# Estimating Excess Female Attrition From STEM Occupations

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Senior Essay

April 21, 2021

## Abstract

The phenomenon of female attrition from science, technology, engineering, and mathematics (STEM) is often referred to as a "leaky pipeline." In my senior essay, I explore attrition rates at two key junctures in this pipeline: before one's first graduate degree and during one's career. I first consider individuals whose undergraduate degrees are in STEM but whose first graduate degrees are in non-STEM fields, and I show how men's and women's predicted attrition probabilities vary by field and birth cohort. While men in the early birth cohorts are more likely to receive first graduate degrees in non-STEM than women, this trend steadily reverses itself over successive birth cohorts. By the 1976-1981 birth cohort, women are more likely than men to leave STEM and pursue non-STEM graduate degrees regardless of undergraduate field. When considering exits from STEM during one's career, I estimate the size of women's excess exits from different STEM disciplines relative to non-STEM fields and identify key reasons for these exits in each field. I find that disaggregating science into mathematics, life sciences, and physical sciences; and engineering into computer science and other engineering fields reveals patterns in attrition that are otherwise masked. In the life sciences, the gender gap in exits is substantially smaller than the gap in exits from non-STEM. I also find evidence of excess exits in computer science and other engineering fields. In computer science and engineering, although exits are driven primarily by pay and promotion, these are larger factors in computer science than in other engineering fields.

*I am incredibly grateful to Professor Altonji for his guidance and support, without which I could never hope to become an economist. I would also like to thank my parents for their unending love and belief in me; Disa Hynsjo for her support, both technical and emotional; Ling Zhong for pushing me to accomplish more than I ever thought I could; and Ioann, Arielle, Anastasia, and Vod for stopping me from becoming a data point myself while writing this essay. This essay uses restricted-use data under a license with the National Center for Science and Engineering Statistics, National Science Foundation. All statistics in the paper that are based on that data went through disclosure review. All errors are my own.

# 1 Introduction

Female attrition from science, technology, engineering, and mathematics (STEM) is often conceptualized as a "leaky pipeline," where individuals must follow a relatively restricted path to professional success, and individuals leak out at certain "joints," such as graduating from college, obtaining an advanced degree, and gaining tenure (Etzkowitz et al., 2000). Unlike in many non-STEM careers, the STEM pathway is nearly impossible to enter without previous levels of preparation, and the requirements for certain achievements and positions become more stringent the more advanced a scientist is in her career. These "leaks" from the pipeline result in very few women "exiting" at the other end and achieving the highest professional honors and success in their fields. Even an individual joint, such as graduate degree attainment, can be considered its own pipeline, where individuals have to reach milestones, including passing qualifying exams, negotiating a thesis topic, and, ultimately, completing a dissertation (Etzkowitz et al., 2000).

I consider two "joints" in the pipeline: the transition between college and the first graduate degree, and during one's career. Using data from the National Survey of College Graduates (NSCG), I estimate attrition probabilities for men and women in different STEM fields.

First, I consider individuals who obtain their undergraduate degrees in a STEM field but whose first graduate degrees are in non-STEM fields. I compute predicted probabilities of leaving STEM before the first graduate degree for men and women by field and birth cohort and analyze how these probabilities change over successive cohorts. I find that men in the early birth cohorts are more likely than women to pursue a graduate degree in a non-STEM field after completing an undergraduate STEM major. However, over time, the gaps in each field either close or reverse themselves, indicating that women with undergraduate STEM degrees who pursue graduate education are more likely than men to transition to a non-STEM field.

I then consider individuals whose highest degrees are in STEM but who exit to occupations in an unrelated field or to non-work. Using a multivariate logistic regression, I compute a difference-in-differences estimate comparing the gender gap in attrition in each STEM field with the gender gap in a non-STEM comparison group for three different measures of attrition: attrition either to an unrelated field or to non-work, attrition to an unrelated field only, and attrition to non-work only. I also compute these estimates for exiting to an unrelated field for a particular reason to determine which aspects of different fields drive women to exit. I find that the gender gap in attrition probabilities in the life sciences is substantially smaller than the gap in non-STEM fields, while the gaps in attrition probabilities for the other sciences are small, positive, and statistically insignificant. I find evidence of female excess exits from engineering, both when considered as one aggregated category and when disaggregated into computer science and other engineering majors. In addition, exits from engineering mainly due to pay and promotion are driven by exits from computer science rather than from other engineering fields. This pattern may be due to the levels of female representation in computer science compared to other engineering fields. Since the share of women in computer science is larger than that in engineering, women in computer science workplaces may feel more comfortable advocating for higher pay and have more outside options than women working in other engineering disciplines. Future research on the relationship between pay levels across fields and rates of exits due to pay dissatisfaction among men and women would help determine why this pattern occurs.

To my knowledge, this is the first study to consider the rates of attrition before the first graduate degree by gender and field. Most studies of attrition from graduate study focus on completion rates among women in doctoral programs rather than on exits from STEM before they start the first graduate degree. Lott et al. (2009) use a discrete-time event history analysis to model attrition for doctoral students in 56 STEM departments at one research institution over 20 years. They find that the odds of attrition are greater for women than men and for individuals in the hard-applied sciences (e.g. engineering, computer science, and certain agricultural sciences) rather than the hard-pure sciences (e.g. chemistry, biology, physics).

A report from the American Association of University Women (Hill et al., 2010) finds a similar pattern in the percentages of women receiving doctorates in different STEM fields. In 2006, women earned 47.9% of doctorates in the life sciences and roughly a third of doctorates in chemistry and in earth, atmospheric, and ocean sciences, compared to only 21.3% and 20.2% of doctorates in computer science and engineering, respectively. These rates represent significant progress compared to 1966, when women earned 12% of doctorates in the life sciences, 3% of doctorates in the earth, atmospheric, and ocean sciences, virtually none of the doctorates in computer science, and 0.3% of doctorates in engineering.

The literature on women's attrition from STEM occupations varies in terms of both the reference category used to determine whether women display "excessive" attrition rates and the definition of attrition used. However, as in this study, most consider attrition in terms of self-reported job/major congruence, differentiate between attrition to an unrelated field and attrition to non-work, and include analysis of the self-reported reasons for attrition.

Preston (1994) analyzes exit rates from science and engineering between 1982 and 1989 using data from the Survey of Natural Sciences and Engineers (SSE). She defines attrition as respondents not working in a position related to the natural sciences, social sciences, or engineering. She finds that men are more likely to leave science and engineering because of a promotion and are as likely as women to be unemployed. She also finds that women are more likely to leave the labor force for both family and non-family reasons (by 3.5 and 2.2 percentage points, respectively) and to leave science and engineering for reasons other than promotion (by 4.2 percentage points). While the gender gap in labor-force exits due to family reasons is responsible for 38% of the gender gap in STEM attrition, gender differences in labor-force exits for non-family reasons and exits to non-STEM occupations account for most of the gap. Preston (2004) extends her 1994 study by incorporating the work histories of 1,688 individuals between 1965 and 1990. Interviews reveal that many of the men, both who stayed and left the sciences, are concerned with income opportunity, while very few women even acknowledge income. Only one of the women leaves science for income reasons, and the concerns of women who even mention income are in the context of a specific job rather than the profession as a whole.

Like Preston, Hunt (2016) considers female attrition from STEM occupations in terms of a lack of self-reported congruence between one's career and a given field. However, Preston considers whether individuals are employed in the natural and social sciences, whereas Hunt is concerned with whether individuals are employed in fields related to their highest degree. Hunt implements a difference-in-differences approach on the 2003 and 2010 waves of the NSCG using a linear probability model in order to determine the size of female "excess exits" from science and engineering. The term "excess exits" refers to the difference between the gender gap in attrition in science or engineering and the gender gap in attrition in non-

STEM fields. Hunt (2016) considers three types of attrition, which I also examine in this study: to an unrelated field or to non-work, to an unrelated field only, and to non-work only. Unlike Preston, Hunt compares the gap in exit rates between men and women in science and engineering with that in non-STEM fields to characterize women's "excess exits" from a given STEM field. Hunt also considers whether individuals leave STEM for one of seven reasons: career interest change, family, location, lack of a suitable job, pay or promotion, working conditions, and other rather than just family or promotion. Hunt finds no evidence of excess exits from the sciences and finds that excess exits from engineering are driven by dissatisfaction with pay and promotion. When she compares the rate of female excess exits from engineering to the rate from economics and finance, she finds no evidence of excess exits from engineering. She also finds that women who cite pay and promotions as reasons for working in a field unrelated to their highest degree account for 51% of the total conditional excess exits of women from engineering, which diverges from Preston's finding that very few women leave STEM for pay reasons.

Glass et al. (2013) compare women's experiences in STEM with those of women in "professional" non-STEM occupations. The authors consider two types of exits: exits to a non-STEM employer and exits to non-work. However, the Glass et al. study diverges from Hunt (2016) in that it directly compares women's attrition levels across fields rather than the variation in the gender gap in retention across fields. The authors make a point of underscoring the importance of considering the level of women's attrition irrespective of whether men face a similarly high attrition rate. They argue that in Hunt's analysis, women could face a much higher attrition rate in a particular STEM field than their non-STEM counterparts, but if men also face high attrition rates in the STEM field, the gaps could ultimately be the same size and no excess exits would be detected. Using a multinomial logistic model, the authors find that women in STEM are much less likely to persist than their non-STEM counterparts, and this is driven by exits to an unrelated field rather than by exits from the labor force. The authors also find that marriage and children are more closely related to attrition from STEM occupations than they are from non-STEM occupations, which they take to suggest that climate factors specific to STEM make it difficult to combine professional and family life.

While this literature provides many insights into the sources of women's attrition from STEM, the fact that many of these studies use an aggregated STEM category or disaggregate only into science and engineering makes it difficult to determine the workplace-specific factors that prevent women from persisting in STEM careers. In light of this, I disaggregate Hunt's "science" category into mathematics, life sciences, and physical sciences and disaggregate Hunt's "engineering" category into computer science and other engineering majors to determine whether gaps in certain fields are obscured when aggregated into one broad "science" category. The laboratory work environment of a biologist is very different from the industrial environment of many engineers and may pose different constraints on women's ability to form families, seek promotions, or experience job satisfaction. Moreover, the life sciences in particular have already achieved gender parity in terms of share of degree recipients; as of 2011, women received 58.1% of bachelor's degrees and 52% of PhDs in the life sciences (NSF; Ceci & Williams, 2011). This means that workplaces in the life sciences are more likely to have a "critical mass" of women (over 15-20%), so these women may face a lower attrition rate because they have sufficient support to redress grievances and advocate for better working conditions (Etzkowitz et al., 2000; Hewlett et al., 2008). This means that considering "science" as one broad category, rather than distinguishing between mathematics, computer science, life sciences, and physical sciences, could result in excess exits from one field being obscured by women's lower relative attrition rate in the life sciences.

I also utilize a logistic model to estimate predicted exit probabilities and characterize the degree of women's excess exits from STEM occupations while also performing Hunt's original analysis by using a linear probability model on both aggregated and disaggregated STEM categories and by performing a logit on her original aggregated categories.

The remainder of the paper proceeds as follows. Section 2 describes the data and measures of attrition. Section 3 discusses trends in attrition before the first graduate degree. Section 4 discusses my approach for estimating excess exits from STEM occupations as well as my results. Section 5 discusses the implications of these results and concludes.

## 2 Data and Descriptive Statistics

I use the 2003 and 2010 waves of the NSCG, a repeated cross-sectional survey of America's college graduates that focuses on the science and engineering workforce. The 2003 NSCG sample was selected from respondents to the 2000 Decennial Census long form. After the Census Bureau discontinued the use of the long form in 2010, the NSCG turned to the 2009 American Community Survey as an alternative frame, as the short form Census does not collect data on the variables used to determine eligibility for the NSCG sample.

In my analysis, I use two different samples: the "Graduate" sample, which I use to measure attrition probabilities before the first graduate degree, and the "Occupation" sample, which I use to measure attrition probabilities from STEM occupations.

The graduate sample is restricted to individuals who obtain graduate degrees after receiving a STEM undergraduate degree. The sample consists of 22,369 individuals, 15,710 of whom are male and 6,659 of whom are female. As my analysis relies on programs that largely exclude individuals with doctorates from the sample, individuals in this sample all have master's or professional degrees as their first graduate degree. I do not require individuals to receive their graduate degree in the same STEM field as their undergraduate degree. I only consider the population receiving their graduate degrees before age 35 so that individuals in each birth cohort are allowed the same amount of time to receive their first graduate degree. The graduate sample also includes the 1993 wave of the NSCG, which sampled from respondents to the 1990 Decennial Census long form.

While Hunt (2016) excludes individuals age 65 and older, I exclude those who are 60 and older from the occupation sample. I also exclude all remaining individuals holding doctorates as their highest degree (Hunt includes these individuals) and individuals working part-time because they are students. In my analysis of occupations, I use two subsamples. The first, which only includes workers, is used to analyze the probability of working in one's major field of study and includes 103,140 individuals. The second excludes individuals who are not working because they are students and includes 115,752 observations; this subsample is used to analyze both the probability of not working and the probability of either not working at all or not working in one's major field of study.

When analyzing exits from STEM occupations, I also consider two different ways of disaggregating STEM fields of study: Hunt's original categorization of "science" and "engineering," where mathematics is included in science and computer science is included in engineering, and what I refer to as a "disaggregated" version, where mathematics, computer science, life sciences, physical sciences, and engineering are all considered separately.

The NSCG has several features that make it useful for analyzing attrition from STEM occupations. First, the survey collects information on respondents' self-reported job/major congruence, asking, "To what extent was your work on your principal job related to your highest degree?" Respondents can answer "Closely related," "Somewhat related," or "Not related." If the respondents select "Not related," they are then asked, "Did these factors influence your decision to work in an area outside the field of your highest degree?" and have the option to choose as many as are applicable from "Pay, promotion opportunities," "Working conditions (e.g. hours, equipment, working environment)," "Job location," "Change in career or professional interests," "Family-related reasons (e.g. children, spouse's job moved)," "Job in highest degree field not available," and "Some other reason." Respondents are then asked to identify the first and second most important reasons for working in an area outside the field of their highest degree from those they selected in the previous question. Like Hunt, I define an individual as having left a field if they report that their principal job was "Not related" to their highest degree. An individual has exited to non-work if they report either being unemployed or not in the labor force.

The NSCG also asks individuals to describe the extent to which they value different job characteristics, including salary, benefits, job security, job location, opportunities for advancement, intellectual challenge, level of responsibility, degree of independence, and contribution to society. Respondents can choose from "Very important," "Somewhat important," "Somewhat unimportant," and "Not important at all."

Unweighted counts of individuals and workers in each field are displayed in Tables A1 and A2 in the appendix. Note that since the NSCG oversamples individuals with STEM degrees, these counts are not representative. Most of my analysis is weighted using cross-section weights.

