The Intergenerational Transmission of Parental Occupation and the Gender Gap in STEM

by

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(Under the Direction of Christopher Cornwell)

Abstract

Despite a vast literature surrounding the topic, little consensus exists explaining the main cause of the gender gap in science, technology, engineering, and math (STEM). Even less research looks at households as sources of variation in labor market decision-making as they pertain to STEM. Using the General Social Survey, I analyze the transmission of occupational preferences from parents to children in the Baby Boomer generation, Generation-X, and the Millennial generation. I consider this effect for both children's choice in jobs and choice in college major. I then test for differential effects among distinct household structures. In general, I find that parents significantly and consistently impact their children's propensity to enter STEM, but a positive effect is concentrated on sons.

Index words: Intergenerational Transmission, Labor Economics, Gender, STEM

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Contents

List of Tables

List of Figures

Chapter 1

The Intergenerational Transmission of Parental Occupation and the Gender Gap in STEM

1.1 Introduction

Over the last forty years, women have outpaced men in educational attainment and gained overall parity in the labor market. In 2015, the U.S. labor market was the least male-dominated in history, with women holding 47% of all jobs. However, the general ascendancy of women in the workforce masks disparities in certain types of skills and occupations, most importantly those related to science, technology, engineering, and mathematics (STEM).

In the 2015-2016 academic year, 58% of young adult women held bachelor's degrees (compared to 42% of men). However, when restricted to STEM, these percentages reverse to 36% and 64%, respectively (Musu-Gillette et al., 2016). The under-representation of women in STEM majors directly leads to a similar gap in the labor market, as women occupy only 24% of STEM occupations. In some industries, the gender gap appears to be widening. For example, computer-related occupations comprised nearly 4 million jobs in 2015, yet in the past thirty years the share of women in that sector has dropped by at least seven percentage points (BLS, 2015).

There are two broad categories of competing explanations for these gaps. Most commonly, researchers focus on the forces within schools. Beginning at the primary education level and beyond, girls' beliefs in their ability to perform STEM-related skills relate to their exposure to female math teachers (Kahn and Ginther, 2017). In high school, a transcript with a greater number of STEM courses may act as a signal of higher STEM readiness in the view of the university. By the time a student arrives at college, these beliefs about one's own ability to perform in STEM may already be formed. The gap may partly be a byproduct of women's higher propensity to attend college. With relatively fewer men in college, pursuing a degree with potentially lower returns comes with greater risk. In short, men appear to have less flexibility to pursue a degree based on interests and instead consider higher returns. As a result, more men enter college with a STEM intent (Card and Payne, 2017). At the same time, female students exposed to signals of poor fit (e.g. male-dominant STEM faculties and majors) find themselves less likely to enroll in, and more likely to switch out of, STEM programs (Kugler et al., 2017).

There is also an extensive body of work concerned with intergenerational influences on labor market outcomes. Among young Canadian men, nearly 40% find employment in firms that their fathers worked in before (Corak and Piraino, 2011). This study also finds a strong relationship between the intergenerational transmission of employment and paternal earnings, indicating that fathers with higher earnings tend to place their sons in similarly high-paying jobs, with many sharing employers. Beyond father-son relationships, evidence suggests that children place in the highest-paying jobs when either of their parents have higher wages (Kramarz and Skans, 2014). This may extend beyond role modeling effects, with biological parents demonstrating nearly twice the level of occupational influence than adoptive parents (Lindquist et al., 2015). But these studies focus on wages earned by children rather than consider the type of occupation that the child occupies. Further, they do not consider heterogeneous influence by parent.

In fact, few studies examine the influence of parents as role models in their children's decision to enter STEM professions. The difficulty in sorting out these mechanisms, especially by individual parent, explains why so few researchers focus on these effects when studying the gender gap. Instead, researchers focus on the combined parental effect. Past analyses explain whether either parent's current job influences the high school aspirations and eventual career decision of children (Cheng et al., 2019). Separately, Gould et al. (2019) use exogenous shocks in household composition to reach a causal interpretation of parental transmission and its effect on children's labor market outcomes, finding a positive relationship between parent occupation and subsequent child occupation. Yet there does not appear to be any study that considers heterogeneity in household composition and differential gender transmission in the context of the gap in STEM. Further, these analyses do not compare trends between distinct generations.

In this paper, I seek to uncover the effect of parental occupation on own occupation in the context of STEM. I do so using a linear probability model with data from the General Social Survey (GSS). I make several contributions to the literature. First, I allow the effect of parent occupation to vary with the gender of the child to test for differential role modeling effects. In addition, I use the long history of the GSS to examine the influence of parents across three distinct generations. I then test for the differential effects of growing up in either a two- or one-parent household. I also consider the impact of family composition shocks (divorce and death) on role modeling. These shocks illustrate whether, in isolation, a parent's impact amplifies or attenuates the total impact from both parents. Lastly, I use newly available data in the GSS to test a similar set of mechanisms on college major choice.

The results are summarized as follows: First, I find that growing up with a parent in a STEM occupation is generally associated with holding a STEM job, but that this positive association exists mainly for sons and not daughters. Second, overall mothers in STEM jobs appear to have greater influence than fathers. Third, these overall findings mask generational heterogeneity. Children belonging to the Baby Boomer generation more likely choose STEM jobs if their parents did as well, compared to those in the Millennial generation, for which this relationship tends to be null. Fourth, the effects of parent occupation is most consistently mediated through two-parent households, suggesting role modeling occurs most frequently in the presence of both biological parents. Fifth, I show that parental influence largely operates outside of spousal influence. Together, these results suggest that a child's occupational choice depends on the birth cohort they belong to, with younger agents pivoting away from their parent's paths. Finally, I find less evidence that the positive association persists at the educational level. In fact, daughters are consistently less likely to graduate college with a STEM degree if their parents (especially their mothers) hold STEM jobs.

The rest of the paper is organized as follows: Section 1.2 defines and explains the intersection of women and STEM, Section 1.3 discusses the importance and relevance of intergenerational transmission, Section 1.4 summarizes the data used, Section 1.5 discusses the emprical strategy, Section 1.6 presents the main findings of the paper, and Section 1.7 concludes.

1.2 STEM Skills and their Importance

1.2.1 Defining STEM

Beyond its general reference to science, technology, engineering, and mathematics, the meaning of "STEM occupation" varies widely. Black et al. (2017) use the U.S. Census definition of STEM, choosing to include STEM-related fields that may not otherwise count, like psychology and economics. Card and Payne (2017) drop social scientists from the definition but include nurses and other health scientists. Kugler et al. (2017) apply a much stricter definition of STEM, limiting a STEM degree to be one of ten available options[1]. Bostwick and Weinberg (2018) instead apply the Ohio Department of Education definition for a STEM major, which includes every degree in the "Natural Science & Mathematics" discipline. In this paper, I rely on the BLS definition of STEM jobs[2].

Because the BLS does not separately provide a list for STEM majors, I use the Department of Homeland Security's "STEM Designated Degree Program List" to denote STEM degrees in the GSS[3]. Using the DHS list, "STEM major" refers to 21 of the 79 college majors in the GSS. Further, the GSS reports two separate measures for college degree but does not specify whether they refer to students with multiple undergraduate degrees or students with undergraduate and graduate degrees. In either case, I consider a respondent to have a STEM degree if either GSS measurement denotes STEM.

[1] STEM degrees here include biochemistry, biology, biology of global health, biophysics, chemistry, computer science, environmental biology, mathematics, neurobiology, and physics exclusively.

[2] Appendix A lists every occupation considered STEM.

[3] Appendix B lists every major considered STEM.

1.2.2 STEM Skill Development from School to Work

STEM-skill development begins early and involves both school and parental inputs. At the elementary-school level, there is no significant difference in girls' and boys' math abilities in the United States; in fact, girls often outperform boys in every subject. But despite the average scores between boys and girls being identical, the rate of attrition among girls between kindergarten and fifth grade is higher (Fryer Jr and Levitt, 2010). In developing countries, gender gaps related to math proficiency emerge sooner. Wide-scale math and science tests illustrate differences in children related to gender from the third to the eighth grade (Bedard and Cho, 2010).

However, by high school, the gender gaps in math emerge in the United States (Hyde et al., 2008). Card and Payne (2017) find that the number of STEM-related courses taken in high school matters greatly in predicting future STEM readiness. Recent work suggests that post-secondary gender match effects between student and teacher increase the rate in which girls take science and math courses in high school, but any associated gains from these experiences largely disappear after high school (Key and Sass, 2019).

By college, the momentum from secondary schooling makes transitioning into STEM difficult. In the first year of college, academic self-confidence of women begins to decline (Brainard and Carlin, 1998). This decay in girls' beliefs about their ability to do math may stem from their own mother's professed inabilities (Eccles et al., 1990). Additionally, signals of poor fit compound and result in more women switching out of STEM classes and majors (Kugler et al., 2017). In any case, the overall productivity of the STEM market may be hindered if women are discouraged from entering.

According to the National Science Board (2018), women often switch out of STEM between college and entering the work force. Women comprise 50% of the workforce for those with a college degree.

Restricted to those with a STEM degree that have found employment anywhere, women make up 40%; restricted to strictly STEM jobs, women make up only 25%. Similarly, the Bureau of Labor Statistics (2015) shows that 25.1% of working women find employment in STEM jobs. Among those that do, 41.3% have an advanced degree[4]. Over 2 million white men find employment in STEM fields, whereas 580,000 white women find employment in the same fields. This disparity grows when looking at the two most in-demand sectors, computer science and engineering: 870,000 white men work in computer science jobs compared to 198,000 white women; in engineering these numbers become 890,000 and 116,000, respectively (Martínez and Gayfield, 2019).

STEM jobs are often associated with higher levels of productivity and are therefore considered to be the most innovative (Peri et al., 2015). The workers with the highest productivity are matched to jobs that most closely mirror their skills. But if the skills of women in and out of STEM are being restricted, this optimal match will not occur. There may also exist market frictions preventing the natural sorting of men and women into STEM education and careers. In the GSS, the comparison can be made between the rate of women in college choosing a STEM major and the subsequent rate of women that then work in a STEM occupation. Among those surveyed post-2010, 8.2% of women completed college with a STEM major. Among that same sample, 5.4% worked in STEM.

1.3 Intergenerational Transmission

A large body of work exists analyzing the ways parents influence their children's career decisions or professional outcomes. There is considerable evidence that parents' own experiences matter when their child makes educational and occupational decisions. In this section, I summarize the past research's focus on

[4] For men, approximately 39% of men find employment in STEM jobs.

intergenerational transmission in general and then explain the theory guiding my strategy to identify role model effects in the context of STEM occupation.

Outside of STEM, parents influence their children's adult outcomes in a variety of ways. Kramarz and Skans (2014) find family ties to be strongest among children that receive poor grades and low levels of education. In fact, children that attain lower levels of education are nearly 12 percentage points more likely to work in a plant with either of their parents. Contextualizing education transmission to STEM yields consistent results. At the high school and college levels, being raised by STEM parents increases one's own probability to do the same (Cheng et al., 2019).

Beyond educational attainment, parents affect their children's professional outcomes through role modeling. There is a positive association between the wages of parents and children. Kramarz and Skans (2014) find that parents earning high wages have more influence in getting their children hired at the same plant. Past research shows intergenerational transmission to be heterogeneous by race (Okumura and Usui, 2016). However, these effects only explain part of the white-black wage gap and likely exist through father-son transmission of skills. Importantly, these trends do not follow for the poorest agents in the distribution. These results likely have implications in STEM, especially given the racial gap in STEM experienced by blacks. But gender differences are not as clear in the literature. For daughters only, having a STEM parent increases the probability to enter a STEM job more so than it does to pursue a STEM education (Cheng et al., 2019). But most STEM jobs require a STEM education, so a weak transmission of skills at the education level could greatly impact labor market outcomes.

Role modeling develops in a variety of household contexts. Additionally, fathers and mothers may influence their children differently. In Canada, fathers and sons frequently share employers. This pattern relates positively to paternal income, indicating that wealthier fathers tend to transmit wealthy career opportunities (Corak and Piraino, 2011). In Norway, the increase in labor force participation by women in the 1950's saw a lagged, asymmetric effect on the next generation of men and women. Time input from mothers in the production function for sons was substituted for newfound labor force requirements, which in turn adversely affected educational attainment for sons. As a result, the educational gender gap may have significantly reduced (Fan et al., 2015).

But have fathers similarly impacted daughters? Evidence suggests rising labor force participation from women accounts for approximately 17% of newfound paternal occupational transmission (Hellerstein and Morrill, 2011). Underlying genetic variation may not be the source of these intergenerational effects. Rather, role model effects may explain the pattern of children adopting the choices of their parents. For children not raised by their biological parents, the adoptive parents' labor market outcomes matter. Some estimates suggest the influence from role modeling may be as much as twice the level brought on from genetic factors (Lindquist et al., 2015).

I contribute to the literature in four ways: (1) I test for differential effects from mothers and fathers, (2) I distinguish between sons and daughters, (3) I analyze effects for three distinct generations, and (4) I consider heterogeneous household structures to isolate individual parent effects. Much of the past research focuses on the combined influence of parents. Those that do distinguish between parents often only look at one child's outcomes. Among the few studies that analyze the influence of either parent on either child, even less consider generational differences[5].

But outside of the intergenerational transmission literature, notable differences in generation behavior have been reported. Koczanski and Rosen (2019) find that, compared to generations before them, Millennials tend to behave in more socially conscious ways. On the basis of charitable giving, Millennials

[5]More frequently, data limitations prevent a cross-generation comparison.

outperform Generation-Xers and Baby Boomers. On the other hand, Millennials have been shown to have larger families, despite marrying later than Baby Boomers (Knittel and Murphy, 2019). In terms of occupational choice, Baby Boomers on average found themselves employed in full-time jobs less often than birth cohorts that came before them (Maestas, 2017). It may too be the case that, between Millennials and Baby Boomers, occupational decisions differ. These differences could be driven by role modeling.

In the context of intergenerational transmission, separating forces of nature versus nurture can be difficult. For one, genetic ability partially determines whether a respondent can handle the rigor of the education and training related to most STEM jobs. A measure of ability does not exist in the GSS. As a result, my reduced-form estimates cannot distinguish nature (ability) and nurturing (parental) effects.

In the case of intergenerational transmission and role modeling, it may also be impossible to separately identify the impact each parent has on their child, especially in a two-parent household. Further, the influence of a father raising their child alone cannot be compared to a father raising their child alongside the child's mother[6]. Given that most agents grow up in a two-parent household, assumptions must be made to determine how much of a child's decision can be owed to either parent, or how to proceed given different household compositions. I explore three different channels through which isolated parent influence can be measured: two-parent households, one-parent households, and households that experience divorce.

[6]In general, comparing a two-parent household and a one-parent household is difficult.

1.4 The General Social Survey

1.4.1 Overview

The GSS began in 1972 and annually surveyed approximately 1,500 respondents for its first fifteen years. Since 1988, the survey has been conducted biennially, but its coverage has expanded to more than 3,000 individuals. The survey includes only Americans ages 18 or older. Its purpose is to provide a holistic overview of the United States. As a result, it does not over-sample any particular demographic groups.

The GSS collects information regarding each respondent's education, career, current lifestyle, family background, and social and political preferences. Importantly for my purpose, the survey contains a rich set of questions about household attributes when the respondent was 16 years old, including details about the education and occupation of the respondent's parents. The GSS uses 2010 Census occupation codes and re-codes all pre-2010 survey responses for homogeneity. These occupation codes are consistent between the respondent, their parents, and their spouse, which allows for direct comparisons. Measurements of father occupation begin in 1972; however, maternal information does not become available until 1994.

Occupational information is available for the entirety of the GSS, but educational information for both the respondent and their parents is scarce until 2012. From 1972 through 2010, educational information is limited to the highest degree earned by the respondent and their parents. From 2012 onward, the GSS contains information on the respondent's college major.

1.4.2 Analysis Sample

My sample initially consists of the entirety of the General Social Survey from 1972 to 2018. I make several restrictions for the purpose of my analysis. First, I include only those respondents that belong to either the Baby Boomer generation, Generation-X, or Millennial generation[7]. In doing so, the sample includes those between ages 18 and 72. For each respondent, I observe measurements of their occupation type at the time of the survey, education level, age, race, marital status, household composition during adolescence, the region of the U.S. they were raised in, and their parents' occupation types.

Because the GSS did not survey respondents about their mother's occupation until 1994, I restrict attention only to GSS waves from 1994 on. Using information on parental death and home composition during adolescence, I restrict my analysis to exclude orphaned respondents[8]. The focus on STEM jobs in the labor force requires two additional restrictions. The jobs classified as STEM under the BLS require 2-4 years of college experience at minimum. As a result, I include only those with at least two years of college experience. Lastly, I allow only for working respondents but make no distinction between those working full-time and those working part-time.

Table 1.1 shows the shares of STEM majors and jobs among the parents of the GSS sample by gender and generation. In my sample, 37.3% of fathers have college experience, compared to 35.6% of mothers. Interestingly, this gap in parent educational attainment changes depending on the gender of the child. Among sons, fathers have college experience approximately 4% more often than mothers; among daughters, mothers have college experience 0.4% more often than fathers. In the labor force, men outnumber

[7] Equivalently, I restrict the sample to include only those born between 1946 and 1996.

[8] A respondent is deemed to be an orphan if they lived with neither biological parent at age 16 and said they reason for their current household type was due to parental death.

Table 1.1: Occupational and Educational Outcomes by Gender

	All	Males	Females
Education			
2+ College	1.000	1.000	1.000
2+ College (Father)	0.373	0.398	0.350
2+ College (Mother)	0.356	0.359	0.354
2+ College (Spouse)	0.355	0.396	0.318
STEM Major†	0.094	0.107	0.082
Occupation			
STEM Job	0.112	0.173	0.057
STEM Job (Father)	0.090	0.101	0.081
STEM Job (Mother)	0.015	0.014	0.016
STEM Job (Spouse)	0.048	0.027	0.068
Working Mother*	0.754	0.738	0.768
Generation			
Boomer	0.500	0.516	0.486
Generation-X	0.387	0.380	0.394
Millennial	0.112	0.103	0.121
N	6172	2929	3243

Notes: *This refers to when the respondent was 16 years old. † refers only to those surveyed post-2010. The respective sample sizes are 1929, 883, and 1046. Column 1 refers to all college-experienced, working-aged, employed respondents. Column 2 restricts this sample to include only men. Column 3 restricts this sample to include only women.

women in STEM jobs by nearly 2.75 times[9]. Those same workers' parents exhibit similar patterns. Sons have fathers (mothers) that work in STEM 1.13 (0.79) times more often than daughters. The relationship between mothers and daughters also becomes apparent through the likelihood of growing up with a working mother. Nearly 77% of daughters grew up in this environment compared to about 74% of sons. Finally, it is important to note that Boomers comprise half of the total sample.

Figure 1.1 presents the distribution of the remaining sample by birth year. Baby Boomers account for half of the respondents and Generation-Xers account for nearly 40%. Approximately 10% of respondents come from the Millennial generation.

[9] 17.3% of 2929 men are employed in STEM jobs compared to 5.7% of 3243 women.

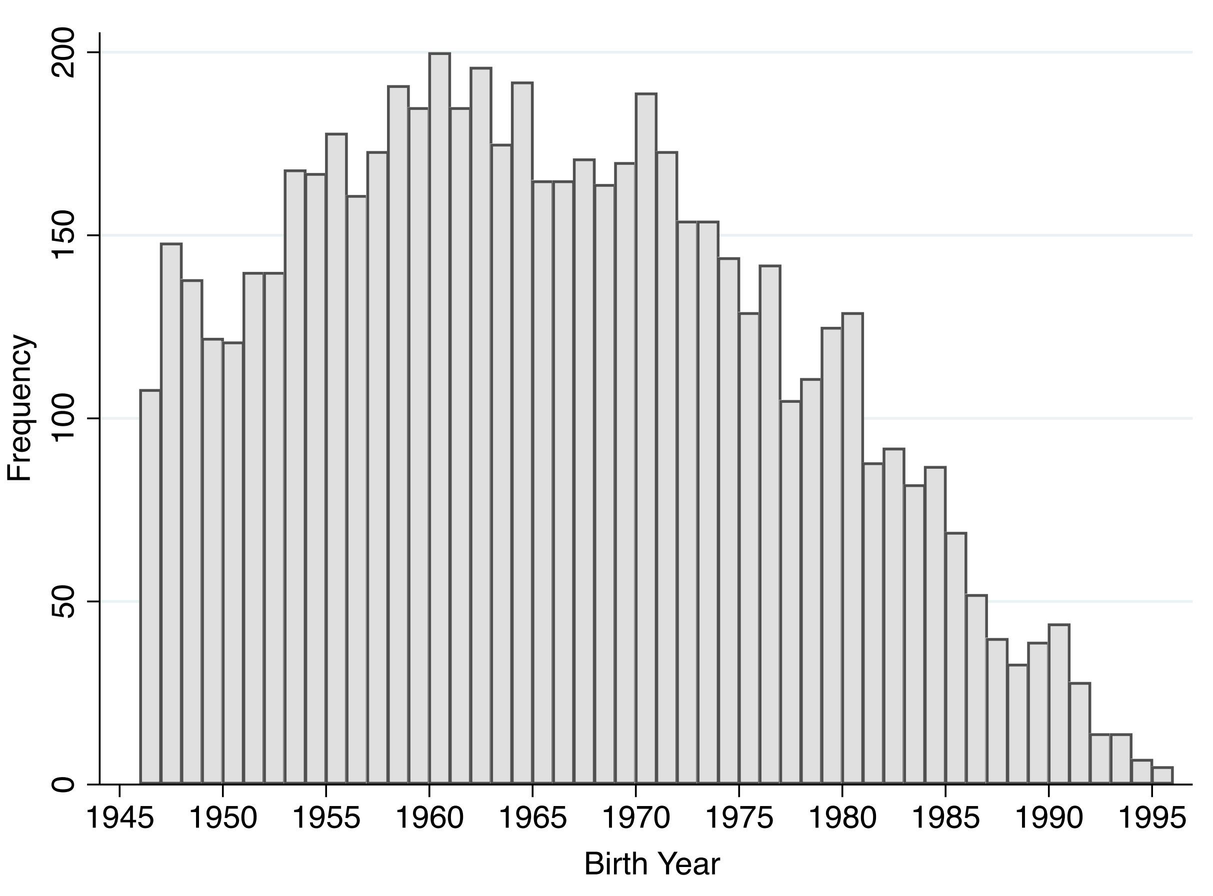

Figure 1.1: Age Distribution in the General Social Survey (Restricted Sample)

Table 1.2 provides summary statistics by generation. Relative to the U.S. population, the sample of GSS respondents contains a higher proportion of women. In the Millennials cohort, women comprise 58.6% of the sample - compared to the actual level of 50.8% (United States Census Bureau). This discrepancy is due to the fact that women attend college at a higher rate than men. Over the period, the rate of whites declines at a rate that matches national trends. Additionally, I include average family sizes across generation to show a declining rate in overall family size.

Table 1.2: Sample Characteristics by Generation

	All	Baby Boomers	Gen-X	Millennials
Gender				
Male	0.475	0.490	0.466	0.437
Female	0.525	0.510	0.534	0.563
Race				
White	0.817	0.850	0.788	0.770
Black	0.104	0.094	0.110	0.128
Other	0.079	0.056	0.102	0.102
Other Demographics				
Married	0.535	0.595	0.508	0.357
Age (Years)	40.66	48.00	34.75	28.40
Family Size*	5.71	6.10	5.37	5.21
Education				
2+ College	1.000	1.000	1.000	1.000
2+ College (Father)	0.373	0.331	0.407	0.441
2+ College (Mother)	0.356	0.276	0.413	0.522
2+ College (Spouse)	0.355	0.381	0.361	0.222
STEM Major†	0.299	0.295	0.294	0.311
Occupation				
Full Time	0.872	0.872	0.880	0.844
Part Time	0.128	0.128	0.120	0.156
STEM Job	0.112	0.109	0.117	0.107
STEM Job (Father)	0.090	0.080	0.100	0.101
STEM Job (Mother)	0.015	0.008	0.021	0.026
STEM Job (Spouse)	0.048	0.052	0.049	0.030
Home Composition*				
Father & Mother	0.786	0.833	0.747	0.709
Father & Stepmother	0.016	0.015	0.018	0.017
Mother & Stepfather	0.044	0.027	0.060	0.062
Father only	0.017	0.011	0.019	0.038
Mother only	0.126	0.105	0.144	0.156
Male relative	0.001	0.001	0.001	0.001
Female relative	0.004	0.004	0.005	0.003
Male & Female relative	0.006	0.005	0.006	0.012
N	6172	3088	2390	694

Notes: *This refers to when the respondent was 16 years old. † refers to a restricted sample surveyed in 2012 or later. The respective sample sizes for each column are 1929, 641, 761, and 527. Column 1 refers to all college-experienced, working-aged, employed respondents. Column 2 restricts this sample to include only those belonging to the Baby Boomer generation. Column 3 restricts this sample to include only those belonging to Generation-X. Column 4 restricts to Millennials.

Among college-educated respondents, there were considerably more first-generation college goers in the Baby Boomer generation than there were in the Millennial generation. Among Baby Boomers, 32.2% of fathers have college experience. 44.7% of fathers to Millennials have college experience, representing an increase in the rate of college-going for fathers by nearly 39%. Over the same period, mothers increase their college-going rate by over twice that amount.

With respect to occupational outcomes, the proportion of full-time workers remains largely unchanged between generations; however, the rate of part-time workers increases by 24%. The fraction of respondents working in a STEM job is steady across generations. The fraction of fathers in a STEM job rose 2 points between the Baby Boomers and Millennials generations, while the fraction of mothers in STEM more than tripled (from 0.008 to 0.026). This increase represents significant gains, but it is important to note that the effects of mothers is being estimated from a very small sample.

Table 1.3: Distribution of Two-Parent Household Alternatives

	Total	Divorce	Death	Other*
Father & Stepmother	101	60 (59.41%)	39 (38.61%)	2 (1.98%)
Mother & Stepfather	270	225 (83.33%)	33 (12.22%)	12 (4.44%)
Father only	105	74 (70.48%)	26 (24.76%)	5 (4.76%)
Mother only	778	559 (71.85%)	165 (21.21%)	54 (6.94%)
Male relative	6	2 (33.33%)	0 (0.00%)	4 (66.67%)
Female relative	25	10 (40.00%)	0 (0.00%)	15 (60.00%)
Male & Female relative	38	10 (26.32%)	0 (0.00%)	28 (73.68%)
N	1323	940 (71.05%)	263 (19.88%)	120 (9.07%)

Notes: *This includes armed forces, institutional relocation, and other relocation circumstances. All information in the above table refers to the home composition of the respondent when they were 16 years old. Column 1 refers to all respondents that grew up in a home not containing both biological parents. Column 2 restricts the sample to those that experienced a broken home due to divorce. Column 3 restricts the sample to those that experienced a broken home due to death. Column 4 refers to those with missing parent(s) due to some type of relocation.

Table 1.3 documents household structures resulting from divorce and parent death. Consistent with the decline in marriage and the rise in divorce, the birth cohorts illustrate a decrease in being raised in two-parent home by 15.3% (Stevenson and Wolfers, 2007). Additionally, single-mother homes experience a 54.5% increase between generations. These home types largely result from divorces, with nearly 72% of divorces leading to the respondent predominantly living in a home without their father.

Finally, Table 1.4 provides the summary statistics for the respective analyses that follow. In each sample type, the gender balance remains relatively unchanged, as does the relative percent of respondents working in STEM jobs. Restricted to those with detailed information on their college major, nearly 30% of respondents overall major in STEM. The most striking difference across analysis samples is with regard to the respondent's father. Among those that grew up in a single-mother household, there is no information on fathers. Additionally, for those that experienced divorce (which resulted in the mother gaining custody, as evident by Table 1.3), fathers again are mostly absent. Despite fathers on average having college experience approximately 40% of the time, the sub-sample of respondents that experienced divorce show that 15% of their fathers have college experience. Despite this, the composition and outcomes of mothers remains consistent throughout. Importantly, mothers in STEM represent no more than 2.3% of all mothers in each sample.

Table 1.4: Occupation and Education Characteristics by Analysis Grouping

	Main Sample	2012-2018 Sample	Two-Parent HH	Parental Divorce	Single-Mother HH	Married
	(1)	(2)	(3)	(4)	(5)	(6)
Gender						
Male	0.475	0.456	0.484	0.445	0.441	0.506
Female	0.525	0.542	0.516	0.555	0.559	0.494
Education						
2+ College (Father)	0.373	0.381	0.435	0.157	0.000	0.378
2+ College (Mother)	0.356	0.410	0.361	0.382	0.366	0.336
STEM Major	0.094	0.299	0.090	0.103	0.098	0.097
STEM Job Type						
Respondent	0.112	0.106	0.116	0.103	0.095	0.117
Either Parent	0.102	0.112	0.113	0.062	0.022	0.106
Father	0.090	0.096	0.104	0.042	0.000	0.096
Mother	0.015	0.018	0.013	0.023	0.022	0.013
Spouse	0.048	0.046	0.053	0.028	0.024	0.090
N	6172	1929	4849	940	778	3299

Notes: This table tracks the occupational and educational outcomes based on the different analysis groups used in regressions. Column (1) refers to the main, restricted sample. Column (2) refers to those surveyed when the GSS asked specifically about college major. Column (3) refers to those that grew up with both biological parents. Column (4) refers to those whose parents divorced by the time they were 16 years old. Column (5) includes only those that grew up in a single-mother household. Column (6) includes those that were married at the time of the survey.

1.5 Empirical Strategy

To examine the relationships between children's and parent's academic and professional choices, I estimate linear probability models of the form:

$$STEMocc_i^R = \delta_0 + \delta_1 STEMocc_i^P + \delta_2 STEMocc_i^P \cdot Female_i + \delta_3 Female_i + Z_i'\gamma + \epsilon_i, \quad (1.1)$$

where $STEMocc_i^R$ denotes whether individual i has a STEM occupation at the time of survey, $STEMocc_i^P$ is a binary variable that denotes whether either of i's parents work in a STEM occupation, Z_i is a vector of control variables[10] and ϵ_i is the standard econometric error[11].

My primary analysis begins by estimating a baseline level of transmission between parents and their child omitting the gender interaction term. I then separately distinguish between the respondent's father's and mother's occupations. Finally, I interact both parent terms with gender to estimate the differential effect of each parent by gender. I test for generational differences by repeating this for each of the three generations.

[10]The controls contained in Z include family size at age 16 and indicators for the respondent's age, race, region of residence at age 16, generation, and survey year.

[11]In every regression, these errors are robust to heteroskedasticity.

1.6 Results

1.6.1 Main findings

Table 1.5 presents my main findings using the multi-generational sample. First, consider the baseline results in column (1). The estimated coefficient of $STEMocc^P$ is 0.05 and statistically significant, suggesting that growing up with a parent in a STEM occupation is associated with a 5 percentage point greater likelihood of working in a STEM job. Consistent with the well-established under-representation of women in STEM employment, I find an 11 percentage point gender gap in my GSS sample. Blacks are also less likely to hold a STEM job, as are individuals who grew up in larger families.

The results in column (2) indicate the influence of parent occupation is concentrated on sons. The estimated coefficient of $STEMocc^P$ is 0.09, while of the estimated coefficient of its interaction with the female indicator is -0.08. This suggests that sons who grow up with a parent who works in a STEM job are 9 percentage points more likely to work in STEM, while daughters are only 1 percentage point more likely to do the same.

I also find a meaningful difference in the influence of fathers and mothers. Column (3) shows that the effect of mothers in STEM occupation is nearly twice that of fathers in STEM – 8.1 versus 4.3 percentage points. Both coefficients are statistically significant at the 5 percent level. Column (4) shows these results are not accounted for by having a working mother.

Finally, I allow for heterogeneous father and mother occupation effects by child gender. The estimated main effect from column (5) for mothers is now triple that of fathers. However, there is some evidence that fathers are more influential in their daughters' decisions to enter STEM careers, as the estimated effect for $STEMocc^F$ is 1.6 percentage points, but -0.9 percentage points for $STEMocc^M$.

Next, I replicate the analysis in Table 1.5 for the Baby Boomer, Generation-X, and Millennial generations. Table 1.6 presents the Baby Boomer results. The baseline influence of having parents in STEM occupations is a little stronger than reported for the entire sample (column (1)). The estimated coefficient of $STEMocc^P$ is .057 and statistically significant. The gender gap decreases to about 9 percentage points and the estimates for the coefficients on race and family size become imprecise. Column (2) suggests that, for Baby Boomer daughters experience a marginally negative effect while sons experience a large, positive one. Based on column (3), the effect of mothers in STEM occupation is over three times that of fathers in STEM, representing an even greater level of influence for mothers among Boomer children. Finally, as column (5) shows, these effects appear to be driven by mothers. The effect of mothers for sons is still over three times that of fathers. Although the coefficient on $STEMocc^F$ interacted with female is not statistically significant, its associated t-statistic is 1.606.

While the Baby Boomer analysis mostly follows the overall pattern of results, the same is not true for Gen-Xers. The estimates in Table 1.7 indicate a generally weaker role for parent occupation on STEM employment. The baseline $STEMocc^P$ coefficient estimate is .037 and less precise. This suggests that respondents in this generation are less likely to draw influence from their parents when making their occupational decisions. Columns (3) and (4) suggest this as well, with neither $STEMocc^F$ or $STEMocc^M$ entering statistically significantly. Interacting these measures of occupation with gender also produces null results, as evident by columns (2) and (5). Despite this, column (2) continues to show a large, positive effect for sons[12]. While the parent-child relationship appears weaker in this generation, the gender gap is not. Among Generation-Xers, women are 12-13 percentage points less likely to work in a STEM job.

Finally, Table 1.8 presents results for Millennials. In terms of statistical significance, the results are similar to those of the Generation-X analysis. However, the null results among Millennials likely derives from the small sample size, leading to larger standard errors. Column (1) shows a continued null estimate for the coefficient on $STEMocc^P$. While the coefficient for parental occupation among Millennials is greater than that of Generation-Xers, the estimate is also more imprecisely measured. Column (2) shows that these results persist at the margin of gender, with older generations experiencing a greater impact. Based on column (3), neither parent's occupation significantly impacts the respondent's choice of obtaining a STEM job. With this, however, the coefficient on $STEMocc^M$ does continue to be larger than that of $STEMocc^F$. Based on columns (4) and (5), the effect from both growing up with a working mother and the interaction between gender and paternal occupation is not statistically significant. However, unlike any other generational results, Millennials show a negative association at the margin of gender between own STEM occupation and maternal STEM occupation, suggesting that mothers in STEM dissuade their daughters to similarly enter STEM by 7 percentage points.

Taken together, the results suggest two key findings: (1) Baby Boomers, comprising 50% of the multi-generational sample, drive the results in Table 1.5, and (2) the influence of STEM-employed parents varies by generation. For Baby Boomers, having parents working in STEM jobs is a strong predictor of their own STEM employment. For Gen-Xers and Millennials, the link is very weak. The reason for this may be that Baby Boomers relied on their parents for guidance and structure more so than Millennials, with Generation-Xers behaving as a muddied, transitional group.

[12] The associated t-statistic is over 1.5.

If role modeling varies by generation, it may also vary by household type; specifically, if a respondent grew up in a two- or one-parent household. In the next section, I analyze the effects of parental occupation on own occupation for respondents that did and did not grow up in a two-parent household[13].

[13]Here, "parent" refers to biological parents.

Table 1.5: Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0505***	0.0894***			
	(0.0149)	(0.0249)			
STEMocc^P * Fem		-0.0802***			
		(0.0292)			
STEMocc^F			0.0427***	0.0417***	0.0671***
			(0.0156)	(0.0157)	(0.0259)
STEMocc^M			0.0805**	0.0789*	0.198***
			(0.0403)	(0.0403)	(0.0763)
STEMocc^F * Fem					-0.0514*
					(0.0307)
STEMocc^M * Fem					-0.207**
					(0.0841)
Working Mom				0.0107	0.0105
				(0.00932)	(0.00931)
Female	-0.110***	-0.102***	-0.111***	-0.108***	-0.101***
	(0.00803)	(0.00834)	(0.00803)	(0.00808)	(0.00838)
Black	-0.0214*	-0.0212*	-0.0217*	-0.0223**	-0.0224**
	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0111)
Other Race	0.0530***	0.0537***	0.0525***	0.0563***	0.0576***
	(0.0184)	(0.0184)	(0.0185)	(0.0188)	(0.0188)
Family Size	-0.00295*	-0.00292*	-0.00293*	-0.00349**	-0.00340**
	(0.00166)	(0.00166)	(0.00166)	(0.00157)	(0.00157)
Constant	0.152***	0.151***	0.151***	0.149***	0.148***
	(0.0438)	(0.0438)	(0.0438)	(0.0446)	(0.0445)
N	6172	6172	6172	6061	6061

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents in the sample. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators and generation indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.6: Baby Boomers – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0569**	0.118***			
	(0.0226)	(0.0384)			
STEMocc^P * Fem		-0.126***			
		(0.0436)			
STEMocc^F			0.0464**	0.0459**	0.0954**
			(0.0231)	(0.0230)	(0.0389)
STEMocc^M			0.141*	0.135*	0.318**
			(0.0816)	(0.0806)	(0.157)
STEMocc^F * Fem					-0.0984**
					(0.0440)
STEMocc^M * Fem					-0.281
					(0.175)
Working Mom				0.0179	0.0169
				(0.0119)	(0.0119)
Female	-0.0924***	-0.0816***	-0.0929***	-0.0926***	-0.0824***
	(0.0111)	(0.0115)	(0.0111)	(0.0111)	(0.0115)
Constant	0.280**	0.288**	0.270**	0.269**	0.279**
	(0.116)	(0.115)	(0.118)	(0.120)	(0.118)
N	3088	3088	3088	3052	3052

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Baby Boomers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.7: Generation-X – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0370	0.0575			
	(0.0227)	(0.0373)			
STEMocc^P * Fem		-0.0425			
		(0.0448)			
STEMocc^F			0.0274	0.0276	0.0385
			(0.0242)	(0.0244)	(0.0391)
STEMocc^M			0.0461	0.0481	0.120
			(0.0550)	(0.0550)	(0.103)
STEMocc^F * Fem					-0.0239
					(0.0474)
STEMocc^M * Fem					-0.128
					(0.116)
Working Mom				0.00233	0.00240
				(0.0168)	(0.0167)
Female	-0.126***	-0.121***	-0.127***	-0.123***	-0.118***
	(0.0132)	(0.0138)	(0.0132)	(0.0134)	(0.0139)
Constant	0.153***	0.153***	0.154***	0.143**	0.140**
	(0.0571)	(0.0572)	(0.0574)	(0.0592)	(0.0589)
N	2390	2390	2390	2342	2342

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Generation-Xers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.8: Millennials – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^{P}	0.0620	0.0832			
	(0.0433)	(0.0708)			
STEMocc^{P} * Fem		-0.0420			
		(0.0848)			
STEMocc^{F}			0.0642	0.0624	0.0539
			(0.0481)	(0.0491)	(0.0759)
STEMocc^{M}			0.0688	0.0735	0.219
			(0.0888)	(0.0890)	(0.161)
STEMocc^{F} * Fem					0.0170
					(0.0966)
STEMocc^{M} * Fem					-0.289^{*}
					(0.166)
Working Mom				-0.00940	-0.00938
				(0.0346)	(0.0346)
Female	-0.133^{***}	-0.128^{***}	-0.133^{***}	-0.129^{***}	-0.123^{***}
	(0.0258)	(0.0268)	(0.0258)	(0.0263)	(0.0273)
Constant	-0.0415	-0.0381	-0.0410	-0.0323	-0.0304
	(0.173)	(0.173)	(0.173)	(0.177)	(0.176)
N	694	694	694	667	667

Heteroskedasticity-robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Millennials in the sample. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

1.6.2 Household Structure

Next, I test for differential effects by household structure. More specifically, I conduct analyses on three separate types of respondents: those that grew up with both biological parents (two-parent households), those that grew up in one-parent households because of divorce, and those that grew up with only one biological parent (one-parent households)[14]. While not an exact subset, divorce is a good predictor for growing up in a single-mother household. As Table 1.3 demonstrated, nearly 79% of respondents grew up in a two-parent household[15] and among those that grew up in a one-parent household, the most common structure involved only their mother. Among the single-mother cases, the mechanism leading to the structure was most commonly divorce. I test for differential effects among these three distinct household types.

Table 1.9 presents the results for respondents that lived in a two-parent household at age 16. Given that the majority of respondents in the sample fall in this category, the results unsurprisingly mirror those from Table 1.5, although the effects for daughters appear to be slightly greater. Column (1) shows that parents in general tend to increase their child's likelihood of working in STEM by about 5 percentage points. Column (2) shows that, for women, this effect is close to 2 percentage points. Columns (3) and (4) make clear that both parents significantly influence their children and that mothers matter over twice as much. These estimates do not appear to be driven by the presence of a working mother in adolescence. Finally, columns (5) suggests that the differential treatment among these household types at the margin of gender is considerably weaker than those estimated in Table 1.5.

[14] The reason for these three groups is that (1) two-parent households are most common, (2) divorce is the most typical reason to not experience a two-parent household, and (3) the most common result of a divorce is a single-mother household.

[15] Calculated as a fraction of those not growing up in a two-parent household (1323) over the total sample (6172).

Next, I consider the most prominent mechanism that results in a single-parent household: divorce. I make no distinction between which parent loses custody and which remains in the household. Instead, I test for effects different than those from Table 1.4 among respondents that experienced divorce by the time they were 16 years old. Table 1.10 reports these estimates. I find both overall and individual parent effects to be indistinguishable from zero, as evident from columns (1), (3), and (4). However, similar to the effects found earlier, daughters receive maternal influence differently. Column (2) shows that daughters exposed to a parent working in STEM are about 4 percentage points less likely to follow suit. The effect for sons is large, albeit imprecisely estimated. Given that column (5) shows no effect between daughters and fathers, these results are again likely driven by mothers. Between mothers and sons, the results continue to suggest a strong, influential relationship.

I lastly consider those raised in a single-mother household – the most common household structure resulting from divorce. As Table 1.3 shows, 58.8% of household shocks result in a single-mother household. I make no distinction between the mechanism that resulted in the absence of the respondent's father. Table 1.11 presents these results. The coefficients on variations of $STEMocc^F$ cannot be estimated due to the absence of fathers among those that live with only their mothers. Column (1) shows no evidence for a significant effect from maternal occupation, but column (3) suggests this may be because these effects channel through daughters. Women that grew up in a single-mother household are approximately 1 percentage point less likely to enter a STEM job if their mother did.

These results have serious implications for the baseline results presented in Table 1.5. For one, it appears that two-parent households likely mask much of the heterogeneity present in the sample, especially in the case of gender-specific effects. For single-mother households, a negative relationship appears between mothers and daughters. Similarly, among children of divorce, mothers influence daughters negatively and their influence tends to be stronger than that of fathers.

Table 1.9: Two-Parent Households – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0492***	0.0777***			
	(0.0162)	(0.0263)			
STEMocc^P * Fem		-0.0602*			
		(0.0317)			
STEMocc^F			0.0412**	0.0413**	0.0631**
			(0.0166)	(0.0166)	(0.0271)
STEMocc^M			0.0956*	0.0918*	0.161*
			(0.0530)	(0.0531)	(0.0845)
STEMocc^F * Fem					-0.0451
					(0.0325)
STEMocc^M * Fem					-0.140
					(0.103)
Working Mom				0.0153	0.0152
				(0.0101)	(0.0101)
Female	-0.108***	-0.102***	-0.109***	-0.109***	-0.102***
	(0.00913)	(0.00956)	(0.00913)	(0.00913)	(0.00955)
Constant	0.255***	0.249***	0.252***	0.253***	0.248***
	(0.0485)	(0.0485)	(0.0485)	(0.0484)	(0.0484)
N	4849	4849	4849	4849	4849

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents that grew up in a two-parent household. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Race effects and family size effects are omitted as well. Year-of-survey indicators and generation indicators are also included. In column (1), the regressor of interest is whether either parent has a STEM job. Column (2) includes an interaction on this term with female. Columns (3)-(5) separate parents, with the latter including interaction terms.

Table 1.10: Parental Divorce – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0268	0.112			
	(0.0431)	(0.0889)			
STEMocc^P * Fem		-0.156*			
		(0.0916)			
STEMocc^F			-0.00283	-0.00103	0.0195
			(0.0484)	(0.0506)	(0.103)
STEMocc^M			0.0712	0.0733	0.451**
			(0.0732)	(0.0728)	(0.178)
STEMocc^F * Fem					-0.0141
					(0.107)
STEMocc^M * Fem					-0.521***
					(0.178)
Working Mom				-0.0174	-0.0181
				(0.0433)	(0.0436)
Female	-0.125***	-0.116***	-0.126***	-0.117***	-0.106***
	(0.0208)	(0.0215)	(0.0210)	(0.0214)	(0.0218)
Constant	0.212*	0.216**	0.209*	0.229*	0.240**
	(0.109)	(0.109)	(0.109)	(0.122)	(0.122)
N	940	940	940	864	864

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents that grew up in a single-parent household caused by divorce. In columns (1)-(5), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Race effects and family size effects are omitted as well. Year-of-survey indicators and generation indicators are also included. In column (1), the regressor of interest is whether either parent has a STEM job. Column (2) includes an interaction on this term with female. Columns (3)-(5) separate parents, with the latter including interaction terms.

Table 1.11: Single Mothers – Differential Effects of Parental Influence on STEM Occupation

	(1)	(2)	(3)
STEMocc^{M}	0.125	0.125	0.501^{**}
	(0.101)	(0.101)	(0.195)
STEMocc^{M} * Fem			-0.575^{***}
			(0.195)
Working Mom		-0.00726	-0.00557
		(0.0451)	(0.0451)
Female	-0.115^{***}	-0.115^{***}	-0.103^{***}
	(0.0225)	(0.0225)	(0.0223)
Constant	0.229^{**}	0.236^{**}	0.236^{**}
	(0.108)	(0.117)	(0.117)
N	778	778	778

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents that grew up in a single-mother household. There is no measure of father occupation because paternal influence is dropped due to multicollinearity. Thus, overall parent effects equate to maternal effects. In columns (1)-(3), the dependent variable is whether the respondent's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Race effects and family size effects are omitted as well. Year-of-survey indicators and generation indicators are also included. In column (1), the regressor of interest is whether the mother has a STEM job. Column (2) includes an interaction on this term with female. Columns (3) controls for the respondent growing up with a working mother.

1.6.3 Education Results

Given the limited information in the GSS, these estimates still rely on parental occupation, not parental education. Additionally, because choice of major did not appear in the GSS before 2012, this sample contains only those surveyed 2012 or later, resulting in a total sample of 1929 respondents.

Using this sample of the GSS, I estimate the parental influence internalized before entering the labor market. I utilize information on college major, available beginning in 2012, to measure the impact of parent STEM occupation on degree choice. Ideally, I would analyze the effects of parent college major on their child's college major, contextualized to STEM. In its current form, the GSS does not survey on parent education beyond the level of education achieved.

Table 1.12 gives the results for STEM education on the multi-generational sample. Between columns (1) and (2), the results suggest that parental occupation matters most on the margin of gender, specifically for daughters. The gender gap in education from the baseline estimates are nearly identical to those from the occupation setting (a difference of 9-10 percentage points). However, in the educations setting, the sign on parental occupation becomes negative, indicating that a respondent with a STEM parent less likely graduates college with a STEM degree. Column (3) shows that each parent's effect on college major is measured imprecisely, with column (4) confirming that these effects are not driven particularly by growing up with a working mother. Finally, column (5) shows evidence of heterogeneous role modeling by gender. The magnitude for $STEMocc^F$ interacted with gender is greater than the same for $STEMocc^M$ and is significant at the 5% level. In summary, women are consistently less likely to major in STEM and growing up with a parent who works in a STEM job further diminishes the prospects. The question is why.

The results from 1.12 appear to be relatively consistent among Baby Boomers. Table 1.13 gives the results for Baby Boomers and shows that again the overall parental effect appear to be negligible, even among women. Columns (3) and (4) show that the negative association between mothers and their college-aged children is greater among Baby Boomers. In fact, I estimate that mothers in STEM decrease the likelihood their Baby Boomer child will work in STEM by nearly 25 percentage points. Column (5) suggests that this is not driven by any particular gender effect.

Table 1.14 implies Generation-Xers do not follow these trends. In columns (1)-(5), no point estimate is precisely estimated. Even at the margin of gender, little evidence exists to suggest a relationship between parental occupation and a child's likelihood to have a STEM major. However, the same cannot be said for Millennials. Indeed, as Table 1.15 shows, Millennials exhibit the same relationships found among Baby Boomers. Again, as column (2) shows, a daughter is estimated to be 12 percentage points less likely to major in STEM given that she has any parent that works in STEM. The estimated effect for sons is instead a positive 19.7 percentage points. These results are consistent at both the father-daughter and mother-daughter level. The total occupational effect from fathers on daughters is estimated to be -8.3 percentage points. For mothers, it becomes -25.4 percentage points.

The results from the education analysis present two major findings. For one, it does not appear that sons derive much influence from their parents' occupations when making college decisions. Secondly, it appears that daughters respond most severely to their mothers' occupation. The reason for the negative relationship may be any of a number of internalized signals. One explanation could be that daughters view their mothers experiencing dissatisfaction in their careers and decide well before entering the job market that they do not want to pursue STEM. Another reason could be that the mother's pathway to her STEM job did not rely on a STEM major in college, and so daughters too value work experience over classroom experience.

Table 1.12: Differential Effects of Parental Influence on STEM Education

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	-0.0178	0.0605			
	(0.0333)	(0.0501)			
STEMocc^P * Fem		-0.164**			
		(0.0645)			
STEMocc^F			-0.00392	-0.00652	0.0685
			(0.0357)	(0.0364)	(0.0539)
STEMocc^M			-0.0707	-0.0715	-0.00451
			(0.0731)	(0.0738)	(0.115)
STEMocc^F * Fem					-0.164**
					(0.0703)
STEMocc^M * Fem					-0.108
					(0.148)
Working Mom				0.0133	0.0105
				(0.0281)	(0.0281)
Female	-0.0983***	-0.0798***	-0.0975***	-0.101***	-0.0835***
	(0.0214)	(0.0228)	(0.0214)	(0.0217)	(0.0231)
Constant	0.495*	0.490*	0.495*	0.475*	0.472*
	(0.283)	(0.286)	(0.284)	(0.283)	(0.286)
N	1929	1929	1929	1878	1878

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents in the sample. In columns (1)-(5), the dependent variable is whether the respondent's college major classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators and generation indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.13: Baby Boomers – Differential Effects of Parental Influence on STEM Education

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	-0.0663	0.0313			
	(0.0601)	(0.109)			
STEMocc^P * Fem		-0.173			
		(0.125)			
STEMocc^F			-0.0423	-0.0324	0.0654
			(0.0639)	(0.0652)	(0.115)
STEMocc^M			-0.247***	-0.265***	-0.267**
			(0.0544)	(0.0590)	(0.106)
STEMocc^F * Fem					-0.176
					(0.134)
STEMocc^M * Fem					0.0259
					(0.131)
Working Mom				0.0202	0.0174
				(0.0424)	(0.0426)
Female	-0.139***	-0.124***	-0.138***	-0.143***	-0.128***
	(0.0374)	(0.0392)	(0.0374)	(0.0377)	(0.0396)
Constant	0.516***	0.504***	0.512***	0.508***	0.500***
	(0.167)	(0.167)	(0.167)	(0.173)	(0.173)
N	641	641	641	631	631

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Baby Boomers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's college major classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.14: Generation-X – Differential Effects of Parental Influence on STEM Education

	(1)	(2)	(3)	(4)	(5)
$STEMocc^{P}$	-0.0139	0.000436			
	(0.0540)	(0.0743)			
$STEMocc^{P}$ * Fem		-0.0340			
		(0.107)			
$STEMocc^{F}$			-0.0176	-0.0134	0.00996
			(0.0578)	(0.0588)	(0.0797)
$STEMocc^{M}$			0.0627	0.0661	0.0282
			(0.133)	(0.135)	(0.192)
$STEMocc^{F}$ * Fem					-0.0621
					(0.114)
$STEMocc^{M}$ * Fem					0.0596
					(0.265)
Working Mom				0.0387	0.0380
				(0.0439)	(0.0440)
Female	-0.106***	-0.102***	-0.107***	-0.115***	-0.111***
	(0.0342)	(0.0364)	(0.0342)	(0.0349)	(0.0371)
Constant	0.454***	0.452***	0.449***	0.400**	0.398**
	(0.153)	(0.154)	(0.154)	(0.157)	(0.157)
N	761	761	761	740	740

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Generation-Xers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's college major classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.15: Millennials – Differential Effects of Parental Influence on STEM Education

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0443	0.197**			
	(0.0612)	(0.0889)			
STEMocc^P * Fem		-0.318***			
		(0.114)			
STEMocc^F			0.0800	0.0627	0.193**
			(0.0678)	(0.0699)	(0.0975)
STEMocc^M			-0.0889	-0.0867	0.0860
			(0.103)	(0.105)	(0.173)
STEMocc^F * Fem					-0.276**
					(0.130)
STEMocc^M * Fem					-0.340*
					(0.187)
Working Mom				-0.0238	-0.0351
				(0.0735)	(0.0742)
Female	-0.0345	0.0101	-0.0336	-0.0225	0.0190
	(0.0418)	(0.0451)	(0.0418)	(0.0426)	(0.0459)
Constant	0.403	0.403	0.399	0.420	0.432
	(0.290)	(0.295)	(0.290)	(0.298)	(0.305)
N	527	527	527	507	507

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents in the sample. In columns (1)-(5), the dependent variable is whether the respondent's college major classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

1.6.4 Parent Occupation and Occupation Matching in Marriage

Marriage market effects act as a competing explanation to role modeling. Especially in the labor market, there may be a trade-off in terms of where agents derive influence. The transition between following parental signals and matching with a potential partner on the basis of skill and interest has been well-documented in the literature. As Fernández et al. (2004) show, sons that grew up with a working mother tend to marry wives that also work, which in turn increases female labor force participation. Motivated by this finding, I test for the impact of parental occupation on the likelihood an agent similarly marries a STEM-working partner among married respondents. To do so, I change the left-hand variable in equation (1.1) to $STEMocc_i^S$, an indicator for whether the respondent's spouse works in STEM. The results from these regressions support or refute role modeling in contrast to assortative matching. Given the change in outcome, I cannot directly compare the estimates to those of Table 1.4.

Table 1.16 gives the baseline estimates for the new analysis. Column (1) shows that parental occupation does not predict the marriage of a STEM-employed partner. The gender gap reverses compared to the past analyses. