so instead I use two nationally representative data sets, one with the requisite information on pre-college and college experiences, and one with a big enough sample size to study STEM labor market outcomes.

The pre-college and college information comes from the National Longitudinal Survey of Youth's 1997 cohort (hereafter, NLSY). The NLSY is a panel data set of about 9000 respondents born between 1980 and 1984. They were first interviewed in 1997 and have been followed through the present. Black and Hispanic people were oversampled, so I use the 1997 cross-sectional weights to better match both the U.S. population and the second data set I use.

For my purposes, the NLSY has several key advantages. The first is the inclusion of the Armed Services Vocational Aptitude Battery (ASVAB) test scores, which measure proficiency in science and math, among other subjects. The tests were taken by respondents in 1999 and thus measure pre-college skills in a variety of areas. This gives me the ability to look at the STEM-related capabilities of students before they enter college. These scores measure proficiency in these subjects at the age of taking, which may be influenced by innate ability but also parental investments, school quality, and other factors.

The NLSY also has data on courses taken by respondents in secondary school. I know if the student has taken biology, chemistry, physics, calculus, and other courses. I do not know if these were mandatory classes or choices, but these course data do show some variation by gender. Respondents are also followed through college, and the survey includes information on fields of study (including switches). This will be important, because many students switch majors during college (Chen, 2013).

Although the NLSY also follows respondents into the labor market, it is too small to study job outcomes in detail, containing only 325 STEM graduates. For the labor market stages, I rely instead on the American Community Survey. In 2009, the ACS began asking people's undergraduate field of degree, allowing me to identify STEM graduates. Combining the ACS from 2009 to 2017, I have 1.2 million STEM college graduates.

The ACS is the annual version of the U.S. census, containing information on demographics, education, college major, occupation, and earnings. The occupations are given in detailed Standard Occupational Classification (SOC) codes, allowing precise coding of STEM fields and subfields. Later in the paper, I discuss how I define STEM occupations, as there are multiple ways to do this. Table 1 provides some summary statistics from the NLSY and ACS samples, both weighted to represent the population.

Note that the two data sets represent roughly the same cohorts of people. The NLSY sample (restricting to those who took the ASVAB before college age) was born between 1981 and 1984, making them age 25 to 36 in 2009–2017, the waves of the ACS I use. In the ACS, I use those age 30 (early career) and 45 (mid-career), so the early-career analysis overlaps with the NLSY's age range, while the mid-career analysis involves a cohort a bit older than that in the NLSY. The share of people completing a STEM degree in the two data sets is similar.

There are other data sources that could have been used, but they have limitations that make the NLSY and ACS the best choices. The National Survey of College Graduates has several waves that could have been used to analyze the path from college to career instead of the ACS. It has the same basic information, but also includes more family background measures. However, the samples are smaller than the ACS. Several data sets maintained by the U.S. Department of Education, such as the Baccalaureate and Beyond, could have also been used, as they have "readiness" information (such as test scores), college major, and early-career outcomes. The samples are somewhat small, and they do not have the detailed multi-subject test scores that the NLSY does. Still, it would be interesting to consider these data sets in future studies of how pre-college competencies relate to career outcomes.

4. Results

4.1. Stage 1: STEM readiness

First, I look at who might be "ready" for STEM fields when entering college. STEM readiness is an umbrella term for many factors. How well a student is prepared at age 17 or 18 for STEM is a function of genetics, parental investments, school quality, childhood discrimination and expectations, courses offered and chosen, and other factors.[5]

In the United States, where there is no STEM "track" and there are many paths to eventually complete a STEM major, there is no clear way to measure STEM readiness. Card and Payne (2021) study Canada, which has a much clearer high school track into STEM majors. They are able to define a binary measure of STEM readiness that almost perfectly predicts entering a college STEM major. This is not possible in the US, with its much greater flexibility, variability of course offerings in high school, and ability to switch majors easily.

Instead, I define six criteria of STEM readiness in the NLSY based on high school courses and test scores. I will show that all six predict majoring in STEM in college and that the more criteria one meets, the more likely one is to major in STEM. Together, these form a measure of STEM readiness that I can use to look at gender gaps and future choices.

[4] According to the 2009–2017 American Community Survey, STEM occupations make up about 10% of total employment, while about 8% of employed people have four-year STEM degrees.

[5] Throughout the NLSY analysis, I use the provided sample weights to better represent the population, because the NLSY oversamples Black and Hispanic people.

Table 1
Summary statistics.

NLSY97 sample	Mean	St Dev	ACS sample (Ages 30–45)	Mean	St Dev
Male	0.51	0.50	Male	0.50	0.50
Black	0.16	0.36	Black	0.13	0.33
Hispanic	0.12	0.33	Hispanic	0.20	0.40
Asian	0.02	0.15	Asian	0.07	0.25
Attends college	0.42	0.49	College grad	0.33	0.47
Graduates college	0.32	0.47	STEM degree	0.08	0.27
Initial STEM major	0.09	0.29	STEM occ (narrow)	0.05	0.22
Graduates w/STEM major	0.07	0.23	STEM occ (broader)	0.06	0.25
			STEM degree + occ (narrow)	0.03	0.16
Share taken each course:			STEM degree + occ (broader)	0.03	0.18
Physics	0.35	0.48			
Biology	0.84	0.37			
Chemistry	0.61	0.49			
Calculus	0.10	0.31			
n	7,227		n	5,346,981	

Note: The NLSY sample is restricted to those who took the ASVAB tests at age 18 or younger. I use the 1997 cross-sectional weights. The ACS sample is restricted to those age 30 to 45 in the ACS's 2009–2017 waves and uses the provided person weights.

The first two criteria come from the ASVAB test scores. Criterion number one is scoring at least one standard deviation above the mean (age-adjusted) on the science knowledge test, and criterion number two is the same for the mathematics knowledge test. The other four criteria are based on science and math courses taken in high school. Having more of these courses can increase the probability of majoring in STEM because they provide important knowledge and training, pique the student's interest, and in the case of Advanced Placement classes, provide credits that shorten the route to finishing the major itself. The course criteria are taking at least two biology courses between grades 8–12, taking at least two chemistry courses, taking at least one physics course, and taking calculus. Some of these are influenced by high school offerings – not all schools offer calculus, for instance – but that does not take away from their predictive power.[6]

Table 2 shows the share of students in the sample that meet each criterion, separately by gender, as well as the average number of criteria met. The last column shows the male–female gap, and the stars show whether that gap is stastically significant. On average, males meet more of the criteria (1.49 vs. 1.38), and the difference is significant. Males are more likely to meet the science test, physics, and calculus criteria, while females score higher on math tests and take more chemistry classes. Males are overrepresented in the upper tail of STEM readiness. They are more likely to have met at least four of the six criteria (9.2% vs. 6.9%) and to have met at least five (3.7% vs. 1.9%).

To show that these criteria predict majoring in STEM, Table 3 shows a regression of choosing an initial major in STEM on the six criteria, both for the whole sample (columns 1–2) and for those who attend college (columns 3–4). All six criteria predict majoring in STEM, with taking calculus the strongest predictor of all; those who take calculus are 18 percentage points more likely to start a STEM major, even controlling for the other criteria. For each criterion that is met, the probability of initially majoring in STEM goes up by 7–8 percentage points.

Defining a single measure of STEM readiness is difficult in the U.S. context, since there is no cutoff that separates the future STEM majors from the non-STEM majors. One might think that an ideal measure of STEM readiness might be a predicted probability of majoring in STEM based on the student's pre-college profile, taken from regressions like those in Table 3. This is problematic, however, because using actual outcomes will conflate readiness with factors that might affect the actual choice, like discrimination and preferences. The mapping of criteria onto STEM majoring likely differs for men and women for these reasons. The criteria themselves give a more objective measure of readiness than the predicted outcome of such a regression.

Table 2
STEM readiness criteria.

