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ABSTRACT

Bye Bye Ms. American Sci: Women and the Leaky STEM Pipeline*

More than two-thirds of STEM jobs are held by men. This paper provides 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. By far the most important stages are the initial college major choice and the college-to-career transition. Men are far more likely than women to start in a STEM major, especially among those who are the most prepared for STEM upon entry. This alone accounts for 57% of the total gender gap in STEM careers. After college, male STEM graduates are far more likely to be found in a STEM job, accounting for 44% of the overall gap. Women who start in STEM majors are also less likely to graduate in STEM (accounting for 16%), while the gap in pre-college STEM-readiness is a small factor (8%). Women attend college at much higher rates than men, which works to reduce the final gender gap in STEM (-14%). The pipeline to STEM jobs is complex, and focusing only on the college experience or only on the labor market misses a large part of the overall story of women in STEM.

JEL Classification: J01, J15, J16
Keywords: STEM, gender gaps, college major

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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 (Jiang 2019, Brown and Corcoran 1997).

In this paper, I trace the experiences of women in this STEM "pipeline" from high school to the labor market in the United States.[1] 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.

Two of these stages stand out in their importance: the initial college major choice and the transition from college to early-career employment. While women are, on average, only slightly less prepared as men for STEM majors and attend college at higher rates, they are far less likely to start a STEM major in college. This is especially true among the most STEM-ready students; of those who are highly prepared for STEM, 55% of men start in a STEM major, compared with 33% of women. This continues after college: even among those who have persisted to

[1] 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 and 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.

complete a STEM college degree, women are far less likely to be found in STEM occupations at age 30 (48% of men vs. 33% of women). Together, these two stages account for essentially the entire gender gap in STEM careers.

I decompose the mid-career gender gap into the contributions of the six pipeline stages. Initial major choice and the transition from college to career dominate the decomposition, accounting for 57% and 44%, respectively, of the total gender gap. Women who start a STEM major are also less likely to persist to graduating in STEM, which accounts for another 16%. While these women actually graduate at higher rates than the men, they do so in other, non-STEM majors. The gender gap in high school STEM-readiness is small, accounting for only 8% of the total gap.

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 it is primarily the less STEM-ready men who do not attend. Overall, college attendance contributes -14% of the total gap. The transition from early- to mid-career also sees the gender gap in STEM decline slightly, although my data are less well-suited to study this stage. All of these conclusions are robust to using very different definitions of STEM majors and occupations.

These results show clearly that little of the gender gap in STEM can be explained by differences in ability or level of preparation. The gap in major choice is driven by the most STEM-ready students, and there are large gaps in job choice among those with STEM degrees. These stages do not represent a weeding out of less able students or workers. They represent a loss of highly qualified and well-prepared women from STEM and from the labor force entirely.

The results also highlight the importance of looking at the entire pipeline when drawing conclusions about when and why women leave STEM. Focusing only on the college experience, for example, misses the important role of labor market choices, and focusing only on the labor market misses the critical choices made in college. And the small gaps in STEM-readiness prior to college, despite girls' overall better performance in school, cannot be ignored either. A comprehensive approach is necessary. There are multiple stages of development in which women may be targeted to recruit and retain them to STEM education and jobs.

The gender gap in STEM fields has been studied extensively by researchers in economics, education, and other fields.[2] 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 and West 2010, Hoffmann and Oreopoulos 2009), the influence of peers (Fischer 2017), and differences in taste for competition (Niederle and Vesterlund 2011). Qualitative evidence from the education literature often highlights "cultural" reasons women leave STEM fields (Seymour and Hewitt 2000, Brainard and Carlin 1998).

I take a different approach in this paper. Instead of trying to identify the sources of the gender gap in STEM directly, I focus on describing the timeline of the STEM pathway. My results speak indirectly to the reasons women leave STEM by looking at who leaves at each stage and where they go. By looking at the destinations of women who could have been STEM majors or STEM workers, we can get some hint of why they did not choose STEM.

The primary contribution of this paper is providing a comprehensive analysis of the STEM pipeline from high school to mid-career. While other researchers have studied parts of the pipeline, 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. There is no single place to look to understand the phenomenon of women leaving STEM.

There are other papers that study parts of the STEM pipeline and try to identify the important stages (e.g., Key and Sass 2019, Levenstein, Morar, and Owen-Smith 2019, Delaney and Devereux 2019, Card and Payne 2017). I discuss these papers more in the next section. The difference in this paper is that I study the entire pipeline, from high school to mid-career, rather than focusing on a particular aspect of it, such as only the college major choice. While doing this requires use of two different data sets, we can still learn important lessons.

My approach makes clear that all the stages matter. The gender gap in STEM appears prior to college, expands significantly in college, and continues to grow

[2] See Kahn and Ginther (2017) for an excellent survey of this literature.

after college. Studies that look only at the college experience miss most of the story. Even those that follow students from pre-college to college miss the important post-college choices that contribute to the gender gap in STEM jobs. Researchers and policymakers must broaden their view of when and why women leave STEM.

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 in a non-STEM major and then graduate in a STEM major, though this is rare. In this context, it is interesting that the two stages that explain the bulk of the gender gap are perhaps the two most binding and significant choices along the way: major choice and first job choice. These are times when students and workers are making a significant commitment to STEM. It is then that we see women leaving in the largest numbers.

The paper proceeds as follows. Section 2 defines the six stages of the STEM pipeline that I will consider. 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. 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 the Bureau of Labor Statistics list for occupations (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 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 is a combination of everything that happens up to the time the person reaches high school. I will measure STEM-readiness using information on test scores and courses taken prior to college.

There is substantial evidence of pre-college gender gaps that may be relevant to STEM. Many papers document differences in test scores between boys and girls, including in STEM-related subjects like math and science (e.g., Bedard and Cho 2010, Fryer and Levitt 2010). These gender gaps in test scores have been linked to later gaps in outcomes (e.g., Speer 2017, Key and Sass 2019). Teachers' biases and stereotypes likely contribute to these gaps (Lavy and Sand 2018, Lavy and Megalokonomou 2019). On the other hand, girls generally perform better in school than boys, even in STEM subjects (O'Dea et al. 2018).