## 3 Trends in Attrition Before Graduate School

I consider the relative attrition rates of men and women from STEM by field of study over six six-year birth cohorts[1] using data from the 1993, 2003, and 2010 waves of the NSCG. An individual is considered to leave STEM before the first graduate degree if they receive their undergraduate degree in either mathematics, computer science, life sciences, physical sciences, or engineering but receive their first graduate degree in a non-STEM field. Note that the sample in this section only includes individuals who receive graduate degrees.

In Table 1, I show the weighted shares of men and women who receive STEM undergraduate degrees and choose to pursue various non-STEM graduate degrees. The most popular field for both men and women is health, which despite not being classified as a STEM field by the National Science Foundation requires the application of content from life sciences and physical sciences. Pursuing graduate study in the health field may allow individuals to accumulate expertise by building on the content of their undergraduate degrees. The other fields, however, do not obviously build on the content of undergraduate STEM degrees or necessarily lead into STEM occupations.

The occupations of individuals who "leave" STEM before the first graduate degree are displayed in Table 2. Notably, some of these professions are closely related to certain STEM fields, namely computer software developers, computer systems analysts/scientists, electrical engineers, not-elsewhere-classified engineers, and mechanical engineers. Pursuing graduate

[1] 1946-1951, 1952-1957, 1958-1963, 1964-1969, 1970-1975, and 1976-1981

Table 1: Graduate Fields of Individuals Who Receive Undergraduate Degrees in STEM and Graduate Degrees in Non-STEM (Weighted Shares by Gender)

| Graduate Field | Male | Female | Total |
|---|---|---|---|
| Art and Humanities Fields | 0.84 | 0.89 | 0.86 |
| Economics | 0.55 | 0.39 | 0.50 |
| Education, except science and math teacher education | 4.50 | 8.66 | 5.84 |
| Health | 47.02 | 48.66 | 47.55 |
| Management and administration fields | 30.46 | 19.30 | 26.86 |
| Other Non-S&E fields | 7.06 | 7.70 | 7.27 |
| Other S&E related fields | 0.79 | 1.61 | 1.06 |
| Other social sciences (including sociology/anthropology) | 0.26 | 0.82 | 0.45 |
| Political and related sciences | 0.53 | 0.19 | 0.42 |
| Psychology | 0.47 | 1.80 | 0.90 |
| Sales and marketing fields | 2.67 | 2.60 | 2.65 |
| Science and mathematics teacher education | 1.64 | 4.99 | 2.72 |
| Social service and related fields | 1.55 | 1.26 | 1.46 |
| Technology and technical fields | 1.63 | 1.14 | 1.48 |
| | 100 | 100 | 100 |

*Note:* Shares weighted with cross-section weights. The sample consists of 6,145 men and 3,165 women, for a total of 9,310 observations. "S & E" refers to science and engineering.

Table 2: Shares of Men and Women Who Leave STEM
Before the First Graduate Degree in Various Occupations

| Occupation | Male | Female | Total |
|---|---|---|---|
| Accountants, auditors, and other financial specialists | 3.24 | 3.50 | 3.32 |
| Computer software developers | 1.96 | 1.10 | 1.70 |
| Computer systems analysts and computer scientists | 2.36 | 1.94 | 2.24 |
| Diagnosing/treating practitioners | 41.79 | 35.69 | 39.94 |
| Electrical engineer | 1.15 | 0.20 | 0.86 |
| Lawyers, judges | 4.85 | 3.81 | 4.53 |
| Mechanical engineers | 1.20 | 0.30 | 0.93 |
| Not-elsewhere-classified engineers | 1.34 | 0.50 | 1.08 |
| Operations and systems researchers | 1.66 | 1.34 | 1.56 |
| Other management related occupations | 3.52 | 3.42 | 3.49 |
| Registered nurses, pharmacists, dieticians | 1.22 | 6.84 | 2.92 |
| Other salespersons | 3.21 | 2.29 | 2.93 |
| Secondary school teachers | 3.52 | 8.91 | 5.15 |
| Subject instructors (HS/college) | 2.68 | 2.99 | 2.78 |
| Top-level managers, executives, administrators | 10.37 | 5.24 | 8.82 |
| Other | 15.93 | 21.93 | 17.75 |
| | 100 | 100 | 100 |

*Note:* Sample includes individuals who receive STEM undergraduate degrees who receive non-STEM graduate degrees and consists of 6,145 men and 3,165 women, for a total of 9,310 observations. Shares weighted with cross-section weights. "HS" refers to high school.

study outside of STEM does not necessarily preclude working in a STEM occupation. Moreover, the most popular profession for both men and women, diagnosing/treating practitioners, applies knowledge and skills from STEM and may be considered sufficiently congruent to STEM fields from a policy perspective. However, the share of women in these STEM or STEM-adjacent professions is lower than for men. For example, 0.2% of women are employed as electrical engineers, compared to 1.15% of men. Similarly, 0.3% of women are mechanical engineers, compared to 1.2% of men. Moreover, while the second most popular occupation among men is top-level management (10.37%), the second most popular occupation among women is secondary school teacher (8.91%). Note that secondary school teachers include individuals who teach STEM or non-STEM subjects, so it is unclear to what extent individuals apply the STEM education they obtained as undergraduates in their careers. However, for the purposes of determining the extent to which individuals are employed in roles that actively advance STEM fields, I do not consider secondary school teachers to be a STEM occupation, even if those individuals teach STEM subjects.

The above results suggest that while receiving a non-STEM graduate degree does not necessarily mean that an individual leaves STEM for good, the majority of individuals who transition out of STEM before graduate study do not pursue STEM careers. Moreover, there is a differential pattern between men and women, where men are more concentrated in STEM occupations than are women, and men are more likely to pursue high-paying non-STEM careers.

Predicted attrition probabilities are calculated by gender, field, and cohort after running the following logistic probability model:

$$ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1\gamma_t + \beta_2\gamma_t \text{ x } female_i + \beta_3 female_i + \beta_4 birthcohort_i$$

$$+ \beta_5 birthcohort_i \text{ x } female_i + \beta_6 undergrad_i + \beta_7 undergrad_i \text{ x } female_i$$

$$P = P(Grad\ Exit_i = 1)$$

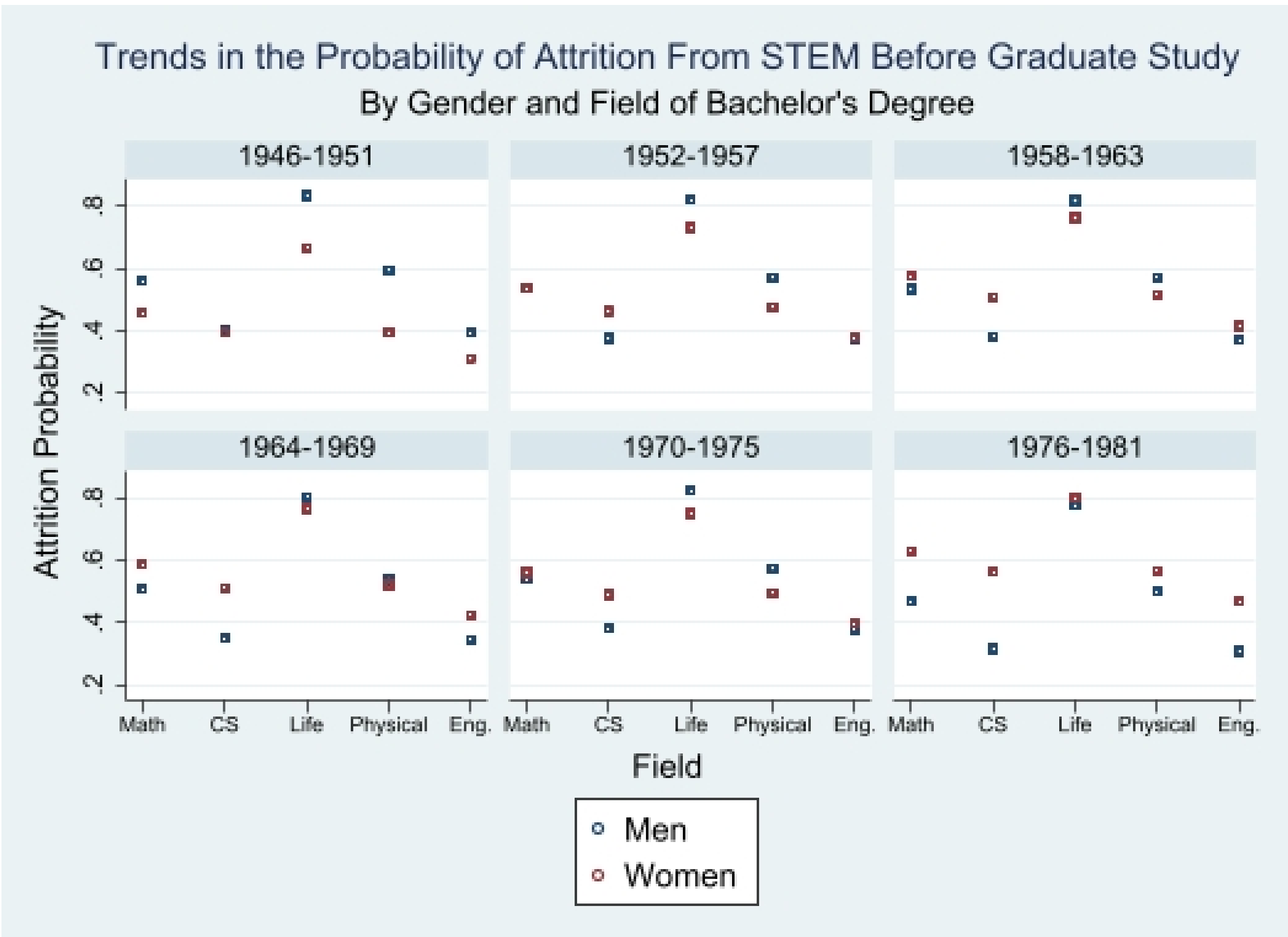
where $Grad\ Exit_i$ is an indicator variable for having received a graduate degree in a non-STEM field after receiving a STEM undergraduate degree, $\gamma_t$ is an indicator for year of observation, $female_i$ is an indicator for being female, and $birthcohort_i$ is an individual's six-year birth cohort. $undergrad_i$ is an individual's undergraduate field of study and is restricted to mathematics, computer science, life sciences, physical sciences, and engineering.

The probabilities are then averaged over different years of observation to produce one predicted probability for men and one for women in each field and birth cohort. The averaged attrition probabilities for men and women in each field are plotted by birth cohort and year in Figure 1 and are displayed in Table A3.

Notably, for the 1946-1951 birth cohort, men have a higher probability of leaving the field of their bachelor's degree before graduate school than do women (except in computer science, where they are roughly equal). However, by the 1976-1981 cohort, women's attrition probabilities are either roughly equal to or greater than the men's probabilities.

The life sciences have the highest probability of attrition before graduate school for both men and women, with the male probability consistently around 80% and the female probability greater than 66% for each cohort. Although the male attrition probability remains consistently high, the female probability increases with each successive birth cohort (with the exception of the 1970-1975 cohort) and is approximately as the same as the male pre-

Figure 1: Predicted Attrition Probabilities for STEM Undergraduates Before the First Advanced Degree, by Gender and Birth Cohort




*Note:* Mean predicted probabilities of receiving an undergraduate degree in a given STEM field and receiving a non-STEM first graduate degree are calculated by birth cohort and gender using a weighted logit. The sample consists of 22,369 individuals. Weighted with cross-section weights.

dicted probability for the 1976-1981 cohort (77.6% for men, 79.9% for women). The physical sciences have a similar pattern; the predicted attrition probabilities for men and women in the 1946-1951 birth cohort are 59.3% and 39.5%, respectively. The male probability remains at roughly 60% for each birth cohort until 1976-1981, when it drops to 49.9%. The female attrition probability grows or holds steady between cohorts (with the exception of the 1970-1975 cohort, when it drops from 52.0% to 49.5%) until it exceeds the male probability in the last cohort (at 56.7%).

In the 1946-1951 birth cohort, mathematics, computer science, and engineering all have higher male attrition probabilities than female attrition probabilities. By the 1952-1957 cohort, however, computer science has higher female attrition probabilities than male probabilities, and female attrition probabilities in mathematics and engineering are roughly similar to the male probabilities (with a gap of less than 1 percentage point). The gender gaps in attrition continue to grow over successive cohorts, growing to 16 percentage points in mathematics and engineering, and 24.9 percentage points in computer science.

# 4 Attrition From STEM Occupations

In the following section, I estimate female excess exits from STEM careers (both to unrelated fields and to non-work) and examine the key reasons behind female attrition from each field. I start by providing some summary tables to give an overview of the data. I then display average attrition rates in the sample by gender and field without adding controls before conducting a multivariate analysis that takes worker attributes and preferences into account.

## 4.1 Summary Statistics

Table 3 displays the weighted employment rates for men and women in each field. Men have consistently high employment rates of at least 93%, with the exception of mathematics, where the employment rate is 89.64%. The female employment rate is at least 81% in most fields, with the exception of mathematics (76.78%) and economics and finance (77.54%).

Table 3: Employment Rates by Field and Gender

| | Male | Female | Total |
|---|---|---|---|
| Mathematics | 89.64 | 76.78 | 84.12 |
| CS | 94.26 | 81.9 | 90.44 |
| Life Sciences | 94.65 | 82.57 | 88.71 |
| Physical Sciences | 93.29 | 81.55 | 89.48 |
| Engineering | 94.27 | 81.06 | 92.33 |
| Econ/Finance | 93.67 | 77.54 | 89.00 |
| Non-STEM | 93.36 | 81.42 | 86.61 |
| Total | 93.51 | 81.42 | 87.25 |

*Note:* Weighted with cross-section weights.
"CS" refers to computer science.

Table 4 displays the weighted shares of male and female workers with highest degrees in individual fields of study, separated into "Science," "Engineering," and "Non-STEM." The most popular science field for both male and female workers is biological sciences, with 2.88% of male workers and 3.22% of female workers with degrees in the field. Computer and information sciences is the most popular engineering degree field, with 5.07% of male workers and 2.11% of female workers having highest degrees in the subject. Of the other engineering fields, electrical and computer engineering is the next most popular, representing 4.33% of male workers and 0.61% of female workers. Among male workers, the most popular non-

Table 4: Field of Study of Highest Degree, by Gender (%)

| Field | Male Workers | Female Workers | All Workers | Job Unrelated | Job Closely Related |
|---|---|---|---|---|---|
| **Science** | | | | | |
| Agricultural and food sciences | 1.03 | 0.60 | 0.82 | 27.26 | 45.21 |
| Biological sciences | 2.88 | 3.22 | 3.05 | 30.48 | 43.86 |
| Chemistry, except biochemistry | 0.92 | 0.59 | 0.76 | 21.36 | 51.73 |
| Earth, atmospheric and ocean sciences | 0.75 | 0.25 | 0.51 | 28.55 | 43.42 |
| Environmental life sciences | 0.70 | 0.33 | 0.52 | 26.30 | 43.38 |
| Mathematics and statistics | 1.63 | 1.12 | 1.38 | 18.75 | 42.79 |
| Other physical sciences | 0.14 | 0.09 | 0.11 | 32.14 | 37.59 |
| Physics and astronomy | 0.49 | 0.10 | 0.30 | 25.62 | 33.55 |
| **Engineering** | | | | | |
| Aerospace, aeronautical, and astronautical | 0.51 | 0.06 | 0.29 | 20.79 | 46.40 |
| Chemical | 0.71 | 0.25 | 0.48 | 13.80 | 44.35 |
| Civil and architectural | 2.11 | 0.35 | 1.26 | 8.01 | 67.83 |
| Computer and information sciences | 5.07 | 2.11 | 3.64 | 9.78 | 67.47 |
| Electrical and computer | 4.33 | 0.61 | 2.53 | 9.45 | 62.19 |
| Industrial | 0.69 | 0.17 | 0.44 | 15.33 | 42.09 |
| Mechanical | 2.80 | 0.27 | 1.57 | 10.39 | 53.32 |
| Other engineering | 1.56 | 0.30 | 0.95 | 14.13 | 51.90 |
| **Non-STEM** | | | | | |
| Accounting | 4.65 | 3.79 | 4.23 | 11.25 | 66.58 |
| Art and Humanities Fields | 7.05 | 9.56 | 8.26 | 39.77 | 36.25 |
| Business administration | 10.57 | 6.59 | 8.65 | 15.75 | 42.15 |
| Economics | 2.70 | 0.93 | 1.84 | 30.38 | 29.02 |
| Education, except STEM education | 5.47 | 11.37 | 8.32 | 16.40 | 68.19 |
| Elementary teacher education | 0.81 | 7.87 | 4.23 | 17.05 | 73.96 |
| Health | 2.64 | 12.60 | 7.45 | 10.18 | 77.56 |
| Law/prelaw/legal studies | 4.15 | 2.84 | 3.51 | 8.76 | 82.34 |
| Other management and administration | 8.62 | 4.80 | 6.78 | 18.14 | 45.71 |
| Medicine | 3.55 | 2.04 | 2.82 | 1.41 | 96.34 |
| Other Non-S&E fields | 5.62 | 7.58 | 6.57 | 30.11 | 42.99 |
| Other S&E related fields | 1.48 | 0.65 | 1.08 | 15.14 | 64.65 |
| Other social sciences | 1.23 | 1.30 | 1.27 | 41.73 | 30.77 |
| Political and related sciences | 2.63 | 1.72 | 2.19 | 44.86 | 21.71 |
| Psychology | 2.42 | 6.01 | 4.16 | 31.02 | 39.80 |
| Sales and marketing | 3.24 | 2.42 | 2.84 | 20.35 | 38.27 |
| Science and mathematics education | 0.80 | 1.14 | 0.96 | 17.56 | 68.60 |
| Social service and related fields | 2.23 | 3.48 | 2.83 | 20.94 | 62.07 |
| Sociology and anthropology | 1.74 | 2.58 | 2.15 | 37.18 | 28.12 |
| Technology and technical fields | 2.11 | 0.32 | 1.25 | 15.18 | 51.99 |
| | 100 | 100 | 100 | | |
| Total Observations | 58,818 | 44,322 | 103,140 | | |

*Note:* Shares weighted with cross-section weights. The “Job Unrelated” column displays shares of individuals who report that their job is unrelated to their field of highest degree in each field. The “Job Closely Related” column displays shares of individuals who report that their job is closely related to their highest degree.

STEM field (and field generally) is business administration (with 10.57% of male workers), followed by other management and administration (with 8.62% of male workers). Non-STEM education is the most popular field overall among female workers, with 11.37% of female workers having highest degrees in the discipline, followed by art and humanities fields, with 8.25% of female workers.

Table 4 also shows the weighted shares of workers with highest degrees in each discipline whose jobs are unrelated to their highest degrees, as well as the corresponding shares of workers in each discipline whose jobs are closely related to their highest degrees. Within the sciences, individuals with highest degrees in mathematics and the life sciences have the highest shares of individuals with jobs closely related to their degrees. Of workers with degrees in mathematics and statistics, 42.79% have jobs that are closely related; and over 43% of workers with highest degrees in the life sciences (agricultural and food sciences, biological sciences, and environmental life sciences) have jobs that are closely related. Within the physical sciences, the relatedness of careers varies with detailed field. 51.73% of workers with highest degrees in chemistry are in jobs that are closely related, while only 33.55% of workers with degrees in physics and astronomy work in closely related jobs.

Over 42% of workers within each engineering field have jobs closely related to their highest degree. Civil and architectural engineering, computer and information sciences, and electrical and computer engineering have the highest shares of workers in jobs closely related to their highest degree, with shares of 67.83%, 67.47%, and 62.19%, respectively. With the exception of aerospace, aeronautical, and astronautical engineering, no more than 16% of workers are in jobs unrelated to their highest degrees.

Within non-STEM, there is considerable heterogeneity among degree fields. Among workers with highest degrees in fields like medicine and health, 96.34% and 77.56% of workers, respectively, have jobs closely related to their degrees (note that health professions are considered to be non-STEM by the National Science Foundation and much of the literature, so I also treat them as non-STEM). In education, there is also high degree-occupation congruence, with over 68% of workers in each of the education-related degree fields working in closely related jobs. In the social sciences, less than 40% of workers are in jobs closely related to their highest degrees. Of workers with highest degrees in psychology, 39.80% are in closely related jobs; in economics, 29.02% of workers are in closely related jobs; and in sociology and anthropology, only 28.12% of workers have closely related jobs.

Table 5 displays the shares of male and female workers with highest degrees in STEM who are employed in occupations unrelated to their highest degrees. While in this subgroup, men are not particularly concentrated in particular professions, with the highest shares of male workers in top-level management (8.83%) and "other salesperson" jobs (8.11%), 20.16% of women are secretaries. This mirrors a pattern described by Joy (2000), where female science and business majors are twice as likely to enter clerical work as their male counterparts, who tend to be employed in management.

In Table 6, I display the shares of male and female workers in each discipline describing the relatedness of their current job to their career in a given way. At the bottom of the table, I display the shares of workers working in jobs unrelated to their highest degree for particular reasons. Men are almost as likely or more likely than women to be in a job unrelated to their highest degree, except in computer science, where 7.80% of men and 14.88% of women are in unrelated jobs, and in engineering, where 10.10% of men and 17.55% of women are in unrelated jobs. Women are also more likely than men to be in a job closely related to their

Table 5: Shares of Workers with Highest Degrees in STEM
in Occupations Unrelated to Highest Degree

| Occupation | Male Workers | Female Workers |
|---|---|---|
| Accountants, auditors, and other financial specialists | 4.39 | 6.36 |
| Computer software developers | 2.62 | 1.90 |
| Computer systems analysts and computer scientists | 4.93 | 3.10 |
| Health technologists and technicians | 1.47 | 5.44 |
| Insurance, securities, real estate and business services | 4.56 | 3.23 |
| Operations and systems researchers | 5.17 | 2.92 |
| Other management related occupations | 6.27 | 6.03 |
| Other service occupations, except health | 3.60 | 3.16 |
| Precision/production occupations | 5.07 | 2.39 |
| Retail sales clerks | 4.00 | 4.57 |
| Other salespersons | 8.11 | 8.12 |
| Secretaries | 4.07 | 20.16 |
| Top-level managers, executives, administrators | 8.83 | 3.44 |
| Transportation and material moving occupations | 6.07 | 2.14 |
| Other | 30.84 | 27.04 |
| | 100 | 100 |

*Note:* Shares weighted with cross-section weights. The sample size is 4,043 and consists of workers with highest degrees in STEM who answered "Unrelated" when asked, "... to what extent was your work on your principal job related to your highest degree? Was it...?" 21.35% of individuals with highest degrees in STEM work in unrelated fields.

Table 6: Relatedness of Job to Field of Highest Degree, by Field and Gender (%)

| | Mathematics | | CS | | Life Sciences | | Physical Sciences | | Engineering | | Non-STEM | | Econ/Finance | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female | Male | Female |
| **Degree of Relatedness** | | | | | | | | | | | | | | |
| Closely | 38.78 | 49.02 | 69.96 | 61.06 | 41.44 | 47.17 | 43.86 | 47.79 | 58.39 | 47.96 | 49.78 | 58.02 | 42.44 | 43.31 |
| Somewhat | 42.48 | 32.22 | 22.24 | 24.06 | 25.95 | 27.26 | 31.84 | 25.46 | 31.51 | 34.49 | 28.21 | 21.22 | 21.21 | 24.16 |
| Not at all | 18.74 | 18.76 | 7.80 | 14.88 | 32.61 | 25.57 | 24.31 | 26.75 | 10.10 | 17.55 | 22.01 | 20.76 | 36.35 | 32.52 |
| Workers | 1,335 | 1,024 | 4,495 | 1,809 | 3,348 | 3,173 | 2,670 | 1,271 | 15,683 | 2,745 | 31,287 | 34,300 | 2,521 | 1,024 |
| **Main Reason** | | | | | | | | | | | | | | |
| Career Change | 3.48 | 2.29 | 1.95 | 2.23 | 5.48 | 4.55 | 5.27 | 5.19 | 1.72 | 3.04 | 4.23 | 3.75 | 4.05 | 5.37 |
| Family | 0.47 | 6.33 | 0.34 | 3.0 | 2.68 | 5.76 | 1.25 | 3.64 | 0.64 | 4.24 | 1.44 | 4.10 | 1.78 | 4.62 |
| Location | 3.08 | 1.76 | 2.45 | 3.81 | 7.25 | 5.24 | 4.98 | 5.63 | 2.36 | 3.13 | 3.09 | 3.12 | 3.26 | 3.24 |
| Job Not Available | 0.96 | 0.98 | 0.53 | 0.49 | 1.93 | 0.80 | 2.47 | 2.45 | 0.84 | 1.02 | 1.45 | 1.07 | 1.70 | 1.46 |
| Pay/Promotion | 7.01 | 2.55 | 1.68 | 2.93 | 11.37 | 5.25 | 6.56 | 3.74 | 3.04 | 2.44 | 7.95 | 4.70 | 7.04 | 4.55 |
| Conditions | 2.13 | 3.21 | 0.40 | 1.82 | 1.97 | 3.00 | 2.02 | 3.23 | 0.60 | 1.99 | 2.27 | 2.74 | 2.40 | 3.92 |
| Total | 17.13 | 17.12 | 7.35 | 14.28 | 30.68 | 24.60 | 22.55 | 23.88 | 9.20 | 15.86 | 20.43 | 19.48 | 20.23 | 23.16 |
| **Any Reason** | | | | | | | | | | | | | | |
| Career Change | 6.38 | 7.66 | 3.45 | 6.14 | 15.68 | 9.77 | 12.52 | 11.73 | 4.58 | 7.29 | 10.48 | 9.20 | 9.40 | 11.41 |
| Family | 2.38 | 10.29 | 1.16 | 5.40 | 6.88 | 10.35 | 5.13 | 11.18 | 2.16 | 8.10 | 4.26 | 7.97 | 4.23 | 11.24 |
| Location | 9.41 | 9.45 | 3.02 | 7.06 | 15.79 | 13.43 | 12.70 | 12.28 | 4.26 | 9.46 | 10.32 | 10.34 | 10.71 | 12.07 |
| Job Not Available | 4.62 | 4.89 | 3.73 | 6.01 | 13.88 | 9.63 | 9.44 | 9.25 | 3.91 | 6.19 | 6.56 | 6.43 | 6.15 | 6.93 |
| Pay/Promotion | 11.32 | 7.59 | 3.36 | 5.05 | 21.35 | 12.12 | 14.50 | 10.12 | 5.56 | 6.71 | 13.78 | 9.78 | 12.82 | 10.02 |
| Conditions | 9.44 | 11.69 | 2.88 | 7.42 | 14.43 | 14.47 | 10.55 | 13.38 | 4.15 | 9.77 | 10.87 | 11.65 | 10.78 | 13.83 |

*Note:* Shares of men and women in each field of study describing the relatedness of their highest degree field and career in a given way. Shares of men and women in each field who report that highest degree field and career are unrelated for a given reason listed below. Shares weighted with cross-section weights.

highest degree in every field, except computer science and engineering.

Less than 2% of the men in any discipline who are working in an unrelated field cite family as the main reason for exiting, compared to at least 3% of women. For women in mathematics or life sciences, family is the most frequently given "main reason" for attrition. However, women in these disciplines mention other reasons more frequently. 11.69% of women in mathematics mention leaving due to working conditions, compared to 10.29% who mention family. Similarly, 14.47% of women in life sciences mention working conditions as a reason for leaving, compared to 10.35% who mention family. This pattern could be due to working conditions that were once tolerable becoming less acceptable after starting a family. Women are especially affected by working conditions, as they are more likely than men to cite working conditions as a reason or the main reason for leaving in every discipline.

Men are more likely than women to leave their field primarily because of pay and promotion in all disciplines, except computer science, where 2.93% of women who exit cite pay and promotion as the main reason, compared to 1.68% of men. This pattern largely carries over to even mentioning pay and promotion, except that more women than men who leave engineering also mention pay or promotion. This is a qualitatively similar result to Preston's (2004) finding that women mention pay and promotion at a lower rate than men when discussing why they choose to leave science. However, Preston's result is more extreme in that only one woman in her sample leaves for pay reasons, whereas at least 5% of women working in an unrelated field cite pay or promotion as the reason in every discipline.

## 4.2 Average Attrition Rates by Field and Gender

I compute the probabilities of exiting either to an unrelated field or to non-work, exiting to an unrelated field only, and exiting to non-work only by field and gender using a linear probability model:

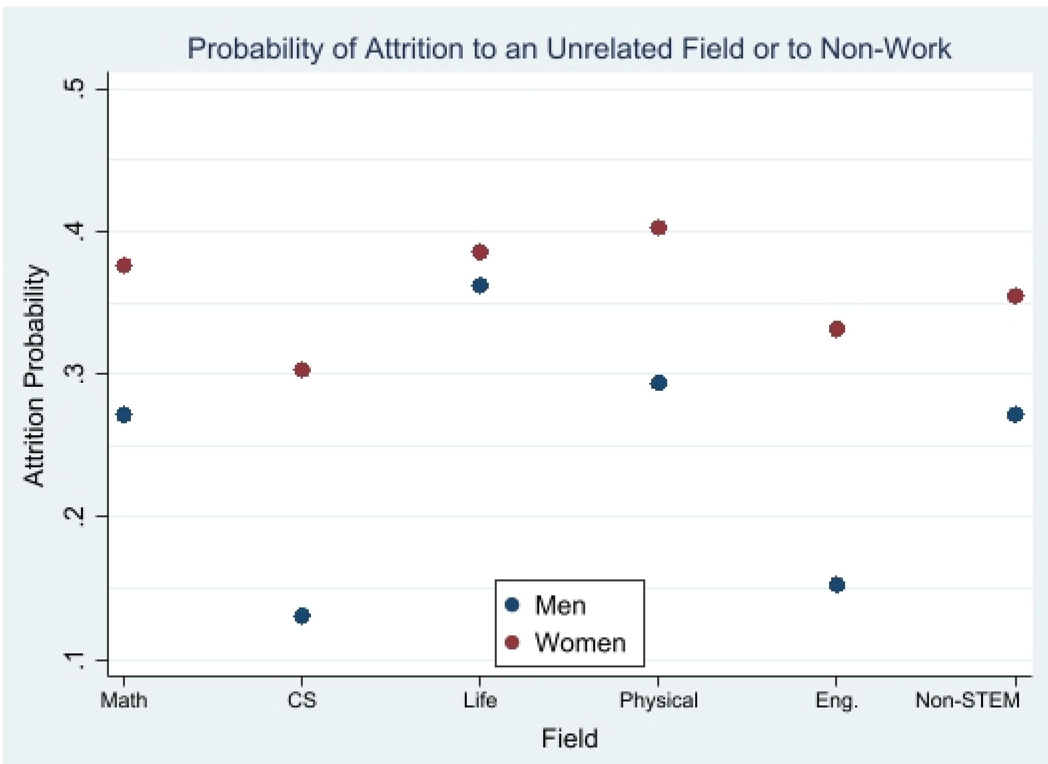
$$Y_{it} = \beta_0 + \beta_1 Female_{it} + \beta_2 Field_{it} + \beta_3 Field_{it} \text{ x } Female_{it} + \epsilon_{it} \tag{1}$$

where $Y_{it}$ is an indicator for one of the three aforementioned types of attrition.

Note that since there are no controls, the estimated attrition probabilities are the sample means of the attrition indicators for each gender and degree field combination. In Figure 2, I display the predicted probabilities of exit for men and women from each STEM discipline and from a non-STEM comparison group. The sample means of this indicator for men and women in each field (which are identical to the probabilities displayed in Figure 2) are displayed in Table 7. Table 7 also displays the differences in the predicted probability of attrition between men and women in each field as well as the difference-in-differences estimates using either economics and finance or non-STEM more generally as a reference category.

Women are more likely than men to exit from every discipline. Physical sciences has the highest female attrition rate (40.26%), while life sciences has the highest male attrition rate (36.22%). Although both men's and women's attrition is relatively high in life sciences, the gender gap in attrition rates (2.33 percentage points) is smallest by far in life sciences. While the rates of female attrition are lower in computer science and engineering (30.29% and 33.17%, respectively) compared to non-STEM (35.48%), the gender gaps in attrition rates in these fields (17.20 and 17.91 percentage points, respectively) are much larger than

Figure 2: Predicted Probabilities of Exiting to an Unrelated Field or Non-Work, by Field and Gender




*Note:* Predicted probabilities of either working in an unrelated field or not working by STEM field. The sample includes 115,752 observations. Weighted with cross-section weights. "Math" refers to mathematics, "CS" refers to computer science, "Life" refers to life sciences, "Physical" refers to physical sciences, and "Eng." refers to engineering.

Table 7: Share of Individuals Exiting to a Job Unrelated to Highest Degree or Not Working, by Gender and Field of Highest Degree

| Field | Share Exiting to an Unrelated Field or to Non-Work | | | |
|---|---|---|---|---|
| | Total | Male | Female | Difference |
| Mathematics | 31.65 | 27.16 | 37.62 | 10.47*** |
| | | | | (3.10) |
| Computer Science | 18.41 | 13.09 | 30.29 | 17.20*** |
| | | | | (1.73) |
| Life Sciences | 37.36 | 36.22 | 38.54 | 2.33 |
| | | | | (1.83) |
| Physical Sciences | 32.91 | 29.39 | 40.26 | 10.87*** |
| | | | | (2.94) |
| Engineering | 17.89 | 15.26 | 33.17 | 17.91*** |
| | | | | (1.73) |
| Econ/Finance | 30.54 | 26.20 | 41.20 | 15.00*** |
| | | | | (2.43) |
| Non-STEM | 31.88 | 27.19 | 35.48 | 8.29*** |
| | | | | (4.88) |

| | Difference in Differences |
|---|---|
| Mathematics-Economics and Finance | -4.53 |
| | (3.94) |
| Mathematics-Non-STEM | 2.18 |
| | (3.14) |
| CS-Economics and Finance | 2.20 |
| | (2.98) |
| CS-Non-STEM | 8.92*** |
| | (1.80) |
| Life Sciences-Economics and Finance | -12.67*** |
| | (3.04) |
| Life Sciences-Non-STEM | -5.96** |
| | (1.89) |
| Physical Sciences-Economics and Finance | -4.13 |
| | (3.81) |
| Physical Sciences-Non-STEM | 2.59 |
| | (2.98) |
| Engineering-Economics and Finance | 2.91 |
| | (2.86) |
| Engineering-Non-STEM | 9.63*** |
| | (1.59) |

*Note:* $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001

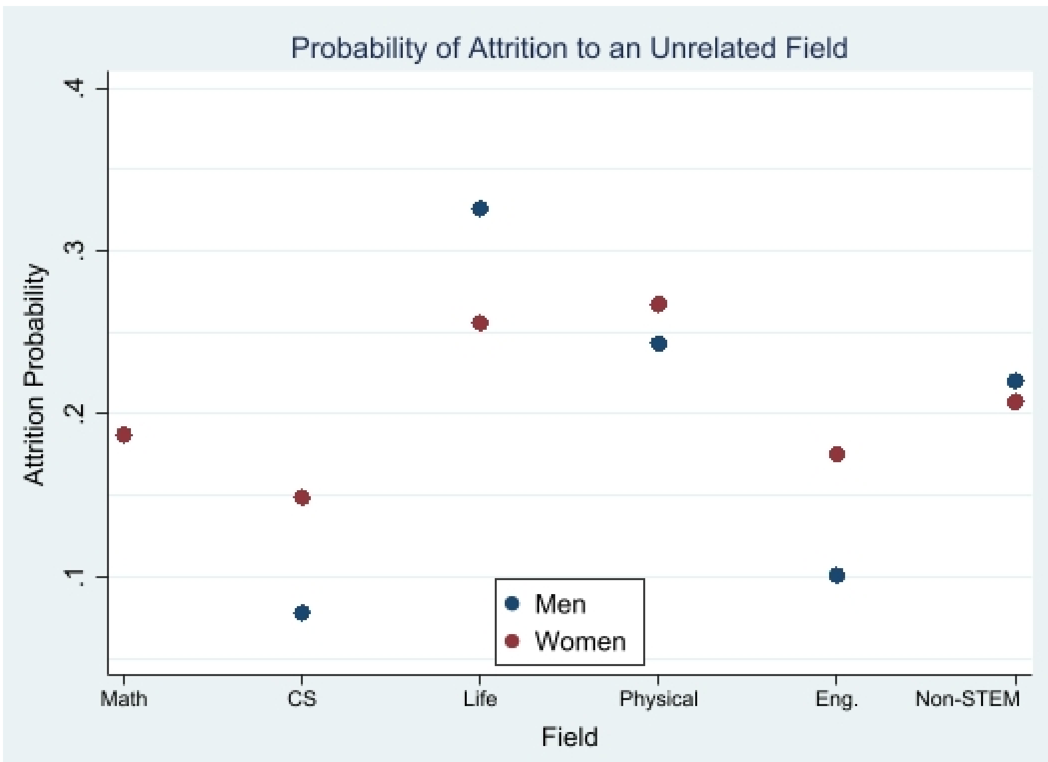
Sample means of an indicator variable for working in a job unrelated to field of highest degree or not working and robust standard errors (in parentheses) are computed using linear probability models with cross-section weights. The sample size for regressions using a non-STEM reference category is 115,752; with economics and finance as the reference category the sample size is 45,106. "Econ" refers to economics; "CS" refers to computer science.

in non-STEM (8.29 percentage points). I do not display the probabilities of attrition in economics and finance in Figure 2, but the male probability (26.2%) is very similar to the general non-STEM probability (27.19%). However, the female probability (41.20%) is almost 6 percentage points higher than the non-STEM female probability (35.48%).

Considering attrition to an unrelated field alone, a different pattern emerges. As seen in Figure 3 and Table 8, men and women with highest degrees in mathematics are equally likely to exit to an unrelated field. As is the case with the more general attrition measure, women have the highest attrition probability in the physical sciences (26.75%), while men are most likely to exit life sciences (32.61%). Women have the lowest probabilities of attrition to an unrelated field in computer science and engineering (14.88% and 17.55%, respectively), but compared to the slightly negative gender gap in exits from non-STEM (-1.25 percentage points), the gender gaps in attrition in these fields are the largest of the STEM disciplines (7.08 and 7.45 percentage points, respectively). Although the attrition probabilities for economics and finance are not displayed in Figure 3, the male attrition probability (21.21%) is approximately the same as the male non-STEM probability (22.01%), while the female probability (24.16%) is 3.4 percentage points higher than the female non-STEM probability (20.76%).

In Figure 4 and Table 9, I consider sample exit rates to non-work only. The male non-employment rate is approximately 6% in every field, except for mathematics, where the rate is 10.36%. The female non-employment rate is approximately 18%, except in mathematics (23.22%) and economics and finance (22.46%). The resulting gender gaps in attrition probabilities are approximately 12% in every field, with the exception of economics and finance (16.13%).

Figure 3: Predicted Probabilities of Exiting to an Unrelated Field, by Field and Gender




*Note:* Predicted probabilities of working in an unrelated field by STEM field.
The sample includes 103,140 observations. Weighted with cross-section weights.
"Math" refers to mathematics, "CS" refers to computer science, "Life" refers to life sciences,
"Physical" refers to physical sciences, and "Eng." refers to engineering.

Table 8: Share of Workers Exiting to a Job Unrelated to Highest Degree, by Gender and Field of Highest Degree

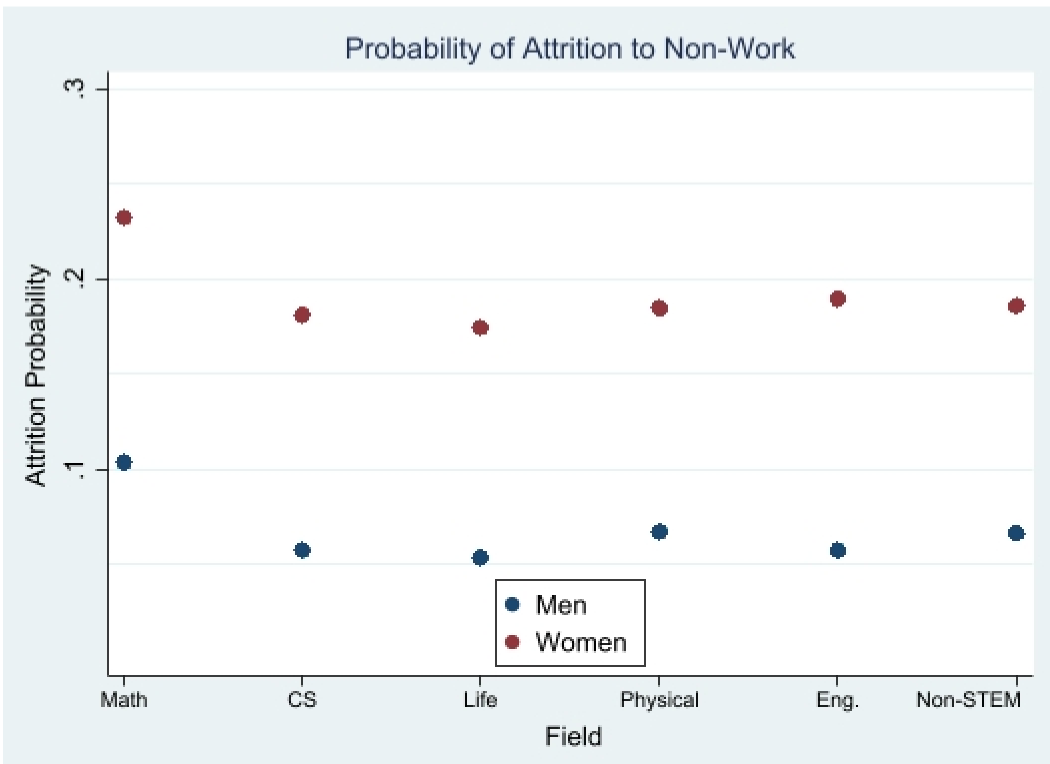
| Field | Share of Workers Exiting to an Unrelated Field | | | |
|---|---|---|---|---|
| | Total | Male | Female | Difference |
| Mathematics | 18.75 | 18.74 | 18.76 | 0.02 |
| | | | | (2.80) |
| Computer Science | 9.78 | 7.80 | 14.88 | 7.08*** |
| | | | | (1.49) |
| Life Sciences | 29.39 | 32.61 | 25.57 | -7.04*** |
| | | | | (1.84) |
| Physical Sciences | 25.03 | 24.31 | 26.75 | 2.44 |
| | | | | (3.11) |
| Engineering | 11.06 | 10.10 | 17.55 | 7.45*** |
| | | | | (1.46) |
| Econ/Finance | 21.96 | 21.21 | 24.16 | 2.95 |
| | | | | (2.29) |
| Non-STEM | 21.35 | 22.01 | 20.76 | -1.25** |
| | | | | (0.47) |

| | Difference in Differences |
|---|---|
| Mathematics-Economics and Finance | -2.94 |
| | (3.62) |
| Mathematics-Non-STEM | 1.27 |
| | (2.84) |
| CS-Economics and Finance | 4.13 |
| | (2.74) |
| CS-Non-STEM | 8.33*** |
| | (1.56) |
| Life Sciences-Economics and Finance | -9.99*** |
| | (2.94) |
| Life Sciences-Non-STEM | -5.78** |
| | (1.90) |
| Physical Sciences-Economics and Finance | -.51 |
| | (3.86) |
| Physical Sciences-Non-STEM | 3.69 |
| | (3.14) |
| Engineering-Economics and Finance | 4.49 |
| | (2.72) |
| Engineering-Non-STEM | 8.70*** |
| | (1.54) |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Sample means of an indicator variable for working in a job unrelated to field of highest degree and robust standard errors (in parentheses) are computed using linear probability models with cross-section weights. The sample size for regressions using a non-STEM reference category is 103,140; with economics and finance as the reference category the sample size is 41,098. "Econ" refers to economics; "CS" refers to computer science.

Figure 4: Predicted Probabilities of Exiting to Non-Work, by Field and Gender




*Note:* Predicted probabilities of not working by STEM field.
The sample includes 115,752 observations. Weighted with cross-section weights.
"Math" refers to mathematics, "CS" refers to computer science, "Life" refers to life sciences,
"Physical" refers to physical sciences, and "Eng." refers to engineering.

Table 9: Non-Employment Rate, by Gender and Field of Highest Degree (%)

| Field | Non-Employment Rate Among Degree Holders | | | |
|---|---|---|---|---|
| | Total | Male | Female | Difference |
| Mathematics | 15.88 | 10.36 | 23.22 | 12.86*** |
| | | | | (2.64) |
| Computer Science | 9.56 | 5.74 | 18.1 | 12.37*** |
| | | | | (1.36) |
| Life Sciences | 11.29 | 5.35 | 17.43 | 12.08*** |
| | | | | (1.15) |
| Physical Sciences | 10.52 | 6.71 | 18.45 | 11.73*** |
| | | | | (2.13) |
| Engineering | 7.67 | 5.73 | 18.94 | 13.21*** |
| | | | | (1.21) |
| Econ/Finance | 11.00 | 6.33 | 22.46 | 16.13*** |
| | | | | (1.95) |
| Non-STEM | 13.39 | 6.64 | 18.58 | 11.93*** |
| | | | | (0.34) |

| | Difference in Differences |
|---|---|
| Mathematics-Economics and Finance | -3.27 |
| | (3.29) |
| Mathematics-Non-STEM | 0.93 |
| | (2.66) |
| CS-Economics and Finance | -3.76 |
| | (2.38) |
| CS-Non-STEM | 0.44 |
| | (1.40) |
| Life Sciences-Economics and Finance | -4.05 |
| | (2.27) |
| Life Sciences-Non-STEM | 0.14 |
| | (1.20) |
| Physical Sciences-Economics and Finance | -4.40 |
| | (2.89) |
| Physical Sciences-Non-STEM | -.20 |
| | (2.16) |
| Engineering-Economics and Finance | -2.92 |
| | (2.30) |
| Engineering-Non-STEM | 1.28 |
| | (1.26) |

*Note:* $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001

Sample means of an indicator variable for not working and robust standard errors (in parentheses) are computed using linear probability models with cross-section weights. The sample size for regressions using a non-STEM reference category is 115,752; with economics and finance as the reference category the sample size is 45,106. "Econ" refers to economics; "CS" refers to computer science.

### 4.3 Multivariate Analysis

In the following analysis, I add controls to the linear probability model used to compute the average attrition rates. Sections 4.3.1 and 4.3.2 present my empirical approach to estimating female excess exits from different STEM fields, and sections 4.3.3-6 present my results.

#### 4.3.1 Linear Probability Model

Following Hunt (2016), I first use a linear probability model to compute female excess exits using a difference-in-differences approach. I estimate the following regression, weighted with cross-section weights, pooling the years 2003 and 2010:

$$Y_{it} = \beta_0 + \beta_1 Female_{it} + \beta_2 Field_{it} + \beta_3 Field_{it} \text{ x } Female_{it} + \beta_4 X_{it} + \beta_5 \gamma_t + \beta_6 Female_{it} \text{ x } \gamma_t + \epsilon_{it} \quad (2)$$

where $i$ indexes over individuals and $t$ indexes over time. $Y_{it}$ refers to an indicator variable for attrition: either from the field of highest degree or to non-work, from the field only, to non-work only, or from the field for a particular reason. $Female$ is an indicator for female. $Field$ refers to either indicators for highest degrees in science and engineering or indicators for highest degrees in mathematics, computer science, life sciences, physical sciences, and engineering. In later specifications, these field main effects are replaced by more disaggregated field-of-study main effects (listed in Table 4). There are 35 when the comparison group is the aggregate non-STEM category, and there are 16 when the comparison group is limited to economics and finance. Excess exits are seen in positive values of $\beta_3$, the coefficient on the field-of-study-female interactions. $X$ is a set of indicators for a master's degree or professional degree; five indicators for years since receipt of the highest degree; six indicators for age; indicators for Black, Hispanic, or Asian. In a later specification, these include indicators for the importance of the nine job attributes. $\gamma$ is an indicator for the year 2003. I use robust standard errors. Since the sign, magnitudes, and statistical significance of the interaction terms in these models agree with those of the analogous estimates obtained using the logistic model, I display the linear regression results in the Appendix.

### 4.3.2 Logistic Model

Although linear probability models and logistic models often produce estimated parameters with the same magnitude and sign (Pindyck & Rubinfeld, 1981), when models include interactions, important differences can emerge. Ganzach et al. (2000) find that changes in the sign of the interaction coefficients in logistic and linear probability models can occur when there are domains in the variable space when the probability of one of the two binary outcomes is very high. To verify the results of the linear probability model, I also run a logistic model that contains the same covariates as the linear probability model displayed in equation 2.

In order to compute excess exits from each STEM field relative to non-STEM, I first compute the difference in mean predicted attrition probabilities for men and women in each field, assuming that men and women have the same distribution of degree fields and other covariates $X_i$:

$$STEM\ gap = \frac{1}{n}\left(\sum_{Field_{it}=1} P(Y_{it}=1|Field_{it}=1, F_{it}=1, X_i)\right)$$

$$-\frac{1}{n}\left(\sum_{Field_{it}=1} P(Y_{it}=1|Field_{it}=1, F_{it}=0, X_i)\right)$$

I repeat this process for the non-STEM comparison group, which either contains all individuals with a highest degree in a non-STEM field or just individuals with a highest degree in economics or finance:

$$Non\text{-}STEM\ gap = \frac{1}{n}\left(\sum_{Non\text{-}STEM_{it}=1} P(Y_{it} = 1 | Non\text{-}STEM_{it} = 1, F_{it} = 1, X_i)\right)$$

$$-\frac{1}{n}\left(\sum_{Non\text{-}STEM_{it}=1} P(Y_{it} = 1 | Non\text{-}STEM_{it} = 1, F_{it} = 0, X_i)\right)$$

Note that in the linear probability model (equation 2), which is additively separable, female excess exits are given by

$$STEM\ gap - Non\text{-}STEM\ gap$$

which is equivalent to the coefficient $\beta_3$ on the female-field interaction. Assuming the distributions of covariates and detailed degree fields within each aggregate field are roughly the same for men and women, this also gives an estimate of female excess exits using the logistic regression. Note that because the female indicator will be changed to 0 and 1 in the main effect and in the interactions with the year indicator, this procedure produces estimates that are an average of the gender differences across 2003 and 2010 and are not directly comparable to the estimates of excess exits given by the linear probability model.

To compute point estimates and standard errors for this estimate of the excess exits, I implement the following bootstrap procedure:

1. Perform the logistic regression of the probability of attrition on the relevant covariates.
2. Set $Female_{it}$=1 and $Female_{it}$x$Field_{it}$=1 for all individuals in the first aggregated field.
3. Predict the probability of $Y_{it} = 1$ conditional on being in the first aggregated field, $P_{female,field}$.
4. Take the mean of this probability, $\bar{P}_{female,field}$.
5. Set $Female_{it}$=0 and $Female_{it}$x$Field_{it}$=0 for all individuals in the first aggregated field.
6. Predict the probability of $Y_{it} = 1$ conditional on being in the first aggregated field, $P_{male,field}$.
7. Take the mean of this probability, $\bar{P}_{male,field}$.
8. Take the difference $\bar{P}_{female,field} - \bar{P}_{male,field} = Gap_{field}$.
9. Repeat for each STEM field and the non-STEM reference category.
10. Take the difference between each estimate of $Gap_{field}$ and $Gap_{non\text{-}STEM}$ to compute $Excess\ Exits_{field}$.

I iterate this procedure 500 times for each specification of the logistic regression model. When bootstrap iterations fail because the colinearity in the new sample does not match that in the original sample, I increase the number of iterations until there are 500 successful iterations.

### 4.3.3 Attrition From Field of Highest Degree to Unrelated Fields or to Non-Work

The first measure of attrition I consider is whether an individual is working in a field unrelated to their highest degree or not working at all. The bootstrap estimates of women's excess exits from science and engineering are displayed in Table 10. Column (1) includes a female indicator, 2003 indicator, and female x 2003 interaction, science and engineering main effects as well as interactions between female and science and engineering. In column (2), I replace science and engineering main effects with 35 detailed degree field indicators. Column (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for years since highest degree; and six indicators for age.[2] Columns (4) and (5) add controls for the extent to which respondents value job characteristics, but column (5) uses economics and finance as a reference category instead of including all non-STEM field main effects.

First, I estimate female excess exit in the broad science and engineering categories used in Hunt (2016). Like Hunt (2016), I find no evidence of statistically significant excess female attrition in science relative to non-STEM fields. My estimates are slightly larger in magnitude than Hunt's; in the first specification, I find that the gender gap in attrition rates in science is about 2.2 percentage points smaller than the gender gap in attrition rates in non-STEM, while Hunt estimates that the gap in science is 1.2 percentage points smaller. Controlling for detailed degree fields, I estimate that the gender gap in attrition rates in science is 2.4 percentage points smaller than the gap in non-STEM, while Hunt finds that the gap is 0.8

[2]The indicators for years since highest degree include indicators for 5 or fewer, 6-10, 11-20, 21-30, and greater than 30 years. The indicators for age include indicators for being 25 or younger, 26-30, 31-35, 36-40, 41-50, and 51-59.

percentage points smaller. However, when controlling for demographic covariates and job tastes, my findings that the gender gap in science is 1.5 and 1.8 percentage points smaller than the non-STEM gender gap are quite close to Hunt's estimates of 1.8 and 2 percentage points, respectively. When comparing science to economics and finance, my estimate of a -7.1 percentage point difference in the gender gap in science relative to the gender gap in economics and finance is identical to Hunt's. The differences between my results and Hunt's results are most likely due to differences in our underlying samples than differences in our methodologies. My linear probability estimates, displayed in Table A6, are slightly larger in magnitude than the estimates I find using the logit and bootstrap procedure.

I find evidence for excess female exits from engineering relative to the general non-STEM category in all specifications, as does Hunt (2016). As was the case for science, my estimates for female excess exits from engineering are larger in magnitude than Hunt's. In column (1), I find a difference-in-differences estimate of 8.6 percentage points, while Hunt's estimate is 5.2 percentage points. Controlling for detailed degree field in column (2), my estimate of excess female attrition grows to 9.6 percentage points, compared to Hunt's estimate of 6.5 percentage points. In column (3), adding controls for demographic variables causes my estimate to increase to 10.1 percentage points, while Hunt's increases to 7.1 percentage points. Once individuals' job tastes are taken into account in column (4), I find that the gender gap in attrition rates in engineering is 8.8 percentage points larger than the gap in non-STEM, while Hunt estimates that the difference is 6.5 percentage points. Compared to economics and finance, I find that women in engineering have excess exits of 4.1 percentage points, compared to Hunt's estimate of 1.2 percentage points. Neither my nor Hunt's column (5) estimate of excess attrition is statistically significant. As is the case for the science estimates, the difference between my results and those of Hunt (2016) are most likely driven by sample differences, as my linear probability estimates are within 0.03 percentage points of my bootstrap estimates.

Disaggregating science and engineering into finer categories in Table 11, I find evidence of small, statistically insignificant female excess exits from mathematics and the physical sciences and large, statistically significant excess exits from computer science and engineering. In the life sciences, I find that the gender gap in attrition rates is smaller than the gap in non-STEM, and that this difference is statistically significant. These estimates are similar in sign, magnitude, and statistical significance to the results displayed in Table A7.

In mathematics, my estimate of excess attrition widens from 2.1 percentage points in the base specification to 2.8 percentage points after controlling for detailed degree fields. Controlling for demographics and preferences produces an estimate of 2.7 percentage points in both columns (3) and (4). Relative to the gender gap in attrition from economics and finance, the gender gap in mathematics is 2.5 percentage points smaller. Likewise, in the physical sciences, I estimate excess exits of 2.6 percentage points in column (1), which widens to 4.1 percentage points in column (2). Controlling for demographics widens the gap even more to 4.7 percentage points, and adding controls for preferences shrinks the estimate to 4 percentage points. The gender gap in the physical sciences is approximately 1.6 percentage points smaller than in economics and finance.

Computer science and engineering both have statistically significant excess female attrition of roughly equal magnitudes. In column (1), I find that compared to non-STEM, the excess female attrition rates in computer science and engineering are 8.7 and 10 percentage points larger, respectively. In column (2), the estimated gaps widen to 9.3 and 9.4 percentage points in computer science and engineering, respectively. While the gap in computer science shrinks to 9.1 percentage points in column (3) and 8.4 percentage points in column (4), the gap in engineering widens to 10.6 percentage points in column (3) before shrinking to 8.8 percentage points in column (4). Relative to economics and finance, neither of the estimates of excess female attrition in computer science and engineering is statistically significant; the excess exits from computer science are estimated to be 3.5 percentage, while the excess exits from engineering are estimated to be 4.2 percentage points. Note that while separating computer science from engineering results in slightly higher estimates of excess exits in columns (1) and (3), the estimated excess female exit rates are identical in column (4) and only differ by 0.01 percentage points in column (5).

The gender gap in exit rates in the life sciences is a statistically significant 6 percentage points smaller than the gap in non-STEM, a difference that increases slightly to 6.2 percentage points after controlling for detailed degree fields. After controlling for demographics and tastes, the gap is 5.1 percentage points smaller than the gap in non-STEM. Compared to economics and finance, the gap in the life sciences is 10.4 percentage points smaller.

These results support Hunt's finding that there is not evidence of female excess exits from the sciences. However, disaggregating science into several categories reveals that the slightly negative difference-in-differences estimate that both Hunt and I find is driven by the relatively small gender gap in attrition in the life sciences. The estimated gaps in mathematics and the physical sciences, while not statistically significant, are positive and much larger in magnitude than the estimated excess exit rate in the general science category.

Table 10: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field or to Non-Work; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Science | -0.022 | -0.024 | -0.015 | -0.018 | -0.071** |
| | (0.014) | (0.015) | (0.014) | (0.014) | (0.026) |
| Engineering | 0.086*** | 0.096*** | 0.101*** | 0.088*** | 0.041 |
| | (0.012) | (0.013) | (0.013) | (0.012) | (0.026) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |
| *Note:* | | | | | *p<0.05; **p<0.01; ***p<0.001 |

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to a field unrelated to one's highest degree or to non-work assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 115,752 observations. "Field" refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table 11: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field or to Non-Work; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Mathematics | 0.021 | 0.028 | 0.027 | 0.027 | -0.025 |
| | (0.033) | (0.033) | (0.032) | (0.030) | (0.037) |
| Computer Science | 0.087*** | 0.093*** | 0.091*** | 0.084*** | 0.035 |
| | (0.018) | (0.018) | (0.018) | (0.017) | (0.028) |
| Life Sciences | -0.060*** | -0.062*** | -.049** | -0.051** | -.104*** |
| | (0.018) | (0.018) | (0.017) | (0.017) | (0.028) |
| Physical Sciences | 0.026 | 0.041 | 0.047 | 0.040 | -.016 |
| | (0.029) | (0.029) | (0.028) | (0.028) | (0.036) |
| Engineering | 0.010*** | 0.094*** | 0.106*** | 0.088*** | 0.042 |
| | (0.016) | (0.016) | (0.017) | (0.016) | (0.028) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to a field unrelated to one's highest degree or to non-work assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 115,752 observations. "Field" refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Weighted using cross-section weights.

### 4.3.4 Attrition From Field of Highest Degree to Unrelated Fields Only

In Tables 12 and 13, I restrict the sample to workers and consider attrition from the field of respondents' highest degree only (the corresponding linear probability estimates are displayed in A8 and A9, respectively). Since the magnitudes of these estimates are fairly similar to those obtained using the more general measure of attrition and follow a similar pattern with the addition of controls, exits to unrelated fields drive the estimates obtained in Tables 10 and 11 rather than exits to non-work.

In Table 12, I find evidence of excess exits female from engineering to an unrelated field (the exit rate is 7.8 percentage points higher than non-STEM) that are not explained by detailed degree field, demographics, or preferences. The gender gap in engineering is 4.9 percentage points larger than the gap in economics and finance, which is slightly larger than the difference-in-differences measure using the combined measure of attrition, although it is still statistically insignificant. My difference-in-differences estimates for science relative to non-STEM are similar in sign and magnitude to those in Table 10 and are still statistically insignificant. However, the gender gap in attrition to an unrelated field is 5.4 percentage points smaller in science compared to the gap in economics and finance. This estimate is smaller in magnitude than the estimate of -7.1 percentage points obtained using the more general measure of attrition.

Disaggregating science and engineering in Table 13, I find the same pattern in terms of sign, magnitude, and significance of the point estimates as I found using the general measure of attrition. The fact that the difference-in-differences estimates are much smaller in computer science and engineering (and negligible in mathematics and the physical sciences) using economics and finance as a comparison group instead of non-STEM suggests that once one takes the share of men in these fields into account, women's exits to unrelated fields are no longer "excessive". Likewise, the fact that the estimated excess exits from the life sciences compared to economics and finance are negative and twice the magnitude of the negative estimate obtained using non-STEM as a comparison group suggests that the roughly equal gender balance in the life sciences may be partially responsible for women's low excess attrition to unrelated fields. However, if other factors like gender norms influence who pursues different fields of study and occupations, these factors will determine the gender composition of who pursues different subjects and who attrites. Gender composition would be a result of these factors, rather than the actual cause of attrition patterns.

Table 12: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Science | -0.019 | -0.024 | -0.017 | -0.013 | -0.054* |
| | (0.014) | (0.014) | (0.014) | (0.013) | (0.025) |
| Engineering | 0.076*** | 0.084*** | 0.085*** | 0.078*** | 0.049 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.025) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |
| *Note:* | | | | | *p<0.05; **p<0.01; ***p<0.001 |

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to a field unrelated to one's highest degree assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 103,140 observations. "Field" refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table 13: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Mathematics | 0.011 | 0.014 | 0.017 | 0.013 | -0.023 |
| | (0.028) | (0.028) | (0.026) | (0.026) | (0.034) |
| Computer Science | 0.078*** | 0.081*** | 0.079*** | 0.071*** | 0.043 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.027) |
| Life Sciences | -0.057*** | -0.060** | -0.049** | -0.043* | -0.085* |
| | (0.018) | (0.019) | (0.018) | (0.018) | (0.027) |
| Physical Sciences | 0.038 | 0.051 | 0.051 | 0.052 | 0.005 |
| | (0.030) | (0.031) | (0.029) | (0.029) | (0.035) |
| Engineering | 0.084*** | 0.082*** | 0.086*** | 0.078*** | 0.049 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.027) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; **p<0.001

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to a field unrelated to one's highest degree assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 103,140 observations. "Field" refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Weighted using cross-section weights.

### 4.3.5 Attrition to Non-Work Only

None of the estimates of female excess exits to non-work (with the aggregated category results shown in Table 14 and the disaggregated category results shown in Table 15) are statistically significant. The difference-in-differences estimates for science relative to non-STEM are all less than 1 percentage point in magnitude, as are the engineering estimates, with the exception of the column (3) estimate of 1.2 percentage points. Compared to the gender gap in exits to non-work from economics and finance, the gaps in science and engineering are 2.7 and 2 percentage points smaller, respectively. These estimates are very similar to Hunt's difference-in-differences estimates for science and engineering of 2.4 and 2.7 percentage points smaller, respectively.

Using disaggregated categories, the difference-in-differences estimates in Table 15 are similarly small in magnitude and statistically insignificant. The estimates for engineering increase slightly, and are at least 1 percentage point in columns (1)-(3), although the estimate in column (4) of 0.3 percentage points is identical to the corresponding estimate in Table 14. The column (5) estimates for all categories are negative but statistically insignificant. The magnitudes of the column (5) estimates for each field are all within 0.3 percentage points of the estimates of their corresponding aggregate category (displayed in Table 14), with the exception of the physical sciences. Compared to the gender gap in attrition to non-work in science and engineering, the gap in the physical sciences is 3.5 percentage points smaller. Compared to non-STEM generally, the gap in the physical sciences is only 1 percentage point smaller.

Table 14: Effect of Gender and Field of Study on the Probability of Exit to Non-Work; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Science | 0.001 | 0.003 | 0.004 | -0.003 | -0.027 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.020) |
| Engineering | 0.008 | 0.008 | 0.012 | 0.003 | -0.020 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.020) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |
| *Note:* | | | | | $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001 |

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to non-work assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 115,752 observations. "Field" refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table 15: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to Non-Work; Female − Male Differences (Bootstrap Estimates)

| | Relative to Non-STEM | | | | Relative to Economics and Finance |
|---|---|---|---|---|---|
| Field | (1) | (2) | (3) | (4) | (5) |
| Mathematics | 0.008 | 0.009 | 0.004 | 0.001 | -0.025 |
| | (0.027) | (0.028) | (0.026) | (0.024) | (0.029) |
| Computer Science | 0.005 | 0.006 | 0.004 | 0.004 | -0.021 |
| | (0.014) | (0.014) | (0.014) | (0.013) | (0.022) |
| Life Sciences | 0.003 | 0.003 | 0.007 | -0.001 | -0.024 |
| | (0.014) | (0.012) | (0.012) | (0.011) | (0.021) |
| Physical Sciences | -0.002 | -0.004 | -0.002 | -0.010 | -0.035 |
| | (0.021) | (0.021) | (0.020) | (0.018) | (0.026) |
| Engineering | 0.012 | 0.010 | 0.018 | 0.003 | -0.019 |
| | (0.012) | (0.012) | (0.013) | (0.012) | (0.021) |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001

Estimates refer to the amount of excess exits among women in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to non-work assuming men and women had the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 115,752 observations. “Field” refers to field of highest degree. All models include a female indicator, 2003 indicator, and female x 2003 interaction, as well as interactions between female and aggregated degree fields. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, and Asian; indicators for holding a master’s degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Weighted using cross-section weights.

### 4.3.6 Reasons for Attrition to Unrelated Work

Next, I consider the particular reasons that female workers give for working in a field unrelated to their highest degree. I implement the same difference-in-differences approach to determine whether the gender gap in a particular reason being cited relative to the general non-STEM comparison group varies by STEM field. I compute these estimates using both the probability that a reason contributed to an exit and the probability that a reason was cited as the main reason for exit.

First, I consider the broad science and engineering categories; the corresponding results are displayed in Table 16. I find that the gender gap in workers mentioning a particular reason for their exiting is larger from engineering than from non-STEM for every reason, with the largest gaps being for location and pay/promotion (with estimates of 4.1 and 4.7 percentage points, respectively). In Hunt (2016), the difference-in-differences for job location being cited is 2.9 percentage points; the estimate for pay/promotion is 4.6 percentage points. Pay and promotion is the only statistically significant difference-in-differences estimate when considering the main reason cited as contributing to an exit (2.9 percentage points). This finding is similar to Hunt's estimate of 3.2 percentage points. Although her estimate for excess exits from engineering due mainly to changes in career interest is statistically significant, while mine is not, our difference-in-differences estimates of 0.009 percentage points are identical.

In science, the only statistically significant difference-in-differences estimates are negative. The gender gap in workers mentioning a lack of job availability as a reason for working in an unrelated field is 1.2 percentage points smaller than in non-STEM, and the gender gap in workers citing pay and promotion as the main reason for working in an unrelated field is

1.4 percentage points smaller than in non-STEM.

Disaggregating science and engineering, I find that the gender gap in individuals mentioning family as a reason for working in an unrelated field is 3.4 percentage points higher in mathematics than in non-STEM (this estimate is statistically significant). Similarly, the gender gap in individuals mentioning family as a reason for working in an unrelated field is 2.4 percentage points higher in engineering than in non-STEM (this estimate is also statistically significant). However, I find no evidence that the gender gap in individuals citing family as the *main* reason for working in an unrelated field is larger in any STEM field than in non-STEM.

I also find that the difference-in-differences estimate for pay and promotion being cited as the main reason for exit in Table 16 may be driven by computer science rather than other engineering fields. In Table 17, the estimate for computer science is 3.7 percentage points (significant at the 0.1% level) while the estimate for engineering is 2 percentage points (significant at the 5% level). I also find another notable difference between computer science and engineering. While the gender gap in citing family as a reason for exiting is not significantly larger in computer science than in non-STEM, the gap in engineering is 2.4 percentage points larger and is significant at the 5% level.

Notably, the statistically significant estimates in the life sciences are all negative. I find that the gender gaps in individuals mentioning career interest changes, a lack of available jobs, and pay/promotion for a reason for exit are all smaller than the corresponding gaps in non-STEM (by -3.9, -3.9, and -3.7 percentage points, respectively) and statistically significant at the 1% level. The difference-in-differences estimate for pay/promotion being cited as the main reason for exiting is -2.3 percentage points (significant at the 5% level).

Table 16: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field for a Given Reason (Bootstrap Estimates)

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| **Any Reason** | | | | | | |
| Science | -0.017 | 0.014 | -0.011 | -0.020* | -0.019 | 0.005 |
| | (0.010) | (0.009) | (0.011) | (0.010) | (0.010) | (0.011) |
| Engineering | 0.035*** | 0.020* | 0.041*** | 0.019* | 0.047*** | 0.042*** |
| | (0.009) | (0.008) | (0.010) | (0.009) | (0.009) | (0.009) |
| **Main Reason** | | | | | | |
| Science | -0.004 | 0.007 | -0.002 | -0.010 | -0.014* | 0.006 |
| | (0.007) | (0.006) | (0.004) | (0.008) | (0.007) | (0.005) |
| Engineering | 0.009 | 0.008 | 0.003 | 0.008 | 0.029*** | 0.008 |
| | (0.006) | (0.005) | (0.003) | (0.007) | (0.007) | (0.005) |
| *Note:* | | | | *p<0.05; **p<0.01; ***p<0.001 | | |

Estimates refer to the amount of excess exits among female workers in a particular field relative to non-STEM. These are computed using a weighted logit to determine the mean predicted probabilities of attrition to an unrelated field for a given reason, assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program is run for 500 repetitions on a sample of 103,240 observations. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table 17: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field for a Given Reason (Bootstrap Estimates)

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| **Any Reason** | | | | | | |
| Mathematics | 0.022 | 0.034* | -0.005 | 0.003 | 0.008 | 0.012 |
| | (0.016) | (0.016) | (0.020) | (0.015) | (0.019) | (0.021) |
| Computer Science | 0.032** | 0.006 | 0.033** | 0.020 | 0.047*** | 0.035** |
| | (0.012) | (0.009) | (0.011) | (0.011) | (0.010) | (0.011) |
| Life Sciences | -0.039** | 0.004 | -0.017 | -0.039** | -0.037** | -0.002 |
| | (0.013) | (0.011) | (0.014) | (0.014) | (0.014) | (0.013) |
| Physical Sciences | 0.012 | 0.026 | 0.003 | 0.018 | 0.009 | 0.022 |
| | (0.023) | (0.023) | (0.023) | (0.025) | (0.020) | (0.025) |
| Engineering | 0.036** | 0.024* | 0.043*** | 0.019 | 0.045*** | 0.044*** |
| | (0.011) | (0.011) | (0.012) | (0.013) | (0.012) | (0.011) |
| **Main Reason** | | | | | | |
| Mathematics | -0.009 | 0.023 | 0.003 | -0.015 | -0.011 | 0.004 |
| | (0.010) | (0.012) | (0.006) | (0.011) | (0.013) | (0.011) |
| Computer Science | 0.003 | 0.002 | 0.001 | 0.013 | 0.037*** | 0.008 |
| | (0.009) | (0.006) | (0.004) | (0.009) | (0.008) | (0.006) |
| Life Sciences | -0.005 | 0.007 | -0.006 | -0.018 | -0.023* | 0.007 |
| | (0.009) | (0.008) | (0.005) | (0.010) | (0.011) | (0.006) |
| Physical Sciences | 0.005 | -0.001 | 0.007 | 0.025 | 0.0005 | 0.004 |
| | (0.014) | (0.010) | (0.014) | (0.022) | (0.012) | (0.015) |
| Engineering | 0.015 | 0.009 | 0.004 | 0.004 | 0.020* | 0.008 |
| | (0.008) | (0.007) | (0.003) | (0.009) | (0.009) | (0.006) |
| *Note:* | | | | *p<0.05; **p<0.01; **p<0.001 | | |

Estimates refer to the amount of excess exits among female workers in a particular field relative to non-STEM. These are computed using a weighted logit to determine mean the mean predicted probabilities of attrition to an unrelated field for a given reason, assuming men and women have the same distribution of covariates, taking first differences within each STEM field and a non-STEM comparison group, and then taking second differences between STEM fields and the non-STEM group. Bootstrap standard errors in parentheses. The bootstrap program was run for 500 repetitions on a sample of 103,240 observations. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. Weighted using cross-section weights.

# 5 Discussion and Conclusion

I show that, over time, the probability of women receiving a first graduate degree in a non-STEM field after receiving a STEM undergraduate degree has risen. While the probability of “leaving” STEM before the first graduate degree was once greater for men than for women in every discipline, the reverse is true for the most recent birth cohort (1976-1981). Although receiving a graduate degree in a non-STEM discipline does not preclude one from having a career in STEM, men are more likely than women to return to STEM after receiving a non-STEM graduate degree and are more likely to pursue lucrative non-STEM careers in management and sales. In contrast, a large fraction of women (20.16%) pursue secretarial positions.

I also find that women experience excess exits from computer science and other engineering fields relative to non-STEM disciplines. These exits are not explained by worker characteristics or preferences and are primarily driven by exits to unrelated fields rather than by exits to non-work. Compared to economics and finance, I do not find statistically significant female excess exits from engineering. In science, female excess exits in mathematics and physical sciences are relatively small in magnitude, statistically insignificant, and are driven by exits to unrelated fields. However, in life sciences, the gender gap in exits to an unrelated field is *smaller* than the gender gap in exits in non-STEM disciplines, both generally and when restricted to economics and finance.

To understand why these attrition patterns occur, I consider the reasons that individuals cite for working in an unrelated field and estimate the size of female excess exits for a particular reason. In computer science, estimates of female excess exits mentioning a change in career interest, job location, pay/promotion, and working conditions as a reason for leaving are all positive and significant at the 1% level, suggesting that no particular factor is crucial for explaining exits. In other engineering fields, the estimate of excess exits due to family is also positive and statistically significant. However, when considering which reasons are given as being most important for working in fields unrelated to computer science and engineering, pay and promotion is the only reason with positive, statistically significant estimates. Comparing these estimates to the estimate for exits primarily due to pay and promotion from the aggregated engineering category, it appears that exits due mainly to pay and promotion from engineering as an aggregated field are driven by exits from computer science more than from other engineering fields.

Examining the shares of workers in jobs unrelated to their highest degrees who cite a given reason for exiting (displayed in Table 6), I find that a larger share of women exiting computer science cite pay as the main reason compared to women exiting engineering (2.93% vs. 2.44%), but a larger share of men exiting computer science cite pay as the most important reason compared to men exiting engineering (1.68% vs. 3.04%). Note that these shares also reveal that among individuals exiting to unrelated fields, in computer science, women are more likely than men to leave primarily for pay reasons, while in engineering, men are more likely to leave mainly for pay.

While it is difficult to draw conclusions about the factors driving pay dissatisfaction across fields without examining pay levels, there are possible reasons for this pattern that could be considered in future research. For example, the skills gained from computer science degrees may be more transferable to unrelated industries than the skills gained from engineering degrees. If women are dissatisfied with pay and promotion in a job that is related to computer science, they may have higher-paying opportunities in unrelated industries; therefore, these women may be more sensitive to pay dissatisfaction than their counterparts in engineering. Moreover, if women are relatively more represented in computer science than in engineering (which is the case at least in this sample), it could be the case that engineering workplaces are less likely to have a critical mass of women than computer science workplaces. In workplaces without a critical mass of women, women may feel less empowered to seek pay and promotion opportunities, which could explain why women in engineering are less likely than men to leave due to pay reasons. Meanwhile, women in computer science may be more likely to work in jobs where there is a critical mass of women, and discussing pay and promotion opportunities could enable women to realize that they are being underpaid or passed over for promotions and identify viable outside options if they are dissatisfied.

The negative estimate of excess exits from life sciences does not necessarily imply that conditions are better for women in life sciences than in non-STEM. Recalling the average predicted probabilities of exiting to an unrelated field or to non-work (displayed in Table 7), the average probability of women leaving life sciences (38.54%) is slightly higher than the probability of leaving non-STEM (35.48%), but the probability of men leaving life sciences (36.22%) is much higher than non-STEM (27.19%); therefore, the relatively small gender gap in exits from life sciences is driven by high attrition rates among men rather than low attrition rates among women.

Men with degrees in life sciences are more likely than their female counterparts to work in unrelated occupations, suggesting that men are less likely to tolerate working conditions in life sciences and are more likely to seek out opportunities in fields such as management and sales. This result is especially surprising given that Melguizo and Wolniak (2012) estimate a major-job congruence premium of 59% in life sciences (compared to a 20% non-congruence premium), which is the highest major-job congruence premium of all the fields they discuss.

Considering the shares of workers in unrelated fields for a particular reason (Table 6), I find that men are nearly twice as likely as women to mention pay and promotion as a reason for seeking unrelated work (21.35% vs. 12.12%) and are more likely than women to leave due to career interest changes (15.68% vs. 9.77%) and a lack of suitable jobs (13.88% vs. 9.63%). Given these estimates for the levels of attrition, it is unsurprising that the multivariate estimates of excess exits to an unrelated field due in part to career interest changes, a lack of available jobs, and pay and promotion are all negative. These estimates are driven by men's dissatisfaction with careers in life sciences rather than women's relative satisfaction with working in life sciences. These results highlight the importance of considering both the size of the gender gap in attrition probabilities and the levels of attrition across fields.

Since the Cold War, Americans' preparation for careers in STEM has increasingly become a national priority. Anxieties about America's ability to meet new scientific and technological challenges have driven calls to target STEM attrition at the college level. By preventing students who declare STEM majors from moving to a non-STEM field or from leaving post-secondary education, policymakers hope to produce more STEM professionals in a cost- and time-efficient way (Herman, 2019; Chen, 2013). Even though the current popular strategy of training more STEM undergraduates will result in more young Americans being prepared for careers in STEM, focusing on college major choice ignores the high rates of attrition, both before the first graduate degree and over the course of one's career. Convincing more women to stay in STEM throughout college may not be the most effective way to achieve gender parity in STEM occupations if there are professional factors that move interested, capable women to attrite.

Moreover, women who work in unrelated fields after earning a STEM degree face worse career outcomes. Congruence between one's undergraduate field of study and occupation is associated with positive career outcomes, including higher earnings and job satisfaction (Xu, 2013). Intuitively, when individuals' careers align closely with their undergraduate studies, they are better able to develop expertise and receive higher returns to their education than they would if their careers required a different set of skills and knowledge. STEM fields in particular are associated with large earnings premiums due to their well-defined content and skills, as well as their emphasis on quantitative analysis (Melguizo & Wolniak, 2012). However, the financial benefits of majoring in STEM are limited to careers that are closely related to one's field of study, especially for minority students (Melguizo & Wolniak, 2012). Understanding the reasons for women's excess exits from STEM careers, therefore, has important policy implications, in terms of both individual career outcomes and society's need for trained STEM professionals.

This paper points to several potential areas of future research that are important to understanding the factors driving female attrition from STEM occupations as well as identifying potential solutions. For example, exploring how pay levels are related to pay and promotion-related exits in computer science and engineering may help explain whether these fields' relatively larger gender gaps in pay and promotion-related exits are driven by women finding that they are systemically paid less than their male counterparts or the fact that women are more willing than men to work in lucrative unrelated fields. More broadly, one could examine how the occupation premiums of women whose highest degrees are in STEM change when these women switch from STEM careers to non-STEM careers and compare this change with the analogous population of men. This would also help determine the role of pay in driving exits from STEM fields. Moreover, by studying how changes in earnings over time are associated with changes in occupation, one can determine how earnings are related to job characteristics across fields.

Likewise, examining family composition of individuals in mathematics could help determine whether such individuals are more likely to have family structures that lead to female excess exits to unrelated fields or whether mathematics workplaces are less accommodating to workers' family lives than non-STEM workplaces in a way that differentially impacts women.

This study has several limitations. First, considering average attrition rates across fields makes it difficult to draw conclusions about particular workplace conditions, especially in the non-STEM category. While work environments in each of the disaggregated STEM fields are likely to be similar, the non-STEM category contains very heterogeneous fields of study that are likely to have differing levels of female representation and different work environments. This makes it difficult to attribute the attrition patterns that I observe to critical mass or other features of a particular workplace. To address this problem, I would consider removing health professions from the non-STEM category, or focusing on economics and finance (or some other smaller field) as a comparison group. Second, the possible "reasons" for working in an unrelated field given in the NSCG still leave some ambiguity. For example, both workplace harassment and long hours could be considered "working conditions," but each issue requires very different solutions.

I also exclude individuals holding doctorates as their highest degrees, the most highly trained individuals in STEM, from the analysis on careers. Future analysis on occupational attrition should consider how gender gaps in attrition vary for these individuals across fields. I would expect that female excess exits would be driven by exits to non-work rather than exits to unrelated fields, as women with PhDs would be "further along" the STEM pipeline and would have a more difficult time transitioning to unrelated fields given their prior educational investments. Moreover, it is important to consider how the reasons driving exits among PhDs in various fields differ from those driving exits among those with a master's, professional, or bachelor's degree.

Despite these limitations, this paper highlights the importance of considering patterns of attrition in particular fields rather than patterns in "science" and "engineering" as monolithic categories. Continuing to disaggregate science and engineering in future research is crucial for understanding the reasons for women's excess attrition in STEM and proposing solutions specific to these disciplines.

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# Appendix Tables

Table A1: Counts of Men and Women With STEM Undergraduate Degrees
Who Receive First Graduate Degrees Before Age 35, by Undergraduate Field

| | Mathematics | | | Computer Science | | | Life Sciences | | |
|---|---|---|---|---|---|---|---|---|---|
| Cohort | Male | Female | Total | Male | Female | Total | Male | Female | Total |
| 1946-1951 | 274 | 165 | 439 | 32 | 14 | 46 | 696 | 228 | 924 |
| 1952-1957 | 229 | 193 | 422 | 151 | 42 | 193 | 1,081 | 604 | 1,685 |
| 1958-1963 | 170 | 163 | 333 | 310 | 162 | 472 | 794 | 675 | 1,469 |
| 1964-1969 | 144 | 139 | 283 | 261 | 114 | 375 | 406 | 474 | 880 |
| 1970-1975 | 91 | 108 | 199 | 183 | 76 | 259 | 381 | 513 | 894 |
| 1976-1981 | 66 | 79 | 145 | 122 | 62 | 184 | 225 | 395 | 620 |
| | **Physical Sciences** | | | **Engineering** | | | **Attriters** | | |
| | Male | Female | Total | Male | Female | Total | Men | Women | Total |
| 1946-1951 | 474 | 79 | 553 | 1,127 | 19 | 1,146 | 1,159 | 225 | 1,384 |
| 1952-1957 | 607 | 182 | 789 | 1,498 | 142 | 1,640 | 1,530 | 598 | 2,128 |
| 1958-1963 | 566 | 238 | 804 | 2,069 | 417 | 2,486 | 1,510 | 795 | 2,305 |
| 1964-1969 | 272 | 176 | 448 | 1,475 | 366 | 1,841 | 871 | 599 | 1,470 |
| 1970-1975 | 212 | 150 | 362 | 1,031 | 309 | 1,340 | 690 | 531 | 1,221 |
| 1976-1981 | 132 | 131 | 263 | 631 | 244 | 875 | 385 | 417 | 802 |
| | | | | | | | 6,145 | 3,165 | 9,310 |

*Note:* The sample consists of 22,369 observations, 15,710 of which are male and 6,659 of which are female. The 1946-1951 cohort consists of 2,184 observations; the 1952-1957 cohort consists of 4,729 observations; the 1958-1963 cohort consists of 5,564 observations; the 1964-1969 cohort consists of 3,827 observations; the 1970-1975 cohort consists of 3,054 observations; the 1976-1981 cohort consists of 1,467 observations. The term “Attriters” refers to individuals who receive a STEM undergraduate degree followed by a non-STEM first graduate degree.

Table A2: Counts of Men and Women by Field

**Full Sample**

| Field | Male | Female | Total |
|---|---|---|---|
| Mathematics | 1,463 | 1,223 | 2,686 |
| Computer Science | 4,771 | 2,203 | 6,974 |
| Life Sciences | 3,580 | 3,713 | 7,293 |
| Physical Sciences | 2,849 | 1,491 | 4,340 |
| Engineering | 16,621 | 3,235 | 19,856 |
| Economics and Finance | 2,701 | 1,256 | 3,957 |
| Non-STEM | 33,634 | 40,969 | 74,603 |
| Total | 62,918 | 52,834 | 115,752 |

**Workers**

| Field | Male | Female | Total |
|---|---|---|---|
| Mathematics | 1,335 | 1,024 | 2,359 |
| Computer Science | 4,495 | 1,809 | 6,304 |
| Life Sciences | 3,348 | 3,173 | 6,521 |
| Physical Sciences | 2,670 | 1,271 | 3,941 |
| Engineering | 15,683 | 2,745 | 18,428 |
| Economics and Finance | 2,521 | 1,024 | 3,545 |
| Non-STEM | 31,287 | 34,300 | 65,587 |
| Total | 58,818 | 44,322 | 103,140 |

*Note:* The sample of workers consists of individuals who are employed at the time of the survey. “Field” refers to field of highest degree. “Non-STEM” includes individuals with highest degrees in economics and finance.

Table A3: Probability of Exit From STEM Before the First Graduate Degree

| | Mathematics | | | Computer Science | | | Life Sciences | | |
|---|---|---|---|---|---|---|---|---|---|
| Cohort | Male | Female | Difference | Male | Female | Difference | Male | Female | Difference |
| 1946-1951 | 0.561 | 0.458 | -0.103 | 0.403 | 0.395 | -0.008 | 0.834 | 0.666 | -0.168 |
| 1952-1957 | 0.535 | 0.536 | 0.000 | 0.375 | 0.463 | 0.088 | 0.820 | 0.730 | -0.090 |
| 1958-1963 | 0.533 | 0.577 | 0.044 | 0.379 | 0.506 | 0.127 | 0.818 | 0.762 | -0.056 |
| 1964-1969 | 0.508 | 0.586 | 0.078 | 0.351 | 0.510 | 0.159 | 0.803 | 0.766 | -0.037 |
| 1970-1975 | 0.540 | 0.560 | 0.020 | 0.380 | 0.489 | 0.109 | 0.823 | 0.750 | -0.074 |
| 1976-1981 | 0.467 | 0.628 | 0.160 | 0.314 | 0.563 | 0.249 | 0.776 | 0.799 | 0.023 |

| | Physical Sciences | | | Engineering | | |
|---|---|---|---|---|---|---|
| Cohort | Male | Female | Difference | Male | Female | Difference |
| 1946-1951 | 0.593 | 0.395 | -0.198 | 0.395 | 0.309 | -0.085 |
| 1952-1957 | 0.570 | 0.475 | -0.095 | 0.371 | 0.377 | 0.006 |
| 1958-1963 | 0.569 | 0.514 | -0.055 | 0.371 | 0.415 | 0.044 |
| 1964-1969 | 0.538 | 0.520 | -0.018 | 0.345 | 0.423 | 0.078 |
| 1970-1975 | 0.574 | 0.495 | -0.078 | 0.375 | 0.397 | 0.022 |
| 1976-1981 | 0.499 | 0.567 | 0.067 | 0.308 | 0.469 | 0.160 |

*Note:* Predicted probability of attrition from STEM before first graduate degree are computed using a weighted logistic regression. The sample includes 22,369 individuals who receive undergraduate degrees in a STEM field (mathematics, computer science, life sciences, physical sciences, or engineering) who receive graduate degrees in a non-STEM field before age 35.

Table A4: Sample Means of Covariates for Workers

| | Men | Women | Total |
|---|---|---|---|
| **Workers** | | | |
| Female | | | 0.48 |
| Bachelor's | 0.69 | 0.67 | 0.68 |
| Master's | 0.24 | 0.28 | 0.26 |
| Professional | 0.07 | 0.05 | 0.06 |
| Age | 42.49 | 41.35 | 41.94 |
| | (9.25) | (9.42) | (9.35) |
| Years Since Highest Degree | 16.60 | 15.11 | 15.88 |
| | (9.52) | (9.52) | (9.55) |
| Black | 0.05 | 0.08 | 0.07 |
| Hispanic | 0.05 | 0.06 | 0.06 |
| Asian | 0.07 | 0.06 | 0.07 |
| 2010 | 0.34 | 0.36 | 0.35 |
| Observations | 58,818 | 44,322 | 103,140 |
| | | | |
| **Workers and Non-workers** | | | |
| Non-employment | 6.49 | 18.58 | 12.75 |
| Observations | 62,918 | 52,834 | 115,752 |

*Note:* Means weighted with cross-section weights. Standard deviations of age and years since highest degree are reported in parentheses.

Table A5: Share of Workers Describing a Particular Job Attribute as Very Important

| | Male Workers | Female Workers | All Workers |
|---|---|---|---|
| Advancement | 46.34 | 40.57 | 43.56 |
| Benefits | 65.85 | 69.03 | 67.39 |
| Challenge | 58.64 | 63.76 | 61.12 |
| Independence | 60.47 | 64.00 | 62.18 |
| Location | 49.84 | 58.54 | 54.05 |
| Responsibility | 45.87 | 47.40 | 46.61 |
| Salary | 62.65 | 60.85 | 61.78 |
| Securtiy | 65.05 | 70.53 | 67.69 |
| Contribution | 40.95 | 57.56 | 49.00 |
| | | | |
| Observations | 58,818 | 44,322 | 103,140 |

*Note:* Shares weighted with cross-section weights.

Table A6: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field or to Non-Work

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | 0.008 | 0.010 | 0.003 | 0.003 | 0.003 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.008) |
| 2003 x Female | -0.007 | -0.009 | -0.008 | -0.011 | 0.009 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.016) |
| Female | 0.087*** | 0.084*** | 0.088*** | 0.090*** | 0.120*** |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.026) |
| Science x Female | -0.023 | -0.026 | -0.019 | -0.022 | -0.073** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.027) |
| Engineering x Female | 0.087*** | 0.094*** | 0.098*** | 0.086*** | 0.038 |
| | (0.012) | (0.013) | (0.013) | (0.012) | (0.026) |
| Constant | 0.266*** | 0.219*** | 0.169*** | 0.719*** | 0.825*** |
| | (0.006) | (0.016) | (0.027) | (0.033) | (0.049) |
| Observations | 115,752 | 115,752 | 115,752 | 115,478 | 45,005 |
| Adjusted $R^2$ | 0.018 | 0.068 | 0.099 | 0.136 | 0.107 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 2 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interaction. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table A7: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field or to Non-Work

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | 0.008 | 0.010 | 0.004 | 0.003 | 0.003 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.008) |
| 2003 x Female | -0.006 | -0.009 | -0.009 | -0.011 | 0.008 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.016) |
| Female | 0.087*** | 0.084*** | 0.089*** | 0.091*** | 0.121*** |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.026) |
| Mathematics x Female | 0.021 | 0.026 | 0.026 | 0.027 | -0.025 |
| | (0.031) | (0.031) | (0.031) | (0.030) | (0.037) |
| CS x Female | 0.088*** | 0.092*** | 0.087*** | 0.081*** | 0.031 |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.029) |
| Life Sciences x Female | -0.060** | -0.064*** | -0.055** | -0.057** | -0.108*** |
| | (0.019) | (0.020) | (0.019) | (0.019) | (0.020) |
| Physical Sciences x Female | 0.026 | 0.039 | 0.045 | 0.038 | -0.016 |
| | (0.030) | (0.031) | (0.027) | (0.030) | (0.038) |
| Engineering x Female | 0.096*** | 0.096*** | 0.108*** | 0.089*** | 0.043 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.028) |
| Constant | 0.266*** | 0.219*** | 0.169*** | 0.719*** | 0.824*** |
| | (0.006) | (0.016) | (0.027) | (0.033) | (0.049) |
| Observations | 115,752 | 115,752 | 115,752 | 115,478 | 45,005 |
| Adjusted $R^2$ | 0.019 | 0.069 | 0.099 | 0.137 | 0.107 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interactions. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree. Weighted using cross-section weights. "CS" refers to computer science.

Table A8: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | 0.012* | 0.015* | 0.010 | 0.012* | 0.006 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| 2003 x Female | -0.014 | -0.015 | -0.015 | -0.018* | 0.002 |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.016) |
| Female | -0.003 | -0.006 | -0.003 | 0.010 | 0.024 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.025) |
| Science x Female | -0.020 | -0.026 | -0.021 | -0.019 | -0.059* |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.027) |
| Engineering x Female | 0.078*** | 0.085*** | 0.089*** | 0.081*** | 0.046 |
| | (0.011) | (0.012) | (0.012) | (0.012) | (0.025) |
| Constant | 0.212*** | 0.145*** | 0.134*** | 0.484*** | 0.635*** |
| | (0.00565) | (0.0152) | (0.0253) | (0.0350) | (0.0544) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 41,098 |
| Adjusted $R^2$ | 0.009 | 0.071 | 0.098 | 0.120 | 0.080 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 2 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interaction. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights.

Table A9: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | 0.012* | 0.015* | 0.010 | 0.012* | 0.007 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| 2003 x Female | -0.014 | -0.015 | -0.016 | -0.018* | 0.001 |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.016) |
| Female | -0.003 | -0.006 | -0.003 | 0.011 | 0.025 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.025) |
| Mathematics x Female | 0.012 | 0.015 | 0.019 | 0.0168 | -0.023 |
| | (0.028) | (0.028) | (0.028) | (0.027) | (0.035) |
| CS x Female | 0.081*** | 0.084*** | 0.082*** | 0.075*** | 0.040 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.027) |
| Life Sciences x Female | -0.059** | -0.063** | -0.056** | -0.053** | -0.091** |
| | (0.019) | (0.020) | (0.020) | (0.019) | (0.029) |
| Physical Sciences x Female | 0.036 | 0.049 | 0.052 | 0.050 | 0.007 |
| | (0.031) | (0.032) | (0.031) | (0.031) | (0.038) |
| Engineering x Female | 0.086*** | 0.086*** | 0.094*** | 0.086*** | 0.052 |
| | (0.015) | (0.016) | (0.016) | (0.016) | (0.027) |
| Constant | 0.212*** | 0.145*** | 0.134*** | 0.484*** | 0.633*** |
| | (0.00565) | (0.0152) | (0.0253) | (0.0349) | (0.0542) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 41,098 |
| Adjusted $R^2$ | 0.010 | 0.072 | 0.098 | 0.120 | 0.081 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interaction. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree. Weighted using cross-section weights. "CS" refers to computer science.

Table A10: Effect of Gender and Field of Study on the Probability of Exit to Non-Work

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | -0.004 | -0.005 | -0.009* | -0.011** | -0.004 |
| | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) |
| 2003 x Female | 0.008 | 0.007 | 0.008 | 0.006 | 0.010 |
| | (0.007) | (0.007) | (0.007) | (0.006) | (0.012) |
| Female | 0.114*** | 0.116*** | 0.120*** | 0.111*** | 0.131*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.020) |
| Science x Female | 0.001 | 0.0001 | 0.002 | -0.005 | -0.026 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.020) |
| Engineering x Female | 0.009 | 0.008 | 0.008 | 0.001 | -0.020 |
| | (0.010) | (0.010) | (0.010) | (0.009) | (0.020) |
| Constant | 0.069*** | 0.086*** | 0.031 | 0.451*** | 0.373*** |
| | (0.003) | (0.011) | (0.018) | (0.026) | (0.035) |
| Observations | 115,752 | 115,752 | 115,752 | 115,478 | 45,005 |
| Adjusted $R^2$ | 0.033 | 0.039 | 0.054 | 0.102 | 0.096 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 2 | 35 | 35 | 35 | 16 |
| *Note:* | | | *p<0.05; **p<0.01; ***p<0.001 | | |

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interaction. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree. Weighted using cross-section weights.

Table A11: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to Non-Work

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 2003 | -0.004 | -0.005 | -0.009* | -0.011** | -0.004 |
| | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) |
| 2003 x Female | 0.008 | 0.007 | 0.008 | 0.006 | 0.010 |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.012) |
| Female | 0.114*** | 0.116*** | 0.120*** | 0.111*** | 0.131*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.020) |
| Mathematics x Female | 0.010 | 0.009 | 0.006 | 0.003 | -0.020 |
| | (0.027) | (0.027) | (0.026) | (0.025) | (0.031) |
| CS x Female | 0.006 | 0.005 | -0.0003 | -0.00002 | -0.023 |
| | (0.014) | (0.014) | (0.014) | (0.013) | (0.022) |
| Life Sciences x Female | 0.002 | -0.001 | 0.003 | -0.005 | -0.026 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.021) |
| Physical Sciences x Female | -0.002 | -0.005 | -0.001 | -0.012 | -0.033 |
| | (0.022) | (0.021) | (0.021) | (0.020) | (0.027) |
| Engineering x Female | 0.014 | 0.011 | 0.016 | 0.002 | -0.018 |
| | (0.013) | (0.013) | (0.013) | (0.012) | (0.022) |
| Constant | 0.070*** | 0.086*** | 0.030 | 0.451*** | 0.373*** |
| | (0.003) | (0.011) | (0.018) | (0.026) | (0.035) |
| Observations | 115,752 | 115,752 | 115,752 | 115478 | 45005 |
| Adjusted $R^2$ | 0.033 | 0.039 | 0.054 | 0.102 | 0.096 |
| Other Covariates | No | No | Yes | Yes | Yes |
| Job Preferences | No | No | No | Yes | Yes |
| Fields of Study | 5 | 35 | 35 | 35 | 16 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

Weighted linear probability coefficients with robust standard errors in parentheses. All regressions include an indicator for 2003, a Female indicator, and a 2003 x Female interaction. (2) replaces aggregated degree field main effects with 35 detailed degree field indicators. (3) adds indicators for Black, Hispanic, or Asian; indicators for a master's or professional degree; five indicators for year since highest degree; and six indicators for age. (4) and (5) add controls for the extent to which respondents value job characteristics. (5) uses economics and finance as a reference category instead of including all non-STEM degree field main effects. Fields of study refer to the field of highest degree field main effects. Weighted using cross-section weights. "CS" refers to computer science.

Table A12: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field for a Given Reason

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| Female | -0.0001 | 0.037*** | 0.010 | 0.009 | -0.031*** | 0.011 |
| | (0.006) | (0.005) | (0.006) | (0.005) | (0.006) | (0.006) |
| Science x Female | -0.021 | 0.013 | -0.014 | -0.024* | -0.022 | 0.004 |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.012) | (0.012) |
| Engineering x Female | 0.040*** | 0.013 | 0.039*** | 0.020* | 0.057*** | 0.041*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 |
| Adjusted $R^2$ | 0.047 | 0.043 | 0.071 | 0.036 | 0.088 | 0.065 |

*Note:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Weighted linear probability estimates of the effect of field of study on female excess exits to an unrelated field for a given reason. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. All models also include 35 detailed degree field main effects. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights. Robust standard errors in parentheses.

Table A13: Effect of Gender and Field of Study on the Probability of Exit to an Unrelated Field for a Given Reason (Main Reason)

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| Female | 0.003 | 0.020*** | -0.001 | 0.007 | -0.025*** | 0.008* |
| | (0.004) | (0.003) | (0.002) | (0.004) | (0.005) | (0.003) |
| Science x Female | -0.005 | 0.010 | -0.002 | -0.012 | -0.015 | 0.006 |
| | (0.007) | (0.007) | (0.005) | (0.008) | (0.009) | (0.006) |
| Engineering x Female | 0.013* | 0.005 | 0.003 | 0.008 | 0.038*** | 0.008 |
| | (0.006) | (0.005) | (0.003) | (0.006) | (0.006) | (0.004) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 |
| Adjusted $R^2$ | 0.017 | 0.030 | 0.012 | 0.017 | 0.059 | 0.017 |

*Note:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Weighted linear probability estimates of the effect of field of study on female excess exits to an unrelated field for a given reason. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. All models also include 35 detailed degree field main effects. Note that "Science" includes mathematics, and "Engineering" includes computer science. Weighted using cross-section weights. Robust standard errors in parentheses.

Table A14: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field for a Given Reason

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| Female | 0.00001 | 0.037*** | 0.010 | 0.010 | -0.031*** | 0.011 |
| | (0.006) | (0.005) | (0.006) | (0.005) | (0.006) | (0.006) |
| Mathematics x Female | 0.029 | 0.038* | -0.0045 | 0.007 | 0.017 | 0.014 |
| | (0.017) | (0.019) | (0.021) | (0.015) | (0.020) | (0.023) |
| CS x Female | 0.038*** | 0.002 | 0.031** | 0.020 | 0.058*** | 0.034** |
| | (0.011) | (0.010) | (0.011) | (0.010) | (0.010) | (0.011) |
| Life Sciences x Female | -0.046** | 0.001 | -0.022 | -0.045** | -0.044** | -0.004 |
| | (0.015) | (0.012) | (0.015) | (0.014) | (0.016) | (0.015) |
| Physical Sciences x Female | 0.009 | 0.027 | 0.002 | 0.012 | 0.011 | 0.022 |
| | (0.023) | (0.024) | (0.024) | (0.022) | (0.022) | (0.026) |
| Engineering x Female | 0.043*** | 0.023* | 0.046*** | 0.020 | 0.057*** | 0.047*** |
| | (0.010) | (0.011) | (0.012) | (0.012) | (0.011) | (0.012) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 |
| Adjusted $R^2$ | 0.047 | 0.043 | 0.071 | 0.037 | 0.088 | 0.065 |

*Note:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Weighted linear probability estimates of the effect of field of study on female excess exits to an unrelated field for a given reason. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. All models also include 35 detailed degree field main effects. Weighted using cross-section weights. Robust standard errors in parentheses. "CS" refers to computer science.

Table A15: Effect of Gender and Field of Study (Disaggregated) on the Probability of Exit to an Unrelated Field for a Given Reason (Main Reason)

| | Career Interest Change | Family | Location | Job in Field Not Available | Pay, Promotion | Conditions |
|---|---|---|---|---|---|---|
| Female | 0.003 | 0.020*** | -0.001 | 0.007 | -0.025*** | 0.008* |
| | (0.004) | (0.003) | (0.002) | (0.004) | (0.005) | (0.003) |
| Mathematics x Female | -0.007 | 0.030 | 0.003 | -0.012 | -0.003 | 0.004 |
| | (0.011) | (0.016) | (0.006) | (0.011) | (0.015) | (0.012) |
| CS x Female | 0.006 | -0.001 | 0.002 | 0.012 | 0.045*** | 0.007 |
| | (0.008) | (0.007) | (0.003) | (0.008) | (0.007) | (0.006) |
| Life Sciences x Female | -0.007 | 0.007 | -0.007 | -0.021 | -0.025* | 0.007 |
| | (0.010) | (0.008) | (0.005) | (0.011) | (0.013) | (0.006) |
| Physical Sciences x Female | 0.002 | -0.002 | 0.005 | 0.016 | 0.007 | 0.004 |
| | (0.0142) | (0.0113) | (0.0146) | (0.0187) | (0.0139) | (0.0161) |
| Engineering x Female | 0.018* | 0.010 | 0.005 | 0.004 | 0.031*** | 0.008 |
| | (0.007) | (0.007) | (0.003) | (0.008) | (0.008) | (0.005) |
| Observations | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 | 103,140 |
| Adjusted $R^2$ | 0.017 | 0.030 | 0.012 | 0.017 | 0.059 | 0.017 |

*Note:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Weighted linear probability estimates of the effect of field of study on female excess exits to an unrelated field for a given reason. All models include a female indicator, 2003 indicator, and female x 2003 interaction; interactions between female and aggregated degree fields; indicators for Black, Hispanic, and Asian; indicators for holding a master's degree and for holding a professional degree; five indicators for year since highest degree; and six indicators for age; and controls for the extent to which respondents value job characteristics. All models also include 35 detailed degree field main effects. Weighted using cross-section weights. Robust standard errors in parentheses. "CS" refers to computer science.