Share of people who meet each criterion	Everyone	Males	Females	Male–Female gap
Criterion 1: science test	0.16	0.20	0.13	0.07***
Criterion 2: math test	0.15	0.14	0.16	−0.02***
Criterion 3: biology courses	0.43	0.44	0.42	0.02
Criterion 4: chemistry courses	0.24	0.23	0.26	−0.03***
Criterion 5: physics course	0.35	0.37	0.32	0.05***
Criterion 6: calculus course	0.10	0.11	0.09	0.02***
Meets at least 3 criteria	0.19	0.20	0.17	0.024***
Meets at least 4 criteria	0.08	0.09	0.07	0.023***
Meets at least 5 criteria	0.03	0.04	0.02	0.018***
Avg no. of criteria met	1.44	1.49	1.38	0.11***

Note: The sample is taken from the NLSY97 and uses the 1997 cross-sectional sample weights. The table shows the share of people who meet each of the six criteria and the share that meet certain thresholds, as well as the average number of the six criteria met. Criteria 1 and 2 are equal to 1 if the person scores at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests, respectively. Criteria 3–6 are equal to one if the person reports that, between grades 8 and 12, they took at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course, respectively. The p-values used to determine significance in the last column are taken from regressions of the criterion on a dummy for male, again using the sample weights.

I will defer some of this discussion until Section 5, where I decompose the total gender gap into stages. For now, I note the following things. First, males meet more of the STEM readiness criteria by the time they are going to college. Second, males are more likely to be in the upper tail of STEM readiness, which (as I will show in Section 4.3) is important for understanding the gender gap in STEM.[7]

[6] The grades received in these courses are available only for a subset of the sample, who are part of the NLSY's transcript survey. My conclusions are similar when using this information to define the criteria for the smaller sample size, so I opt for the larger sample.

[7] Speer (2017), also studying the determinants of majoring in STEM, found large gender gaps in some ASVAB test scores and concluded that women were far less STEM-ready than men. However, he did not use course-taking data, which show that females are ahead in some respects. High school performance better predicts college performance than test scores do (Allensworth & Clark, 2020). Speer (2017) also used ASVAB scores in subjects like electronics information, auto and shop information, and mechanical comprehension. These tests, while predictive of majoring in STEM (though less so for women), were developed to measure aptitude for military jobs, not academic subjects. The

Table 3
STEM readiness criteria and majoring in STEM.

Dependent variable: initial major is STEM				
	Full sample		College attendees	
Criterion 1: science test	0.056***		0.046**	
	(0.010)		(0.018)	
Criterion 2: math test	0.111***		0.078***	
	(0.010)		(0.019)	
Criterion 3: biology courses	0.022***		0.054***	
	(0.006)		(0.015)	
Criterion 4: chemistry courses	0.035***		0.024	
	(0.008)		(0.016)	
Criterion 5: physics courses	0.059***		0.073***	
	(0.007)		(0.016)	
Criterion 6: calculus course	0.182***		0.169***	
	(0.012)		(0.021)	
No. of criteria met		0.075***		0.077***
		(0.003)		(0.005)
Constant	0.010*	−0.015***	0.082***	0.062***
	(0.005)	(0.005)	(0.015)	(0.013)
Mean of dep. var.	0.09	0.09	0.22	0.22
Observations	7,227	7,227	2,825	2,825
R-squared	0.135	0.111	0.079	0.068

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The sample is from the NLSY, including all students with valid test scores. Criteria 1 and 2 are equal to 1 if the person scores at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests, respectively. Criteria 3–6 are equal to one if the person reports that, between grades 8 and 12, they took at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course, respectively. The dependent variable is 1 for reporting a STEM major as the first major. This outcome is 0 if the student does not attend college. Column 1 is the full sample, while column 2 restricts to all students who attend a 4 year college and report at least one major. All regressions are linear probability models.

Table 4
College attendance rates by STEM readiness.

Share of people who attend four-year college				
	Everyone	Males	Females	Male–Female Gap
Overall	0.42	0.37	0.47	−0.10***
Meet 0 criteria	0.20	0.14	0.25	−0.11***
Meet 1 criterion	0.33	0.26	0.40	−0.14***
Meet 2 criteria	0.52	0.47	0.56	−0.09***
Meet 3 criteria	0.70	0.64	0.76	−0.12***
Meet 4 criteria	0.88	0.86	0.91	−0.05
Meet 5 or 6 criteria	0.94	0.93	0.98	−0.05
Meets at least 3 criteria	0.79	0.75	0.83	−0.08***
Meets at least 4 criteria	0.94	0.89	0.93	−0.04
STEM readiness among attendees				
Meets at least 3 criteria	0.35	0.40	0.30	0.09***
Meets at least 4 criteria	0.17	0.22	0.14	0.08***
Meets at least 5 criteria	0.06	0.09	0.04	0.05***
Avg no. of criteria met	2.07	2.27	1.90	0.37***

Note: The sample is all respondents in the NLSY who took the ASVAB tests at age 18 or younger. The outcome is college attendance, defined as attending a four-year college and reporting a major at any point. The p-values used to determine significance in the last column are taken from regressions of the criterion on a dummy for male, again using the sample weights. The six STEM readiness criteria, each a binary variable, are scoring at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests and taking at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course.

4.2. Stage 2: College attendance

The next step to a career in a STEM job is attending college. As detailed by Goldin et al. (2006), women have a significant advantage over men in college attendance and graduation. To know how this affects the pipeline to STEM jobs and the gender gap in outcomes, we need to know how attendance patterns differ by STEM readiness. Because my focus is on four-year STEM degrees, I define anyone who attends a four-year college and reports a major at any point as an attendee, which may eliminate some students who attend only briefly. In my sample, 47% of females attend college, while only 37% of males do.

Attendance is strongly related to the STEM readiness criteria, as shown in Table 4. Those who meet none of the six criteria have a 20% chance of attending college, which grows monotonically with the number of criteria met. Since more STEM-ready students tend to have higher test scores across the board, this relationship is not surprising.

For every level of STEM readiness, females are more likely than males to attend college. But the gap is especially large among those who are less STEM-ready: only 14% of the least-STEM-ready males attend, while 25% of such females do, and the gap is even larger for those who meet one criterion (26% vs. 40%). For the most STEM-ready students, the gender gaps in attendance are smaller and insignificant.

These patterns show that while women clearly attend college at higher rates than men, they are also differentially selected into college in terms of STEM readiness. Male college attendees are more "positively selected" than females – meaning that the men who actually attend college tend to be those who are usually the most STEM-ready, while the women who attend college include both the STEM-ready and less-STEM-ready. We can see this in a couple of ways. First, the overall gender gap in STEM criteria met (as seen in Table 2) is 0.11. Among college attendees, this gap is 0.37 (2.27 for males, 1.90 for females). Second, among all students in the sample, males were 2.3 percentage points more likely to have met at least four of the six criteria (9.2% vs. 6.9%). Among attendees, this gap is 8.2 percentage points (21.9% vs. 13.7%). So there is an especially large gender gap in the upper tail of STEM readiness among those who attend college.

The effects of these patterns on the STEM gender gap is unclear at first glance. There are many more women in college, but the women are less positively selected on STEM readiness. I will revisit this in Section 5, when I decompose the gender gap into the contributions of each stage.

4.3. Stage 3: Initial major choice

In the US, a student often does not have to choose a major at the time of college entry, and many students enter college uncertain of what they will study. The initial major choice typically occurs by the student's second year. While switching majors after this choice is common, there are costs involved, and the majority of students stick with their initial choice (Astorne-Figari & Speer, 2019; Patterson et al., 2019). STEM majors often have a large set of introductory coursework that must be completed, making it difficult to switch into a STEM major from a non-STEM major, so this initial major choice is important.

Table 5 shows the percentage of college attendees that choose an initial STEM major, defined as the first major the student reports in the NLSY survey, which asks for the field of study each year.[8]

ASVAB was first introduced by the U.S. military in 1968, at which time the military was only about 2%–4% female (Patten & Parker, 2011), so it is likely that these tests were designed largely to measure the aptitude of males.

[8] I define STEM majors, as closely as possible, using the list from the Department of Homeland Security. This includes: computer science, biology, physical sciences, engineering, mathematics, agriculture, pre-med, pre-dental, and pre-veterinary. Other agencies such as the National Science Foundation have different lists. The paper's main conclusions hold no matter the major definition used, as I show in Table A.5.

Table 5
Share of college attendees choosing STEM major initially.

Share of attendees whose first major is STEM				
	Everyone	Males	Females	Male–Female Gap
Overall	0.22	0.30	0.15	0.15***
Meet 0 criteria	0.10	0.15	0.07	0.08***
Meet 1 criterion	0.14	0.19	0.11	0.08***
Meet 2 criteria	0.20	0.26	0.16	0.10***
Meet 3 criteria	0.23	0.33	0.15	0.18***
Meet 4 criteria	0.41	0.52	0.30	0.22***
Meet 5 or 6 criteria	0.52	0.57	0.41	0.16*

Note: The sample is all students in the NLSY97 who attended a four-year college and ever reported a major. I use the 1997 survey weights. The outcome is the first major ever reported being a STEM major. The p-values used to determine significance in the last column are taken from regressions of the criterion on a dummy for male, again using the sample weights. The six STEM readiness criteria, each a binary variable, are scoring at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests and taking at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course.

The likelihood of choosing a STEM major rises with STEM readiness, from a 10% chance if a student meets none of the criteria to a 52% chance for the most STEM-ready students. The largest jump in the probability of doing STEM is between three and four criteria met (23% to 41% chance).

Overall, 22% of attendees start with a STEM major, including 30% of males and 15% of females. At every level of STEM readiness, men are more likely to go into STEM majors. The gaps are especially large among the more STEM-ready students (where men are already overrepresented). Put another way, the probability of initially majoring in STEM for women with a moderate level of STEM readiness (2–3 criteria) is the same as the rate for men who meet only one of the criteria. It is clear that STEM readiness differences between men and women cannot account for all of the differences in initial major choice: even among the most STEM-ready students, there are large gender gaps in choosing STEM majors.

The STEM category is diverse, though, and it is worth looking at the individual majors to better understand these patterns. Table A.1 shows the most common majors chosen by students at each level of STEM readiness. The numbers in parentheses represent the share of all students choosing that major. Women tend to choose biology most often, while engineering and computer science are more common for men. Among the most STEM-ready students, about one quarter of men (including those who do not choose STEM at all) choose engineering, while only 7% of women do, but women double up men in choice of biology (16% vs. 8%). Engineering, in particular, seems to draw from the most STEM-ready students, particularly men. Panel B of the table shows that STEM-ready women are often found in business (though this is mostly because it is such a large/broad major in the NLSY). Psychology and fine arts also draw STEM-ready women away. These majors may be targets for recruiting if the goal is to increase representation of women in STEM at this stage.

4.4. Stage 4: Graduating with a STEM degree

The next stage of the pipeline is persistence to graduation with a STEM degree. An initial STEM major could fail to graduate with a STEM degree if they drop out of college or if they switch out of their STEM major. Women are far more likely to switch out of STEM to other majors (Astorne-Figari & Speer, 2019), while men are more likely to drop out of college altogether (Astorne-Figari & Speer, 2018). In this section, I expand on this prior analysis by looking at how persistence in STEM is related to STEM readiness.

Panel A of Table 6 shows the share of all college attendees who graduate college with a STEM major. This share is much higher for male students (21% vs. 9%) and also much lower than the share of students who begin a STEM major. At every level of STEM readiness, women are less likely to get a STEM degree.

Table 6
Share of college attendees who graduate with a STEM major.

Panel A: All college attendees				
	Everyone	Males	Females	Male–Female Gap
Overall	0.15	0.21	0.09	0.0.12***
Meet 0 criteria	0.03	0.05	0.02	0.03
Meet 1 criterion	0.08	0.12	0.06	0.06***
Meet 2 criteria	0.12	0.18	0.07	0.11***
Meet 3 criteria	0.17	0.23	0.11	0.12***
Meet 4 criteria	0.31	0.40	0.21	0.19***
Meet 5 or 6 criteria	0.41	0.41	0.40	0.01
Panel B: Conditional on first major being STEM				
	Everyone	Males	Females	Gender diff. *p*-value
Overall	0.47	0.50	0.43	0.07*
Meet 0 criteria	0.12	0.14	0.10	0.04
Meet 1 criterion	0.37	0.38	0.35	0.03
Meet 2 criteria	0.39	0.45	0.31	0.14*
Meet 3 criteria	0.50	0.48	0.54	−0.06
Meet 4 criteria	0.62	0.62	0.62	0.00
Meet 5 or 6 criteria	0.65	0.67	0.62	0.05

Note: The sample in Panel A is all students who attended a four-year college and ever reported a major. The sample in Panel B is all students who attended a four-year college and first reported a STEM major. The outcome is graduating from college, reporting a STEM major as the last major. The p-values used to determine significance in the last column are taken from regressions of the criterion on a dummy for male, again using the sample weights. The six STEM readiness criteria, each a binary variable, are scoring at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests and taking at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course.

When I condition on starting a STEM major in Panel B to focus on persistence, we also see a gender gap in the probability of graduating in STEM. Half of men who start in STEM also graduate in STEM, compared with 43% of women. This is driven by the less STEM-ready students. At high levels of STEM readiness, there is no gap in the probability of persistence in STEM. So while the gap in initial major choice was largest among the most STEM-ready students, the gap in *persistence*, which is smaller, is being driven by the least STEM-ready students.

The gender gap in STEM grows at this stage, but only slightly. In the NLSY data, 63% of those who attend college and initially major in a STEM field are male, and 65% of those who graduate with a STEM degree are male.

4.5. Stage 5: College to early career

The next step on the path to a STEM career is the transition from college graduation to the labor market. Here the question is whether graduates from STEM majors enter STEM-related jobs. It is not necessarily a bad thing if STEM graduates take their skills to different fields where those skills are also valued highly, but if we are thinking about the pipeline to STEM jobs, this is an important transition.

There are a number of reasons why a STEM graduate, who has invested at least four years in STEM study and has valuable human capital, might choose a non-STEM job. There may be more STEM graduates than STEM jobs available. STEM graduates may also find their skills valued highly in other fields, like finance (Marin & Vona, 2017). They may also have bad experiences in college that lead them to leave the field (Smith & Gayles, 2017). Some of these may not be of concern, but if women are leaving in disproportionate numbers, it may point to cultural problems or discrimination in these fields.

It is not possible to continue using the NLSY to analyze this step, because the sample size of STEM graduates is too small (only 325). Instead I turn to the American Community Survey for its large sample size of STEM graduates. The ACS has asked for field of undergraduate study since 2009, so I use the 2009–2017 data. I will start by looking at early-career outcomes, using age 30. The NLSY97 sample, born between 1981 and 1984, would have been age 25–36 during this time period, so these are approximately the same cohorts of people. The main disadvantage of switching to the ACS is that I can no longer look at outcomes by the degree of STEM readiness.[9]

Focusing on the college-to-job transition is tricky for two reasons. The first is the graduate school option. My goal is to look at something approximating the first job out of college, but in the ACS, 36% of STEM graduates are in graduate school of some kind at age 24 (33% for men and 40% for women; see Fig. A.1). I do not know what type of graduate school they are in (medical school, Ph.D. program, etc.), so I cannot tell if these graduates are still "in" the STEM pipeline or not. Because of this, I will look at STEM graduates' outcomes first at age 30, when most are out of graduate school, even though this is likely not the first job for those who did not go to graduate school. All of my conclusions are robust to using different age ranges around 30, including the late 20s.[10]

The second difficulty is that defining what constitutes a STEM job is not straightforward. Various definitions are used by government agencies, and job task data show no clear, robust definition of STEM occupations (Light & Rama, 2019; Rothwell, 2013; Speer, 2020). For instance, the Bureau of Labor Statistics usually does not include any medical or social science occupations as STEM jobs, while the BLS's O*Net data on occupation tasks uses a much broader definition.

Here, I will use two different definitions, one narrow and one broader. For the narrow approach, I use the BLS's definition of STEM occupations, and for the broader approach, I add in medical practicing and diagnosing occupations (what one might call STEMM). This includes things like physicians, dentists, and nurse practitioners, but not nurses, therapists, aides, or technicians.[11] The STEMM measure is my preferred definition of STEM occupations.

Fig. 1 shows the distribution of outcomes for STEM graduates at age 30 separately for men and women. The top two graphs use the full sample, while the bottom two graphs are conditional on being employed at age 30. The two graphs on the left use the narrow BLS definition of STEM jobs, while the right two graphs use my preferred STEMM measure.

Using the narrow definition of STEM, men with STEM degrees are about twice as likely as women to be in STEM occupations (41% vs. 20%) at age 30. Women with STEM degrees are much more likely than men to be in medical jobs or out of the labor force. Conditional on employment, the gap in STEM employment is just as large (49% for men vs. 28% for women).[12]

When the definition of STEM is broadened, the gender gap in going into STEM occupations at age 30 is narrowed some, to 15 percentage points (47.5% vs. 32.3%), or 12 percentage points when conditioning on employment (57.2% vs. 44.9%). This is because many of the women in medical jobs in the left panel now move to STEM in the right panel. At age 30, 13% of women with STEM degrees are in medical practicing and diagnosing jobs, compared with only 7% of such men. So the gender gap in who is actually using STEM-related skills in the labor market is not as large as the BLS definition makes it appear. Even with that adjustment, though, there are large gaps in the probability of being in a STEM job.

To see how important this stage is, consider how the gender gap in STEM grows from degree receipt to age 30 occupation. In the ACS, 62% of those age 30 with a STEM degree are men. But among those with a STEM degree and a STEM occupation, 77% are men under the narrow definition and 71% under the broader definition. This is clearly a stage at which the gender gap grows larger.

Women with STEM degrees who do not go to STEM jobs are often not working at all: 13% are out of the labor force, an even higher share than college graduates from non-STEM majors (11%). This is surprising given the high opportunity cost of leaving the labor force for higher earners, but if the penalty for career interruptions is higher in STEM jobs, women who leave the labor force from STEM may be more likely to stay out. Even considering this, though, there is a substantial gap in working in STEM even conditioning on employment. The most common non-STEM occupation (using the broader definition of STEM) at age 30 among female STEM graduates is elementary and middle school teachers (4.0% of female STEM graduates).

Fig. A.3 gives a deeper look, showing where STEM graduates are at age 30, separately by STEM major, using the broader definition of STEM jobs (not conditioning on employment). From all STEM majors, men are more likely to go into a STEM job, but the gap is particularly large in computer science. Biology majors have a much smaller gender gap in STEM jobs, largely because many biology majors enter medical occupations. Female math majors are more likely to work in education than in STEM jobs, which is not true for male math majors. Women are more likely than men to be out of the labor force at age 30 in every major, but computer science stands out most. 20% of women from computer science are out of the labor force, compared with only 9% of women from biology. This seems an important pathway to understand.

Clearly, one reason for the gender gap in STEM – as in other fields – is women's decision to have children and stay out of the labor force. Table A.3 looks at rates of marriage and having children at age 30 by major, also comparing with non-STEM graduates. Women who are computer science graduates are more likely to be married (68%) and have children (45%) than graduates from most other STEM majors. Biology graduates, who are about half as likely to be out of the labor force, are also far less likely to be married (59%) and have children (34%). This could be because they delay marriage and family to enter medical occupations.

4.6. Stage 6: Early career to mid-career

Finally, I look at STEM graduates later in their careers, to see how many stick with STEM occupations. Of all the stages, this is the one least suited to my data. The ACS is not a panel survey, so I cannot follow the same graduates over time, but I can look at the difference between early-career outcomes and mid-career outcomes of STEM graduates. This confounds experience effects with cohort effects, so these results will be imperfect.[13]

Despite the data limitations, this is an important step to include. Women are known to frequently leave STEM careers when they have children (Cech & Blair-Loy, 2019), leading to concern that STEM jobs are not family-friendly (Wiesgram & Diekman, 2015). How these outcomes compare to non-STEM jobs, and whether women who leave STEM after having children eventually come back, is an open question. Given that women who are in STEM jobs at age 30 are those who have already cleared several major hurdles, ensuring that they can stay and advance in STEM if they so choose would seem to be a major priority.

[9] While the ACS has more detailed major codes than the NLSY, matching the definition of most STEM majors across surveys is straightforward. I include pharmacy and "medical preparatory programs" as STEM majors in the ACS in order to match the inclusion of pre-medical majors in the NLSY.

[10] For analysis of the STEM pipeline in graduate school specifically, see Bostwick and Weinberg (2022) and Miller and Wai (2015).

[11] This distinction is based on the fact that medical practicing and diagnosing occupations have high STEM task content, while the other medical professions generally do not (Speer, 2020). Riise, Willage, and Willen (2022) show that children exposed to female physicians are more likely to study and major in STEM fields later on in life. This suggests that medical professions merit strong consideration as being considered STEM.

[12] Fig. A.1 shows these graphs for age 25, when a large number of STEM graduates are still in graduate school.

[13] Though they face the same issue of not being able to separate experience and cohort effects, Delaney and Devereux (2021) provide a detailed study of gender gaps in STEM persistence over the course of a career using UK data.

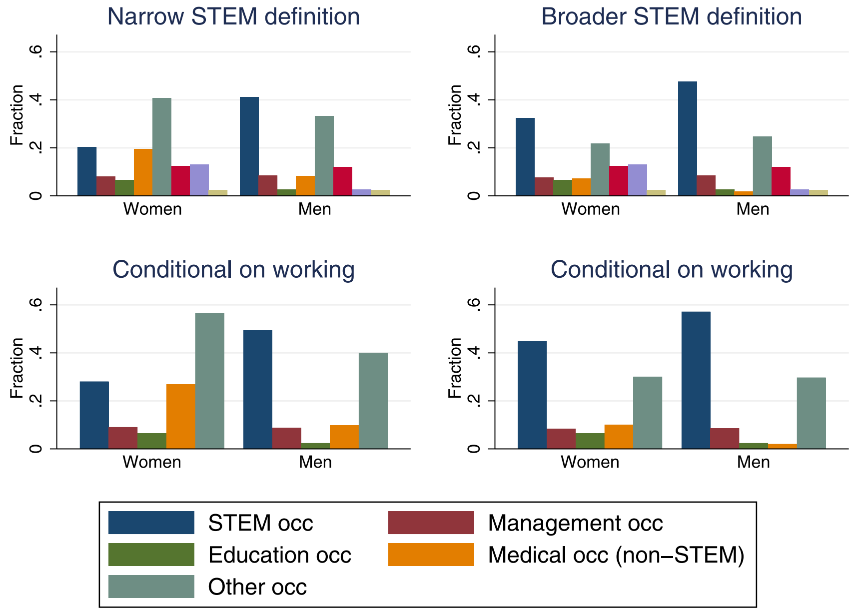

Fig. 1. Distribution of STEM graduates by gender, age 30.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 30 holding a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. The left two graphs use the BLS definition of STEM occupations. The right two graphs also include medical practicing/diagnosing occupations as part of STEM. The bottom two graphs only include those who are employed.

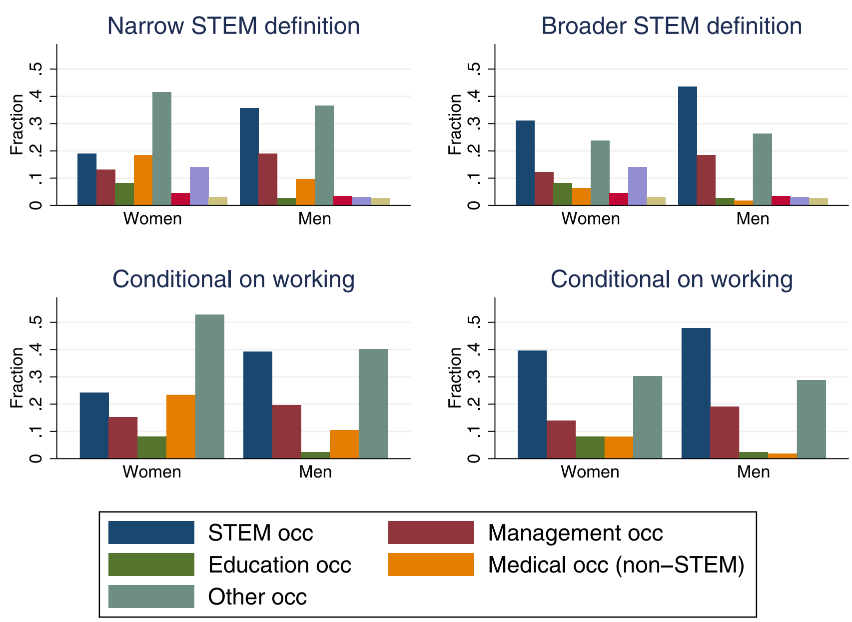

Fig. 2. Distribution of STEM graduates by gender, age 45.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 45 holding a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. The left two graphs use the BLS definition of STEM occupations. The right two graphs also include medical practicing/diagnosing occupations as part of STEM. The bottom two graphs only include those who are employed.

Fig. 2 looks at the distribution of STEM graduates at age 45. Using the broader STEM job definition in the right side of the figure, the gender gap is 12.5 percentage points (43.5% for men vs. 31.0% for women). Fig. 3 compares the distribution of outcomes for men and women at ages 30 and 45, using the broader definition of STEM jobs. For the most part, the distributions are similar. Both men and women are slightly less likely to be in STEM occupations at age 45 than at age 30. The gender gap actually shrinks slightly from age 30 to age 45.

Both men and women – but especially men – are more likely to be in management positions at age 45. Note that STEM managers (architecture, engineering, natural sciences, etc.) are included in the STEM category, not the management category. Interestingly, women are about as likely to be out of the labor force at age 45 than age 30. The (net) exodus of female STEM graduates from the labor force seems to occur almost entirely by age 30 and not later.

Unfortunately, the ACS is not a panel survey, so it does not allow me to look at age-45 outcomes conditional on being in a STEM occupation at age 30, so I cannot say anything about the flows from category to category. Still, these data do not suggest any big changes in the gender gap in STEM between early- and mid-career.

There is one caveat. The cohorts I am looking at in the ACS are quite different. 38% of STEM graduates in the ACS at age 30 are female; for

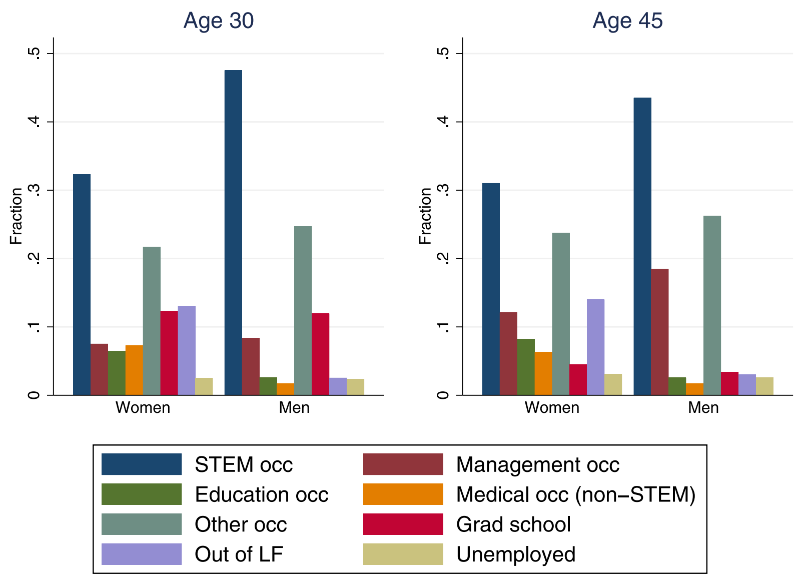

Fig. 3. Distribution of STEM Graduates, Age 30 and 45.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 30 (left panel) or age 45 (right panel) holding a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. STEM occupations are defined using the BLS list of STEM occupations plus medical practicing/diagnosing occupations.

those age 45, it is only 31%. Some of this is due to women's increasing share of college graduates in general, which grows from 54% to 57% during this time. These differences mean that any comparison between age 30 and 45 should be treated with caution. It is difficult to know how the changing selection into STEM majors during this time would alter the distribution of job outcomes.

5. Decomposing the leaky pipeline

The goal in this section is to decompose the STEM pipeline and quantify the importance of each stage. In understanding the leaking of women from the pipeline, and in knowing where we might target efforts to retain them, it is important to understand which stages are the most significant.

There are a few difficulties to overcome. First, I have used two different data sources (the NLSY and ACS), which do not always line up perfectly. I use the person weights in both data sets, but they are still different: for example, the NLSY sample is 51.2% male overall, while the ACS age 30–45 sample is 49.9% male. Second, the older and younger cohorts in the ACS are somewhat different. Both of these issues will require a type of reweighting.

Third, as noted earlier, there are multiple definitions of STEM jobs. My preferred approach will use the broader definition of STEM occupations, which includes medical diagnosing/practitioner jobs and social science occupations. The overall results will be similar when using the narrow definition. Fourth, one of my stages is STEM readiness, but there is no binary indicator of readiness in the U.S., because there are different paths into and out of STEM majors and jobs. Because of these difficulties, the decomposition that follows should be seen as a back-of-the-envelope calculation rather than a definitive breakdown of this complex process.

The first adjustment is to make the overall NLSY and ACS samples comparable. The ACS is nationally representative, while the NLSY oversamples certain groups, so I use the ACS as my benchmark. The age 30–45 sample of the ACS is 49.9% male, so I use this as my "starting point". The NLSY sample is 51.2% male, so I adjust all of the NLSY male shares downward by 1.3 percentage points to match the ACS. I use similar adjustments to make the age-30 and age-45 ACS cohorts comparable. After these adjustments, my "endpoint" is the age-45 STEM job male share, which is 70.7%. So the total gender gap to "explain" is the difference between the endpoint and starting point, or 20.8 percentage points.

The last decision is how to incorporate STEM readiness. The decomposition will be most intuitive if I can define a binary measure of readiness, which is difficult in the US system. The biggest jump in STEM majoring probability is from those who meet three or fewer of the readiness criteria (17%) to those who meet four or more (45%). For my main decomposition, then, I will define someone as STEM-ready if they meet at least four of the six readiness criteria. I will explore alternatives in the following section.

The results of the main decomposition are in Table 7, using the broader STEMM occupational definition at mid-career in the left panel. To illustrate how the decomposition works, first look at the numbers under the heading "% male". This shows the share of the sample that is male at each stage of the pipeline. I calculate the contribution of each stage x as

$$contribution_x = \frac{(maleshare_x - maleshare_{x-1})}{(maleshare_N - maleshare_0)}$$

where $maleshare_N$ is the male share after the final stage and $maleshare_0$ is the male share of the baseline sample.

Reading from the bottom, the overall sample ($maleshare_0$) is 49.9% male; the sample of those who are STEM-ready is 57.1% male; the sample of those are STEM-ready and attend college is 55.9% male; and so on. When we reach the final stage, the sample of those with a STEM degree and a STEM occupation at age 45 is 70.7% male ($maleshare_N$). So the overall gender gap to "explain" is the difference between 70.7 and the starting point, 49.9, or 20.8 percentage points. This is how much the gender gap grows from the initial sample to the final stage.

When we go from the overall sample (49.9% male) to only those who are STEM-ready (57.1% male), the male share has increased by 57.1 − 49.9 = 7.2 percentage points. So the STEM readiness stage can account for 7.2/20.8 = 34.6% of the total gender gap in STEM careers. Since the male share of the sample actually shrinks by 1.2 ppt to 55.9% once we look only at attendees, the attendance stage accounts for −1.2/20.8 = −5.8% of the total gap. I calculate the contribution of the other stages in the same way.

Table 7
Decomposing the STEM pipeline.

	Outcome: STEM Degree and STEM Occ (Broad) Age 45		Outcome: STEM Degree and STEM Occ (Broad) Age 30		Outcome: STEM Degree and STEM Occ (Narrow) Age 45	
	% male	Share explained	% male	Share explained	% male	Share explained
STEM degree + STEM occ age 45	70.7	**−9.1%**			75.6	**−12.5%**
STEM degree + STEM occ age 30	72.6	**41.3%**	72.6	**37.9%**	78.8	**57.8%**
STEM degree	64.0	**13.0%**	64.0	**11.9%**	64.0	**10.5%**
STEM initial major	61.3	**26.0%**	61.3	**23.8%**	61.3	**21.0%**
STEM-ready attendees	55.9	**−5.8%**	55.9	**−5.3%**	55.9	**−4.7%**
STEM-ready sample	57.1	**34.6%**	57.1	**31.7%**	57.1	**28.0%**
Sample	49.9		49.9		49.9	

Note: The shares are the author's calculations from the NLSY and ACS samples. See the text for a description of how the samples are joined together. The narrow definition of STEM jobs is taken from the Bureau of Labor Statistics. The broader definition includes the BLS list and medical practicing/diagnosing jobs.

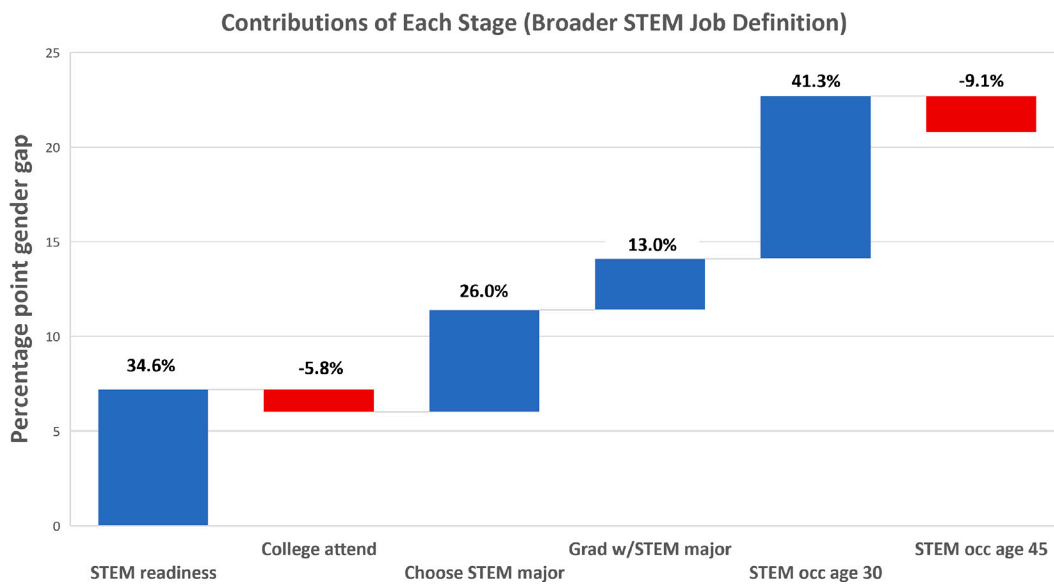

Fig. 4. Decomposition of the STEM gender gap.
Note: Author's calculations from the American Community Survey, 2009–2017, and NLSY97, as taken from the left panel of Table 7.

There are three stages that stand out and explain most of the gender gap in STEM careers: one before college, one during college, and one after college. The most important is the gap in age-30 job choice – the college-to-job transition – which accounts for 41% of the overall gap. Second is the gender gap in STEM readiness, which accounts for 35%; third is the gap in the initial major choice, which accounts for 26%. The other stage of some importance is persistence from initial major to graduation, which accounts for 13%.[14]

Women's higher rates of college attendance mean that this stage actually narrows the gender gap in STEM, so it accounts for -6%. This stage would have a larger negative contribution, but recall that it tends to be only the more STEM-ready men who attend college. This positive selection of men int college means that the attendance phase has only a small effect on the final gap. The main lesson from this exercise is that there is no single stage which can account for the loss of women from the STEM pipeline. It is happening before college, in college, and after college. Fig. 4 shows graphically how the gender gap in STEM evolves, using the figures from the left panel of Table 7.

There is an important note to add regarding the interpretation of the decomposition. Some of the stages I have defined are "cumulative", while others are not. A person may skip some stages and still rejoin the STEM pipeline later. One must be STEM-ready to count in stage 1 (STEM-readiness) and stage 2 (STEM-ready and attending college). On the other hand, one need not be STEM-ready to start a STEM major (stage 3), nor does one have to start in a STEM major to graduate with a STEM degree (stage 4). In addition, since I am using two different data sources, I cannot observe STEM readiness or initial major for those in the ACS with a STEM degree.

These choices reflect the flexibility of the U.S. system, where there are many pathways into and out of STEM majors and careers, but they affect the interpretation of my decomposition, and the exact percentage that each stage contributes should be interpreted with caution. For example, because someone can be *not* STEM-ready and still end up starting a STEM major in college, the contribution of the STEM-readiness stage should be seen as an upper bound of its true importance. The same is true for initially majoring in STEM, which is not a necessary condition for eventually graduating in STEM, and for working in a STEM job at age 30, which is not necessary for working in STEM later.[15]

[14] Card and Payne (2021) find that 81%–85% of the gender gap in initial STEM major choice in Canada is due to gaps in STEM readiness. Here my outcome is mid-career job, not initial major. If I re-run the decomposition treating initial major choice as the outcome, I find that STEM readiness accounts for 63% of the gap. This lower figure likely reflects the fact that high school choices are not as binding in the U.S. as they are in Canada.

[15] In my NLSY sample of college attendees, 17% are STEM-ready; of those who start in a STEM major, this figure is 35%. So while STEM-ready students are far more likely than others to start a STEM major, the majority of those

I have tried alternative specifications in which I define the stages to be as cumulative as possible (e.g., looking only at STEM graduates who were also STEM-ready) and in which I do the opposite (e.g., looking at all college attendees rather than just those who are STEM-ready). In both cases, the same three stages stand out: STEM readiness, initial major, and early-career job.

5.1. Robustness to alternative specifications

I have run several other alternative specifications to see how they change the results. First, I use age 30 as the final outcome rather than age 45, due to the differences in cohort composition (see the middle panel of Table 7). This gives a similar result as the main specification.

The second alternative (right panel of Table 7) is to use the narrower BLS definition of STEM occupations. This widens the gender gap in occupation choice and thus increases the importance of the labor market choices, but the overall story is similar. The college-to-career step is now clearly the most important, accounting for 58% of the gap, with STEM readiness (28%) and initial major choice (21%) next. Again, the pipeline is leaking before, during, and after college.

The definition of STEM readiness and the STEM readiness criteria were important to my decomposition. As I emphasized earlier, particularly in the U.S., there is no ideal way of defining STEM readiness, as there are many paths into and out of STEM. I made two key choices in defining readiness. First, I defined the two test score-based criteria as scoring at least one standard deviation above the mean on the math and science ASVAB tests. Second, I defined STEM readiness as meeting at least four of the six readiness criteria.

Both of these choices were designed to match the observed data as well as possible. Table 5 shows that by far the largest jump in the probability of initially majoring in STEM among college attendees is between those who meet three criteria and those who meet four.[16] On math test scores, the biggest jumps in STEM majoring probability occur from those 0.5 to 1 standard deviations above mean (20%) to those 1 to 1.5 above mean (29%) and to those 1.5 or more above mean (40%). On science tests, the biggest jump in STEM major probability is at 1.5 standard deviations, with a smaller jump at 1 and no jump at 0.5. This would justify using either 1 or 1.5 standard deviations above mean as a good cutoff for the test scores.

Thus, the choices I made in defining STEM readiness are supported by the data, but they are still somewhat arbitrary given the nature of the exercise. To see how different choices affect the decomposition, I alter both the number of criteria and score cutoffs needed to be called STEM ready in Tables A.4 and A.5.

When the definition of STEM readiness is broadened, seen in the middle panels of each table, this reduces the contribution of STEM readiness and increases the contribution of the first major choice. Particularly for the test score cutoffs, the broader definition of readiness does not seem justified from the data. When the definition of readiness is narrowed – which is more justified for the test scores than for the number of criteria needed to be counted as ready – as in the right panels of each table, the contribution of STEM readiness increases, making it dominant factor in the decomposition and mechanically reducing the contribution of the initial major choice.

These alternatives show that, while I have tried to be as consistent with the data as possible in my choices, the quantitative results of the decomposition are sensitive to the choices I made. Still, it is consistently true across specifications that there is a gender gap in STEM readiness that can account for a significant portion of the overall gender gap in STEM careers, even when using a liberal definition of readiness.

In results I do not show here, I have also used merely holding a STEM occupation as my outcome, rather than both that and having a STEM degree. This does not alter the results much, because the gender gap in all STEM jobs is similar to the gap among those that also have a degree. Finally, I have also altered the definition of STEM majors to use the National Science Foundation definition (which is arguably too broad, including all social sciences like history and psychology) and only "math-intensive" STEM majors (physical sciences, engineering, mathematics, computer science, and economics), where Kahn and Ginther (2017) show most of the gender gap is concentrated. While the numbers vary from definition to definition, the main conclusions do not. STEM readiness, initial major choice, and early-career job choices are the dominant stages in understanding the overall gender gap.

6. Discussion

The path from high school to a STEM career in the United States is complex, where there are many possible pathways into and out of STEM. I show in this paper that the pipeline is "leaking" before, during, and after college. Fewer women are STEM-ready when entering college, fewer of them choose STEM majors, fewer of those stick with the STEM majors, and still fewer of those choose a STEM job after college. There is no single stage that we can focus on to understand or reduce the gender gap in STEM careers.

Of particular concern to policymakers and schools is the loss of highly prepared and able women from the pipeline. Major choice shows a huge gap in the probability of entering STEM among the most well-prepared students. And among those who persist all the way to a STEM college degree – no small feat – women are still fleeing STEM careers. These stages do not represent a weeding-out of less able students or workers. They represent a loss of well-prepared and highly qualified women to other fields.

It is worth noting that my results are specific to the United States, where there are many pathways into and out of STEM. Unlike in some other countries, one may not appear to be on a STEM-type track in high school, but may change one's mind later. One may even start college in a non-STEM major and then graduate in a STEM major, though this is rare in my data and rare even in experimental settings where the cost is low (Rury, 2022).

Taken together, my results suggest that there are no easy remedies or policy interventions that would substantially reduce the gender gap in STEM. For researchers, it is important to have a broad focus when trying to understand what is going on in STEM. Focusing only on childhood, only on college, or only on the labor market misses important parts of the story.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Appendix tables and figures

See Tables A.1–A.5 and Figs. A.1–A.3.

who start STEM majors are not STEM-ready. Of those who complete a STEM degree, 72% also started in a STEM major. I do not have data on the percentage of people who work in STEM at age 45 who also worked in STEM at age 30.

[16] One might argue that using the final major, rather than initial major, is a better way to find the right cutoff for STEM readiness. Fortunately, the same pattern holds when using "graduating with a STEM major" as the outcome. The largest jump in probability is between those who meet three criteria and those who meet four.

Table A.1
Most common initial major choices, by STEM readiness.

Panel A: Most common STEM initial major choices (% of all students)			
	Everyone	Males	Females
Overall	Computer sci (6.0%)	Computer sci (10.5%)	Biology (6.7%)
	Engineering (5.6%)	Engineering (10.2%)	Computer sci (2.3%)
	Biology (5.4%)	Biology (3.7%)	Engineering (1.9%)
Meets 0–1 criteria	Computer sci (5.0%)	Computer sci (9.5%)	Biology (4.9%)
	Biology (3.7%)	Engineering (4.0%)	Computer sci (1.9%)
	Engineering (2.1%)	Biology (1.9%)	Physical sci (0.9%)
Meets 2–3 criteria	Computer sci (6.1%)	Computer sci (10.3%)	Biology (6.1%)
	Engineering (5.2%)	Engineering (9.6%)	Computer sci (2.7%)
	Biology (4.8%)	Biology (3.2%)	Physical sci (1.8%)
Meets 4–6 criteria	Engineering (16.4%)	Engineering (23.9%)	Biology (16.0%)
	Biology (11.7%)	Computer sci (13.0%)	Engineering (6.9%)
	Computer sci (8.2%)	Biology (8.4%)	Pre-med (3.7%)
Panel B: Most common non-STEM initial major choices (% of all students)			
	Everyone	Males	Females
Overall	Business (19.3%)	Business (22.9%)	Business (16.4%)
	Education (9.5%)	Education (6.0%)	Education (12.3%)
	Psychology (5.9%)	Fine arts/communications (5.6%)	Nursing (8.1%)
Meets 0–1 criteria	Business (20.8%)	Business (27.5%)	Business (16.3%)
	Education (12.2%)	Education (7.6%)	Education (15.3%)
	Fine arts/nursing (6.8%)	Fine arts (6.6%)	Nursing (10.3%)
Meets 2–3 criteria	Business (20.4%)	Business (23.6%)	Business (17.7%)
	Education (9.0%)	Education (6.0%)	Education (11.5%)
	Communications (6.6%)	Communications (6.0%)	Psychology (8.2%)
Meets 4–6 criteria	Business (11.9%)	Business (12.1%)	Business (11.7%)
	Psychology (5.6%)	Communications (4.2%)	Psychology (9.0%)
	Fine arts (4.5%)	Fine arts (3.8%)	Fine arts (7.9%)

Note: The table shows the most common first-major choices among students who attended a four-year college, separately by gender and STEM readiness criteria. The six STEM readiness criteria, each a binary variable, are scoring at least one standard deviation above the mean on the ASVAB science knowledge and mathematics knowledge tests and taking at least two biology courses, at least two chemistry courses, at least one physics course, and at least one calculus course.

Table A.2
Most common graduation majors of women who leave STEM.

Most common graduation majors for women leaving STEM (% of leavers who graduate)			
All Leavers	Meet 0–1 Criteria	Meet 2–3 Criteria	Meet 4–6 Criteria
Business (18.2%)	Business (24.1%)	Business (17.5%)	Fine Arts (15.8%)
Psychology (15.9%)	Psychology (17.2%)	Nursing (17.5%)	Psychology (15.8%)
Nursing/Education (11.4% each)	Comms./Educ. (10.3% each)	Psychology (15.0%)	Bus./Educ./Interdisc. (10.5% each)

Note: The table shows the most common majors of graduation for women whose first major was a STEM major but who did not graduate in a STEM major.

Table A.3
Marital status and children for women at age 30, by major.

	Major						
	Comp Sci	Engineering	Biology	Math/Stats	Phys Sci	Other STEM	Non-STEM
Percent out of LF	20.4	16.8	8.9	13.2	11.8	12.8	10.7
Percent married	67.8	65.9	55.9	57.6	52.5	58.0	56.1
Percent with children	43.9	38.6	32.5	38.6	36.6	35.3	41.0
Average no. of children	0.65	0.56	0.50	0.65	0.57	0.55	0.67
Avg. no. of children, if positive	1.49	1.46	1.54	1.68	1.57	1.57	1.63

Note: The sample is taken from the ACS and includes women with a bachelor's degree in the given field, using the ACS's person weights.

Table A.4
Decomposing the STEM pipeline with changing criteria number for STEM readiness.

	Outcome: STEM Degree and STEM Occupation (Broad), Age 45					
	Ready = meets at least 4 criteria		Ready = meets at least 3 criteria		Ready = meets at least 5 criteria	
	% male	Share explained	% male	Share explained	% male	Share explained
STEM degree + STEM occ age 45	70.7	**−9.1%**	70.7	**−9.1%**	70.7	**−9.1%**
STEM degree + STEM occ age 30	72.6	**41.3%**	72.6	**41.3%**	72.6	**41.3%**
STEM degree	64.0	**13.0%**	64.0	**13.0%**	64.0	**13.0%**
STEM initial major	61.3	**26.0%**	61.3	**50.5%**	61.3	**−20.2%**
STEM-ready attendees	55.9	**−5.8%**	50.8	**−11.5%**	65.5	**−5.8%**
STEM-ready sample	57.1	**34.6%**	53.2	**15.9%**	66.7	**80.8%**
Sample	49.9		49.9		49.9	

Note: The shares are the author's calculations from the NLSY and ACS samples. See the text for a description of how the samples are joined together. The left panel defines STEM readiness as meeting at least 4 of the STEM criteria; this is the same as the left panel of Table 7. The middle panel defines STEM readiness as meeting at least 3 of the STEM criteria. The right panel defines STEM readiness as meeting at least 5 of the STEM criteria.

Table A.5
Decomposing the STEM pipeline with changing test score cutoffs.

	Outcome: STEM Degree and STEM Occupation (Broad), Age 45					
	Math and science tests at least 1 sd avove mean		Math and science tests at least 0.5 sd avove mean		Math and science tests at least 1.5 sd avove mean	
	% male	Share explained	% male	Share explained	% male	Share explained
STEM degree + STEM occ age 45	70.7	**−9.1%**	70.7	**−9.1%**	70.7	**−9.1%**
STEM degree + STEM occ age 30	72.6	**41.3%**	72.6	**41.3%**	72.6	**41.3%**
STEM degree	64.0	**13.0%**	64.0	**13.0%**	64.0	**13.0%**
STEM initial major	61.3	**26.0%**	61.3	**53.8%**	61.3	**−6.3%**
STEM-ready attendees	55.9	**−5.8%**	50.1	**−8.2%**	62.6	**−3.4%**
STEM-ready sample	57.1	**34.6%**	51.8	**9.1%**	63.3	**64.4%**
Sample	49.9		49.9		49.9	

Note: The shares are the author's calculations from the NLSY and ACS samples. See the text for a description of how the samples are joined together. The left panel defines the two test-score STEM criteria as being at least 1 standard deviation above the age-adjusted mean score on the math and science ASVAB tests; this is the same as the left panel of Table 7. The middle panel uses 0.5 standard deviations above mean as the cutoff. The right panel uses 1.5 standard deviations above mean as the cutoff.

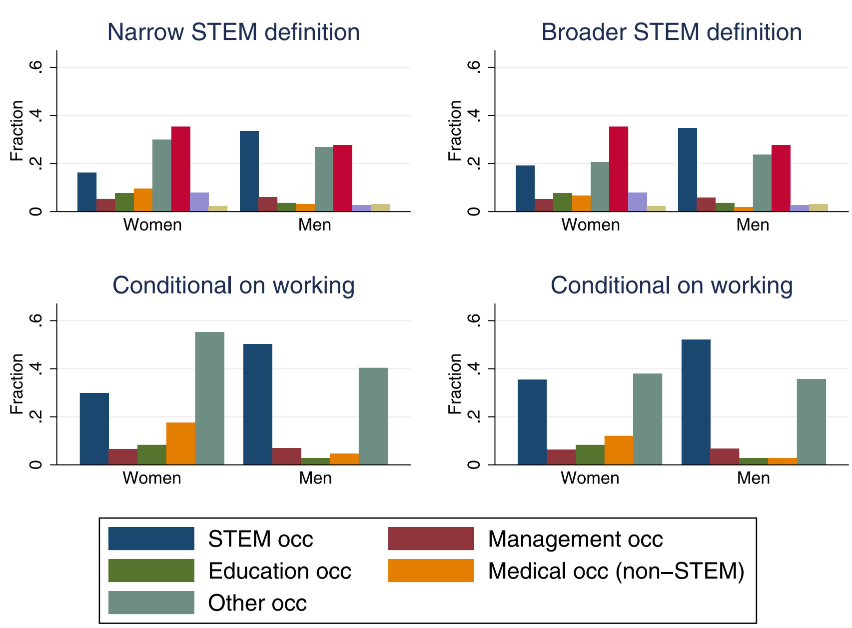

Fig. A.1. Distribution of STEM graduates by gender, age 25.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 25 holding a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. The left two graphs use the BLS definition of STEM occupations. The right two graphs also include medical practicing/diagnosing occupations as part of STEM. The bottom two graphs only include those who are employed.

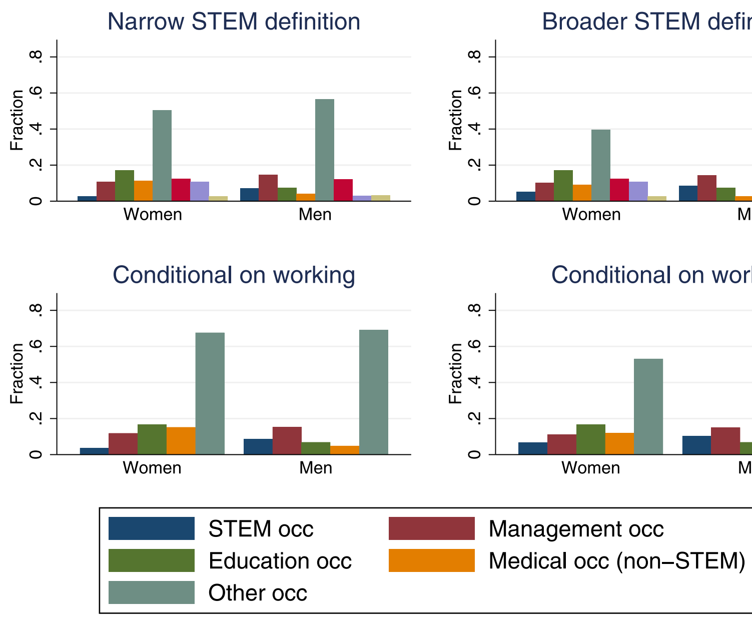

Fig. A.2. Distribution of Non-STEM-graduates by gender, age 30.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 30 who does not hold a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. The left two graphs use the BLS definition of STEM occupations. The right two graphs also include medical practicing/diagnosing occupations as part of STEM. The bottom two graphs only include those who are employed.

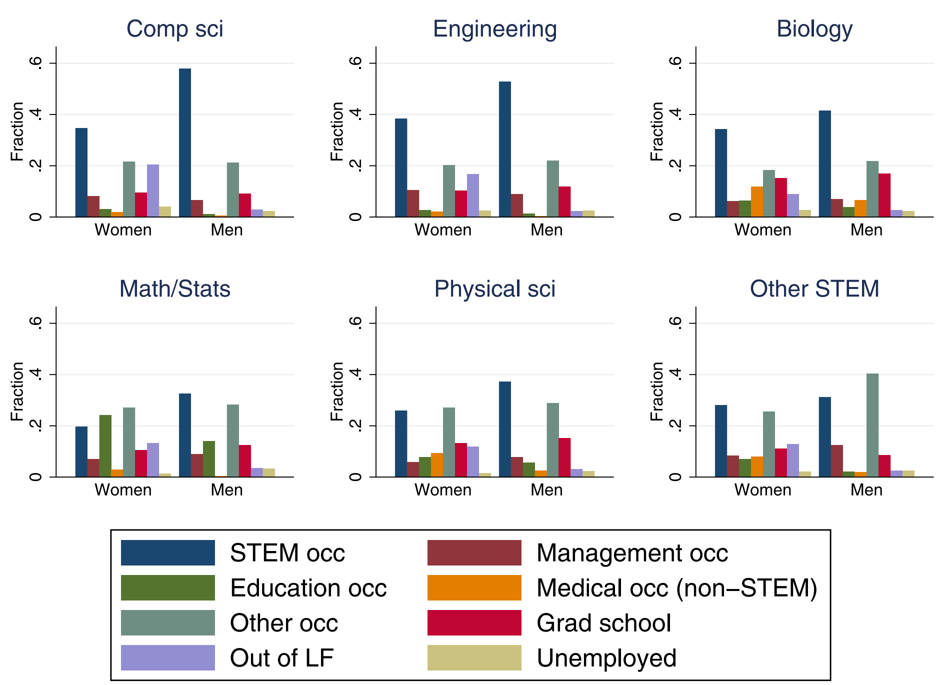

Fig. A.3. Distribution of STEM graduates by major and gender, age 30.
Note: Author's calculations from the American Community Survey, 2009–2017. The sample is everyone age 30 holding a bachelor's degree in a STEM field, using the Department of Homeland Security's definition of STEM majors. STEM occupations are defined using the BLS list of STEM occupations plus medical practicing/diagnosing occupations.

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