The second stage of the pipeline is college attendance, where I look specifically at four-year colleges. On average, women are more likely to attend college than men (Goldin, Katz and Kuziemko 2006), but if there is differential selection in attendance by STEM-readiness, the impact on the gender gap in STEM majors is unclear.[3]

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 choice is not binding, but it represents a declaration of intent and interest. While there is surely a relationship between major choice and preparedness, major choice also depends on many other factors, including preferences (Wiswall and Zafar 2015), peer effects (Fischer 2017, Zölitz and Feld Forthcoming), and factors as seemingly unimportant as the order in which college courses are taken (Patterson, Pope and Feudo 2019). Preferences for majors have been found to differ on average by gender (Zafar 2013, Arcidiacono 2004).

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 and Speer 2019), while men are more likely to drop out of college entirely (Astorne-

[3] It would be interesting to consider the path to STEM-related fields through two-year colleges. Because the ACS does not contain field of study for these graduates, it is not possible to link these graduates to labor market outcomes, so I leave this for future work.

Figari and 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 early-career occupation outcomes. Men and women are known to take different types of occupations (e.g., Blau and Kahn 2007, Altonji and Blank 1999), 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 signfiicant 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 (Miller and Wai 2015, Bostwick and Weinberg 2018, Ceci et al. 2014), 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 (Weisgram and Diekman 2015, Frome et al. 2006). I cannot say anything causal about the reasons women may leave STEM jobs, but I can compare labor market outcomes for younger women and older women to ask how their choices change over time.

There are many other excellent studies of the STEM gender gap which focus in more detail on the individual stages. Kahn and Ginther (2017) summarize much of this literature in their excellent survey. 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 choices such as major, but not grades and test scores, then my approach will wrongly attribute the gap to those choices rather than to early-life factors.

A few other papers try to decompose the STEM pipeline into stages, but with a narrower focus. Key and Sass (2019) use Florida data to look at the determinants of the STEM college major gender gap using math test scores from as early as fourth grade, which are similar by gender. Levenstein, Morar and Owen-Smith (2019) study the STEM pipeline at a large university, finding that the initial major choice explains most of the gender gap in STEM degrees.

Delaney and Devereux (2019) decompose the gap in initial major preferences in Ireland, finding that subject choices in high school are the most important factor. Card and Payne (2021) study the gap in STEM major entry in Canada and find that the gender gap in STEM-readiness and women's higher college attendance rates explain most of the initial major choice gap. Ceci et al. (2014) focus on the pipeline to science careers in academia specificaly.

My paper gives a comprehensive approach, weaving together all the stages of the STEM pipeline. Delaney and Devereux (2019) and Card and Payne (2021) use initial major as their outcome, so they are studying what I call stages 1-3. Key and Sass (2019) study STEM degree completion, or stages 1-4. Levenstein et al. (2019) look only at the college experience, so this is stages 3 and 4. Studies of job choices like Wiesgram and Diekman (2015) and Cech and Blair-Loy (2019) are typically studying stages 5 and 6. My results show that all stages of the pipeline are important.

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

[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.

about 9,000 respondents born between 1980 and 1984. They were first interviewed in 1997 and have been followed through the present.

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, containing only 325 STEM graduates. For the labor market stages, I rely instead on the American Community Survey. Combining the ACS from 2009 to 2017 (the years which contain college major), 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.

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

Table 1: Summary Statistics

NLSY97 Sample			ACS Sample (Ages 30-45)		
	Mean	St Dev		Mean	St Dev
Male	0.51	0.50	Male	0.50	0.50
Black	0.26	0.44	Black	0.11	0.31
Hispanic	0.21	0.41	Hispanic	0.17	0.37
Asian	0.02	0.13	Asian	0.06	0.24
Attends college	0.39	0.49	College grad	0.35	0.48
Graduates college	0.26	0.44	STEM degree	0.08	0.27
Initial STEM major	0.08	0.28	STEM occ (narrow)	0.05	0.22
Graduates w/STEM major	0.05	0.21	STEM occ (broader)	0.07	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	0.85	0.37			
Chemistry	0.60	0.49			
Calculus	0.09	0.29			
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. The ACS sample is restricted to those age 30 to 45 in the ACS's 2009-2017 waves.

the ACS I use. In the ACS, I use those age 30 (early career) and 45 (mid-career), overlapping with the NLSY cohort's age range.

4 Results

4.1 Stage 1: STEM-Readiness

It is natural to first look at who might be ready for STEM fields before 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.

In the United States, where there is no STEM "track" and there 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.

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. [5]

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. Males, on average, meet slightly more of the criteria (1.41 vs. 1.36); while the difference is significant, it is small. Males are more likely to meet the science test, calculus, and physics criteria, while females score slightly higher in math and take more chemistry courses. Males are also a bit more likely than females to meet a high number of criteria, so they are overrepresented in the upper tail of STEM-readiness.

[5] 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.

The median number of criteria met is 1 for both males and females.

Table 2: STEM Readiness Criteria

	Share of People who Meet Each Criteria			
	Everyone	Males	Females	Gender diff. p-value
Criterion 1: science test	0.13	0.16	0.10	0.000***
Criterion 2: math test	0.13	0.12	0.14	0.002***
Criterion 3: biology courses	0.45	0.45	0.44	0.347
Criterion 4: chemistry courses	0.24	0.23	0.26	0.001***
Criterion 5: physics course	0.35	0.36	0.33	0.002***
Criterion 6: calculus course	0.09	0.10	0.09	0.034**
Meets at least 3 criteria	0.166	0.173	0.160	0.068*
Meets at least 4 criteria	0.066	0.074	0.059	0.005*
Meets at least 5 criteria	0.022	0.029	0.015	0.000***
Avg no. of criteria met	1.39	1.41	1.36	0.039**

Note: The sample is taken from the NLSY97. 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.

To show that these criteria make sense, Table 3 shows a simple 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 17 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 about 7 percentage points. So while we cannot define a binary measure of STEM-readiness, these criteria provide a useful measure.

An ideal measure of STEM-readiness might be a predicted probability of majoring in STEM based on the student's pre-college profile. This is problematic, because using actual outcomes will conflate readiness with factors that might affect the actual choice, like discrimination and preferences, but readers might find it useful. Using the second column of Table 3, I can predict the likelihood of initially majoring in STEM for everyone in the sample. The mean for males is 8.7%

Table 3: STEM Readiness Criteria and Majoring in STEM

Dependent variable: initial major is STEM

	Full sample		College attendees	
No. of criteria met	0.070***		0.075***	
	(0.003)		(0.005)	
Criterion 1: science test		0.058***		0.043**
		(0.010)		(0.019)
Criterion 2: math test		0.111***		0.069***
		(0.011)		(0.020)
Criterion 3: biology courses		0.015**		0.044***
		(0.006)		(0.015)
Criterion 4: chemistry courses		0.039***		0.033**
		(0.007)		(0.016)
Criterion 5: physics courses		0.053***		0.074***
		(0.007)		(0.016)
Criterion 6: calculus course		0.175***		0.169***
		(0.012)		(0.021)
Constant	-0.013***	0.012**	0.068***	0.088***
	(0.005)	(0.005)	(0.013)	(0.014)
Mean of dep. var.	0.09	0.09	0.22	0.22
Observations	7,227	7,227	2,825	2,825
Adj. R-squared	0.123	0.096	0.072	0.062

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. 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.

and for females is 8.2%, with the difference significant at the 5% level. The same conclusion holds if I predict using coefficient estimates only for males or only for females.[6]

Speer (2017) found seemingly larger gaps in STEM-readiness using ASVAB test

[6] All of the STEM-readiness analysis is similar when I use continuous variables to predict majorig in STEM (e.g., the test scores themselves) rather than the six binary criteria. The binary measures make it easier to see and interpret gender differences, so I prefer to use these.

scores, but the approach used here is a better one. That paper did not use course-taking data, which show that females are ahead in some respects, and high school performance better predicts college performance than test scores do (Allensworth and Clark 2020). That paper 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 ASVAB was first introduced by the U.S. military in 1968, at which time the military was only about 2-4% female (Patten and Parker 2011), so it is likely that these tests were designed largely to measure the aptitude of males.

Based on these criteria of readiness, males are slightly more STEM-ready than females. Males are also more likely to be in the upper tail of STEM-readiness, which could be important if these are the students who not only choose STEM but are most successful in it. The gap in predicted STEM probability (0.5 percentage points), while significant, is a small fraction of the atual gap in STEM majoring.

4.2 Stage 2: College Attendance

The next step to a career in a STEM job is attending college. As detailed by Goldin, Katz, and Kuziemko (2006), women have a significant advantage over men in college attendance and graduation. To see how this affects the pipeline to STEM jobs and the gender gap in outcomes, I need to look at 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, 44% of females attend college, while only 34% 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 19% chance of attending college, which grows monotonically with the number of criteria met, except for a small drop at the top end, where the sample is small. It is very rare for a student to meet most of the criteria and not attend college. Since more STEM-ready students tend to have higher test scores across the board, this relationship is not surprising.

Table 4: College Attendance Rates by STEM Readiness

	Share of People who Attend Four-Year College			
	Everyone	Males	Females	Gender diff. p-value
Overall	0.39	0.34	0.44	0.000***
Meet 0 criteria	0.19	0.14	0.24	0.000***
Meet 1 criterion	0.32	0.25	0.38	0.000***
Meet 2 criteria	0.48	0.43	0.54	0.000***
Meet 3 criteria	0.65	0.58	0.71	0.000***
Meet 4 criteria	0.86	0.84	0.89	0.103
Meet 5 criteria	0.95	0.93	0.98	0.135
Meet 6 criteria	0.92	0.88	1.00	0.152

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.

What is striking is how the patterns differ by gender. For every level of STEM readiness, females are more likely 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 24% of such females do, and the gap is even larger for those who meet one criterion (38% vs. 25%). Among those who meet most of the criteria, the gender gaps in attendance are smaller and not significant.

These patterns imply that while there is little difference in overall STEM readiness among males and females (Stage 1), there is differential selection into college, which creates differences in STEM readiness among those who attend. Male college attendees are more positively selected than females. The overall gender gap in STEM criteria met, as seen in Table 2, is only 0.05. But among those who attend college, it is 0.31 (an average of 2.16 met criteria for males and 1.85 for females). Using the predicted STEM probability from the last section, male attendees have a predicted 14.9% probability of starting a STEM major, while female attendees have a 12.0% probability.

While the share of women in college who are STEM-ready is lower than that for men, what this means for the absolute number of STEM-ready women in college relative to that of men is unclear. This is because women are much more likely to attend college in general. I will revisit this in Section 5, when I decompose the gender gap into the contributions of each stage.

While females have a significant advantage in college attendance, its effect on the gender gap in STEM is complicated. Much of the attendance advantage is driven by the least STEM-ready students, meaning that among those who do attend, a higher share of males are STEM-ready.

4.3 Stage 3: Initial Major Choice

In the US, a student typically 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 in 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 and Speer 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.[7] Overall, 22% of attendees start with a STEM major, including 30% of males and 15% of females. This gap in major choice is much larger than the gaps we saw in STEM readiness.

The likelihood of choosing a STEM major rises with STEM readiness, from a 10% chance if one meets none of the criteria to an about 50% chance if one meets all or almost all of them. This pattern holds for both men and women, but at

[7] 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 **??**.

Table 5: Share of College Attendees Choosing STEM Major Initially

Share of Attendees Whose First Major is STEM				
	Everyone	Males	Females	Gender diff. p-value
Overall	0.22	0.30	0.15	0.000***
Meet 0 criteria	0.10	0.14	0.08	0.059*
Meet 1 criterion	0.14	0.19	0.11	0.000***
Meet 2 criteria	0.21	0.27	0.16	0.000***
Meet 3 criteria	0.23	0.32	0.15	0.000***
Meet 4 criteria	0.42	0.53	0.30	0.000***
Meet 5 criteria	0.53	0.59	0.41	0.026**
Meet 6 criteria	0.46	0.47	0.44	0.460

Note: The sample is all students who attended a four-year college and ever reported a major. The outcome is the first major ever reported being a STEM major.

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). To put this gender gap 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 do not meet any of the criteria.

While the predicted gap in the probability of majoring in STEM among those who attend college was 2.9 percentage points; the actual gap in initial STEM major choice is 14.3 percentage points. Most of this gap is driven by the decisions of the most STEM-ready students. There are clearly large differences in major choice for men and women, even conditioning on STEM readiness.

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.

There are substantial gender differences in major choice even within STEM. 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.

Another important question is where those who do *not* choose STEM go instead, particularly the women with high levels of STEM-readiness. Panel B 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 and Speer 2019), while men are more likely to drop out of college altogether (Astorne-Figari and 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 college attendees who graduate college with a STEM major. This share is much higher for male students (16% vs. 7%) and also much lower than the share of students who begin a STEM major. At every level of STEM readiness, except for the small number of people meeting all six criteria, women are less likely to get a STEM degree.

Panel B, which conditions on starting in a STEM major, tells the story of why. The samples get smaller here, but we can see that the biggest gender gaps in persistence to a STEM degree are among the least STEM-ready students. Among the most STEM-ready, women are about as likely as men to make it to graduation. But among those who are less prepared, women are far more likely to leave. So while the gap in initial major choice was largest among the most STEM-ready students, the gap in *persistence* is being driven by the least STEM-ready students.

Table 6: Share of College Attendees who Graduate with a STEM Major

Panel A: All College Attendees

	Everyone	Males	Females	Gender diff. p-value
Overall	0.12	0.16	0.07	0.000***
Meet 0 criteria	0.03	0.05	0.01	0.017**
Meet 1 criterion	0.07	0.10	0.05	0.002***
Meet 2 criteria	0.08	0.12	0.05	0.000***
Meet 3 criteria	0.14	0.19	0.10	0.004**
Meet 4 criteria	0.28	0.35	0.19	0.001***
Meet 5 criteria	0.39	0.41	0.36	0.309
Meet 6 criteria	0.33	0.27	0.44	0.197

Panel B: Conditional on First Major Being STEM

	Everyone	Males	Females	Gender diff. p-value
Overall	0.42	0.46	0.37	0.018**
Meet 0 criteria	0.14	0.22	0.06	0.078*
Meet 1 criterion	0.34	0.38	0.29	0.154
Meet 2 criteria	0.32	0.36	0.27	0.107
Meet 3 criteria	0.44	0.42	0.50	0.193
Meet 4 criteria	0.57	0.59	0.55	0.354
Meet 5 criteria	0.66	0.67	0.61	0.320
Meet 6 criteria	0.55	0.57	0.50	0.420

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.

There are two ways of not persisting to a STEM degree: switching majors or not graduating at all. To understand the pipeline and why women are persisting to a STEM degree at lower rates, we need to understand these different pathways out of STEM. Table 7 looks at how these patterns differ by gender and STEM-readiness.

While there is a lot of information to digest in this table, there are a few things that stand out. First, women who start in STEM are actually more likely to graduate college than men are, despite their lower persistence in STEM itself (74% vs. 63%). This is because women switch majors far more often than men. Second, these

Table 7: Where do Initial STEM Majors Go?

	Outcomes for Initial STEM Majors								
	Everyone			Males			Females		
	Grad in STEM	Grad in other	No grad	Grad in STEM	Grad in other	No grad	Grad in STEM	Grad in other	No grad
Overall	0.42	0.25	0.33	0.46	0.17	0.37	0.37	0.37	0.26
Meet 0 criteria	0.14	0.25	0.61	0.22	0.06	0.72	0.06	0.44	0.50
Meet 1 criterion	0.34	0.28	0.38	0.38	0.18	0.44	0.29	0.40	0.31
Meet 2 criteria	0.32	0.28	0.40	0.36	0.18	0.46	0.27	0.42	0.31
Meet 3 criteria	0.44	0.25	0.30	0.41	0.22	0.37	0.50	0.32	0.18
Meet 4 criteria	0.57	0.23	0.19	0.59	0.17	0.24	0.55	0.35	0.10
Meet 5 or 6 criteria	0.64	0.15	0.21	0.66	0.13	0.21	0.59	0.23	0.18

Note: The sample is all students who attended college and first reported a STEM major.

differences are large for all but the most STEM-ready students. Only 28% of the least-ready men graduate college at all, while 50% of these women do, and the differences are similarly large for those meeting one, two, three, or four criteria. The least STEM-ready men essentially either graduate in STEM or do not graduate at all. So while the overall difference in STEM persistence is striking, the differences in what happens to those who do not persist is also striking.

Switching majors is an important phenomenon to understand when thinking about the STEM pipeline, especially for women. Women switch majors more often than men in general (Astorne-Figari and Speer 2019), and also to leave STEM. Looking at the destination majors of these women leaving STEM may help us understand why they are leaving. Table A.2 shows this information.

Business, a very large major, is a common destination, though not among the most STEM-ready women who leave. If these are the women that are most worth targeting to retain in STEM, then they are most likely to go to fine arts and psychology.

To summarize this stage of the pipeline, conditional on starting a STEM major, women are far less likely to graduate in STEM. This is driven by large differences in persistence among the least STEM-ready students. Men with minimal STEM preparation basically either graduate in STEM or do not graduate college at all, while women are much more likely to switch to another major and graduate. Looking only at the share that persist in STEM masks a more complex story.

4.5 Stage 5: College to Job

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 and Vona 2017). They may also have bad experiences in college that lead them to leave the field (Smith and 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.[8]

Focusing on the college-to-job transition is tricky for two reasons. The first is

[8] 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.

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 Figure 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.

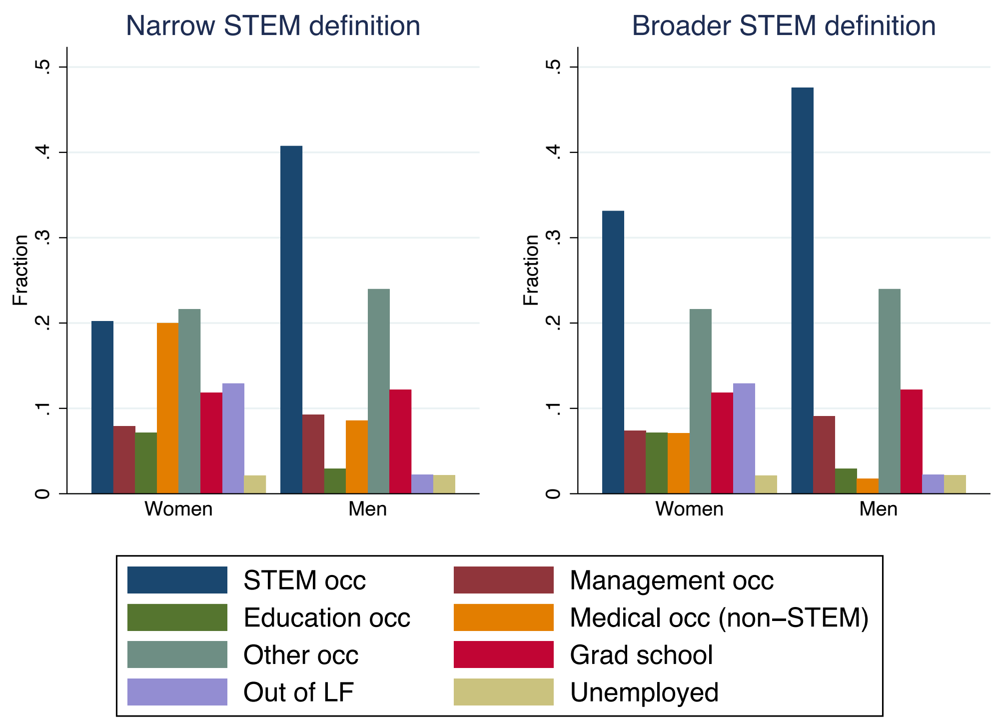
The second reason is that defining what constitutes a STEM job is not straightforward. Various definitions are used by government agencies, and job task data show no clear, robust definition of STEM occupations (Rothwell 2013). For instance, the Bureau of Labor Statistics usually does not include any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

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 social scientists and 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.

Figure 1 shows the distribution of outcomes for STEM graduates at age 30 separately for men and women. 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%). Women with STEM degrees are much more likely to be in medical jobs or out of the labor force.

When the definition of STEM is broadened, the gender gap in going into STEM occupations at age 30 is narrowed some, to 14 percentage points (47.6% vs. 33.2%). 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

Figure 1: Distribution of STEM Graduates by Gender, Age 30



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, 76% are men under the narrow definition and 70% under the broader definition. This is clearly an important stage of the STEM pipeline.

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 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.

The most common non-STEM occupations (using the broader definition of STEM) at age 30 among female STEM graduates are elementary and middle school teachers (4.0% of female STEM graduates) and miscellaneous managers (3.6%). Amazingly, the next most common is secretaries and administrative assistants at 2.0%.

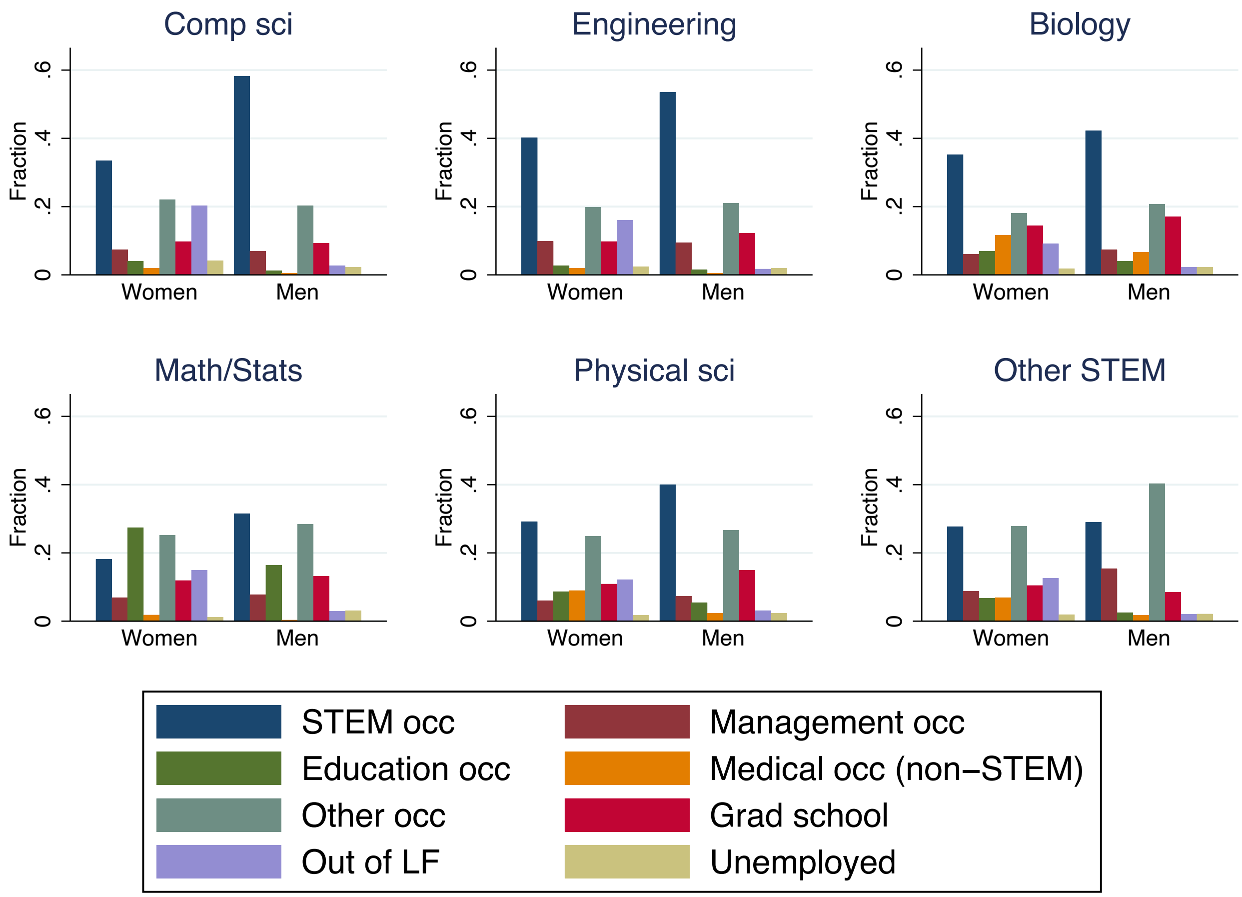
Figure 2 gives a deeper look, showing where STEM graduates are at age 30, separately by STEM major, using the broader definition of STEM jobs. From all STEM majors, men are more likely to go into a STEM job, but the gap is particularly large in computer science. Biology majors have a much smaller gender 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.

Though I cannot know the reasons for being out of the labor force with any certainty, Table A.3 looks at rates of marriage and having children at age 30 by major. Both of these are strongly correlated with being out of the labor force. 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.

While I am not able to draw any firm conclusions, these statistics show that understanding the pipeline to STEM jobs will require understanding a complex set of life *and* career decisions for women, and these decisions seem to play out differently for different types of women even within STEM.

Figure 2: Distribution of STEM Graduates by Major and Gender, Age 30



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.

Despite the data limitations, this is an important step to include. Women are known to frequently leave STEM careers when they have children (Cech and Blair-Loy 2019), leading to concern that STEM jobs are not family-friendly (Wiesgram and 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.

Figure 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 from 14.4 percentage points (47.6%-33.2% at age 30) to 12.7 percentage points (44.1%-31.4% at age 45).

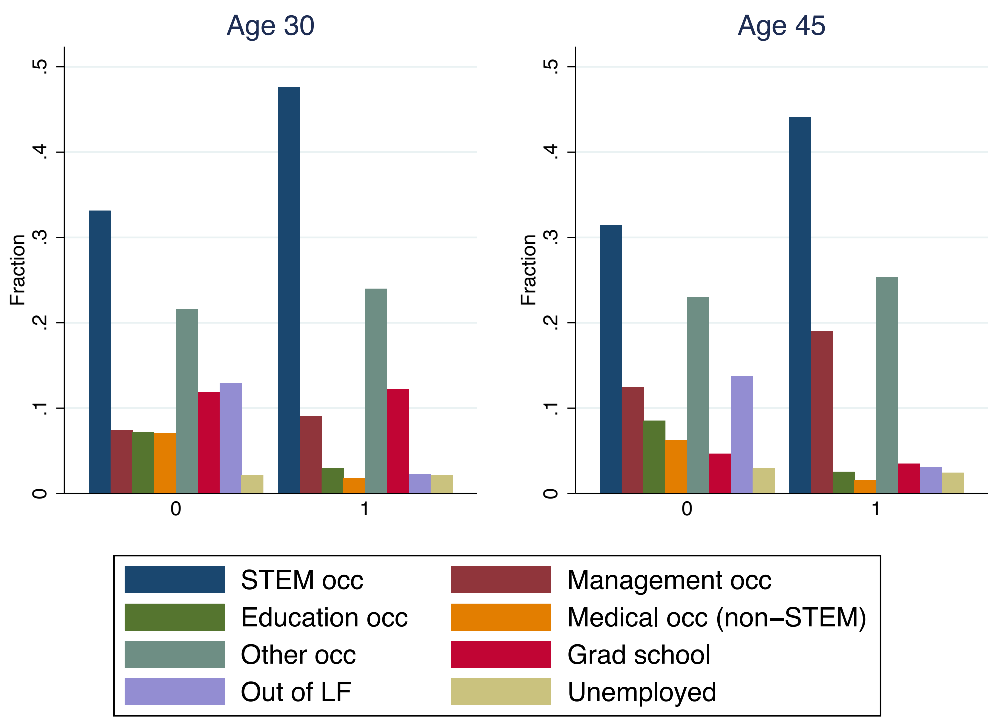
Both men and women – but especially men – are more likely to be in management positions at age 45.[9] Interestingly, women are about as likely to be out of the labor force at age 45 than age 30. The exodus of female STEM graduates from the labor force seems to occur almost entirely by age 30 and not later.

Unfortunately, the ACS 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 major caveat, however. The cohorts I am looking at in the ACS are quite different. 39% of STEM graduates in the ACS at age 30 are female; for those age 45, it is only 32%. 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.

[9]Note that STEM managers (architecture, engineering, natural sciences, etc.) are included in the STEM category, not the management category.

Figure 3: Distribution of STEM Graduates, Age 30 and 45



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.

While this seems like a straightforward exercise, 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 will have to use some type of reweighting to compare them. Second, the older and younger cohorts in the ACS are somewhat different. In this case, I can use another reweighting, and I will also do one version of my decomposition excluding the later-career outcomes and ending the pipeline at age 30. I essentially have three different samples to match up: the NLSY, the age-30 ACS, and the age-45 ACS.

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. Fourth, one of my stages is STEM-readiness, but there is no binary indicator of readiness. Because of these adjustments, the decomposition that follows should be seen as a rough, back-of-the-envelope calculation rather than a definitive breakdown of this complex process.

To start, I can define my "starting point" and "endpoint" of the decomposition. The starting point is the makeup of the NLSY sample, which is 51% male. The endpoint is the makeup of age-45 workers with a STEM degree and STEM occupation (broadly defined), which is 75% male (or 70% male for age-30). So before any adjustments, there is a raw increase of 24 percentage points to explain. The details of the following calculations can be found in Table A.4.

The first adjustment is to make the NLSY and ACS samples comparable. In the NLSY, 64.3% of STEM graduates are male; in the ACS, 61.5% of age-30 STEM graduates are male. So my first adjustment is to alter the ACS male shares at age 30 and age 45 upward to match the NLSY. I multiply the male shares in the ACS by 1.046 (64.3/61.5) so that the two surveys are comparable.

The second adjustment is to make the age-45 ACS cohort look like the age-30 ACS cohort. The age-45 cohort of STEM graduates is more male than the age-30 cohort (68.4% vs. 61.5%), so I multiply the age-45 shares by 0.899 to make them comparable to the age-30 shares. With this adjustment, the share of those with a STEM degree and STEM occupation at age 45 is 70.7%, actually slightly lower than the share at age 30.

The last big decision is how to incorporate STEM-readiness. Unlike the other steps, STEM-readiness is not a hurdle that one must clear to enter STEM, and it is not binary. The more criteria of readiness one meets, the more likely one is to enter STEM, but there are paths to STEM even for those not well-prepared. To measure the contribution of STEM-readiness, I ask: given the levels of readiness we see from male and female students in high school, what would we expect the gender gap in initial STEM majors to be?

In the NLSY, the predicted values from a probit regression of initial STEM majors on dummies for meeting each of the six criteria show that the average predicted "probability" of majoring in STEM is 0.087 for males and 0.082 for females. If, in the NLSY, this percentage of males and females chose an initial STEM major, then 52.9% of STEM majors would be male. This is the gap in STEM majoring that would be predicted by the gap in STEM-readiness.

Finally, I must do something similar for college attendance. The relevant question is not just how many men and women attend college, but about how the composition of attendees contributes to the STEM gender gap. I do the same thing here as I did for STEM-readiness, but now only for college attendees. The average predicted probability of majoring in STEM for those who attend college is 0.149 for men and 0.120 for women (but there are more women who attend). If these shares of college attendees majored in STEM, then initial STEM majors would be 50.2% male.

The results of the final decomposition are in Table 8, using the broader STEM occupational definition in the left panel. Two stages of the pipeline are dominant in explaining the final gender gap. At initial major choice, the male share is 61.2%, compared with the 50.2% predicted by attendance and readiness. This stage alone accounts for 57% of the total gender gap.

The other stage that stands out is the age-30 occupation, representing the transition from college to career. Among STEM graduates, men are much more likely to choose a STEM job, even when this is broadly defined. This stage accounts for 44% of the total gender gap. Together, initial major choice and age-30 career choice explain 101% of the gender gap in STEM outcomes!

STEM-readiness accounts for only 8% of the gender gap in STEM. Persistence from initial STEM major to graduation in STEM matters a bit more (16%). Women's higher rates of college attendance mean that this stage actually narrows the gender gap in STEM, so it accounts for -14%. Essentially, women's higher college attendance and lower persistence in STEM majors cancel each other out. Figure A.1 shows the results of the decomposition visually.

Table 8: 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	70.74	**-10.7%**			75.66	**-17.1%**
STEM degree + STEM occ age 30	72.81	**44.1%**	72.81	**39.8%**	79.79	**63.9%**
STEM degree	64.31	**16.1%**	64.31	**14.5%**	64.31	**12.8%**
STEM initial major	61.21	**57.3%**	61.21	**51.7%**	61.21	**45.6%**
Predicted STEM major among attendees	50.16	**-14.3%**	50.16	**-12.9%**	50.16	**-11.4%**
Predicted STEM major among everyone (STEM-readiness)	52.92	**7.6%**	52.92	**6.9%**	52.92	**6.1%**
Sample	51.45		51.45		51.45	

Note: See Table A.4 and the text for details of adjustments made to reach these calculations. The narrow definition of STEM jobs is taken from the Bureau of Labor Statistics. The broader definition includes the BLS list, medical practicing/diagnosing jobs, and social scientists.

In a recent paper, Card and Payne (2021) (CP) find that 81-85% of the gender gap in initial STEM major choice in Canada is due to gaps in STEM-readiness. Here, I find that STEM-readiness cannot explain much of the gap in major choice. But the findings in my paper and theirs are not as different as they seem at first. In Canada, choices in high school are high-stakes in determining a student's future path, and CP find that this stage is the most important. In the U.S., one could argue that that first pivotal stage – where choices become more binding – is not high school, but the initial major choice. While major switching is common, almost nobody who starts in a non-STEM major switches to STEM. Thus, both this paper and CP find that the first high-stakes stage of the STEM pipeiine is the most important one. What that stage is may differ across places.

The table also shows two alternative decompositions. The first uses age 30 as the final outcome rather than age 45, due to the differences in cohort composition. This gives a similar picture as the first decomposition. Initial major choice and the college-to-career transition are the most important stages again.

The second alternative is to use the narrower definition of STEM occupations, as defined by the BLS. This widens the gender gap in occupation choice and thus increases the importance of the labor market choices. The college-to-career step is now the most important, accounting for 64% of the gap, with initial major choice (46%) next up. Overall, the conclusion is the same: the initial major choice in college and the early-career occupation choice are the stages that account for the bulk of the overall leaky STEM pipeline.

Finally, there are also alternative definitions of STEM major that could be used. Table A.5 looks at how the decomposition changes when I perform all of my analysis with the National Science Foundation definition of STEM majors (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 conclusion does not: the initial major choice and college-to-career transition are the dominant factors in each case, while STEM-readiness is a smaller factor.[10]

These decompositions should be treated as back-of-the-envelope calculations. The numbers themselves are not definitive. But it is clear that major choice and early-career job choice account for the bulk of the gender gap in STEM careers in the United States. The gender gap in STEM-readiness is real, but accounts for significantly less of the overall STEM gap.

6 Discussion

The path from high school to a STEM career is complex, particularly in the United States, where there are many possible pathways into and out of STEM. To under-

[10]Note that with the broad NSF major definition there is essentially no gender gap to explain, so this exercise is trivial. Note also that I am using the broad "STEMM" occupation definition throughout this table.

stand the gender gap in STEM jobs, it is perhaps the two most consequential steps along the way – the initial major choice in college and the choice of early-career job – that are the most important. Men are far more likely to choose STEM at both of these stages, which collectively account for virtually all of the gender gap in STEM careers. Women also fall behind at other stages, including STEM-readiness in high school and persistence to a STEM degree, though these account for smaller fractions of the total gap.

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 prepared and qualified women to other fields.

Taken together, my results do not support explanations for the gender gap in STEM that rest heavily on innate ability or level of preparation. As noted earlier, however, it could be that I am underestimating the importance of early-life factors if there are traits developed early in life that only show up in later choices, like the choice of major. Kahn and Ginther (2017) suggest that this is true, as things like competitiveness, risk-aversion, and interests that contribute to the eventual gender gap in STEM are developed early in life. These traits may arise from different sources, including discrimination against girls by parents and teachers. My results show clear evidence that women are not less able or prepared to enter STEM, but this does not mean that other pre-college factors are not important. It simply means that looking for *academic* gaps between men and women before college is searching in the wrong place.

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A Appendix Tables and Figures

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%) Engineering (5.6%) Biology (5.4%)	Computer sci (10.5%) Engineering (10.2%) Biology (3.7%)	Biology (6.7%) Computer sci (2.3%) Engineering (1.9%)
Meets 0-1 criteria	Computer sci (5.0%) Biology (3.7%) Engineering (2.1%)	Computer sci (9.5%) Engineering (4.0%) Biology (1.9%)	Biology (4.9%) Computer sci (1.9%) Physical sci (0.9%)
Meets 2-3 criteria	Computer sci (6.1%) Engineering (5.2%) Biology (4.8%)	Computer sci (10.3%) Engineering (9.6%) Biology (3.2%)	Biology (6.1%) Computer sci (2.7%) Physical sci (1.8%)
Meets 4-6 criteria	Engineering (16.4%) Biology (11.7%) Computer sci (8.2%)	Engineering (23.9%) Computer sci (13.0%) Biology (8.4%)	Biology (16.0%) Engineering (6.9%) Pre-med (3.7%)

Panel B: Most Common Non-STEM Initial Major Choices (% of All Students)

	Everyone	Males	Females
Overall	Business (19.3%) Education (9.5%) Psychology (5.9%)	Business (22.9%) Education (6.0%) Fine arts/communications (5.6%)	Business (16.4%) Education (12.3%) Nursing (8.1%)
Meets 0-1 criteria	Business (20.8%) Education (12.2%) Fine arts/nursing (6.8%)	Business (27.5%) Education (7.6%) Fine arts (6.6%)	Business (16.3%) Education (15.3%) Nursing (10.3%)
Meets 2-3 criteria	Business (20.4%) Education (9.0%) Communcations (6.6%)	Business (23.6%) Education (6.0%) Communications (6.0%)	Business (17.7%) Education (11.5%) Psychology (8.2%)
Meets 4-6 criteria	Business (11.9%) Psychology (5.6%) Fine arts (4.5%)	Business (12.1%) Communications (4.2%) Fine arts (3.8%)	Business (11.7%) Psychology (9.0%) 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 are scoring one standard deviation or higher on the science and math ASVAB tests, taking at least two biology courses in high school, taking at least two chemistry courses, taking a physics course, and taking a 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	20.3	16.0	9.1	15.0	12.2	12.6	11.2
Percent married	67.9	69.2	59.0	60.9	56.7	62.7	60.5
Percent with children	45.3	39.6	33.8	41.4	37.3	39.3	43.2
Average no. of children	0.68	0.57	0.52	0.69	0.58	0.63	
Avg. no. of children, if positive	1.50	1.44	1.54	1.67	1.57	1.61	

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

Table A.4: Decomposing the STEM Pipeline: Details of Calculation

Stage	Raw male share	Adjustment 1: make NLSY STEM grads like ACS grads	Adjustment 2: make age-45 ACS like age-30 ACS	Adjustment 3: predict initial STEM majors based on STEM readiness	Adjustment 4: predict initial STEM majors among attendees based on readiness	Total % explained
STEM degree + STEM occ age 45	75.22	78.68	70.74	70.74	70.74	-10.7%
STEM degree + STEM occ age 30	69.61	72.81	72.81	72.81	72.81	44.1%
STEM degree	64.31	64.31	64.31	64.31	64.31	16.1%
STEM initial major	61.21	61.21	61.21	61.21	61.21	57.3%
Predicted STEM major among attendees					50.16	-14.3%
Predicted STEM major among everyone (STEM readiness)				52.92	52.92	7.6%
Sample	51.45	51.45	51.45	51.45	51.45	

Note: STEM occupations here include the BLS list, medical practicing/diagnosing jobs, and social scientists. Each column shows an adjustment made to the shares to make samples comparable. The STEM occupation stages come from the ACS, and the others come from the NLSY97.

Figure A.1: Decomposition of the STEM Gender Gap

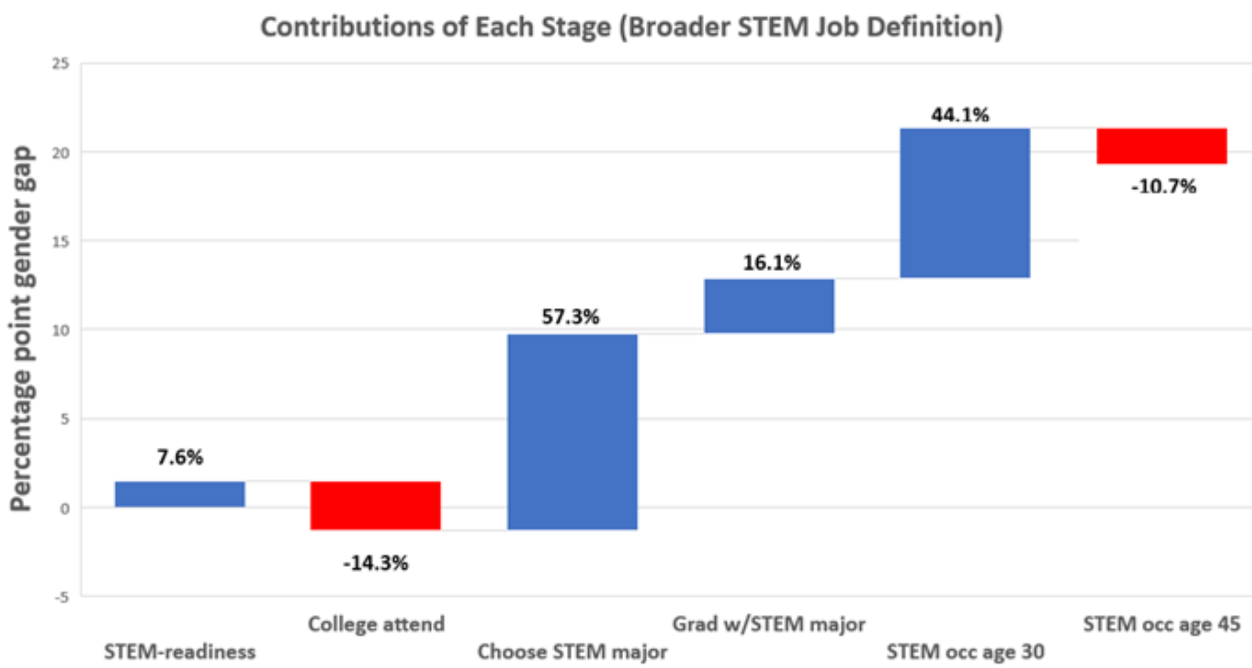

Table A.5: Decomposing the STEM Pipeline: Alternative STEM Major Definitions

	Oucome: STEM Degree and STEM Occupation (Broad), Age 45 Main Major Definition (Same as Table 8)		NSF Major Definition (Much Broader)		Math-Intensive STEM Majors (Narrower)	
	% male	**Share explained**	% male	**Share explained**	% male	**Share explained**
STEM degree + STEM occ age 45	70.74	**-10.7%**	50.60	**-27.3%**	80.13	**-5.7%**
STEM degree + STEM occ age 30	72.81	**44.1%**	61.83	**167.1%**	81.77	**26.8%**
STEM degree	64.31	**16.1%**	48.21	**-34.2%**	74.10	**-1.4%**
STEM initial major	61.21	**57.3%**	51.00	**56.0%**	74.49	**90.8%**
Predicted STEM major among attendees	50.16	**-14.3%**	46.44	**-74.0%**	48.46	**-17.9%**
Predicted STEM major among everyone (STEM readiness)	52.92	**7.6%**	52.47	**12.5%**	53.61	**7.5%**
Sample	51.45		51.45		51.45	

Note: See Table A.4 and the text for details of adjustments made to reach these calculations. The first two columns are copied from Table 8 and use the "broad" definition of STEM occupations from the paper. The middle columns use the NSF definition of STEM major, which includes all social sciences. The last two columns only use "math-intensive" STEM majors, which include physical sciences, mathematics, computer science, engineering, and economics.

Figure A.2: Distribution of STEM Graduates by Gender, Age 24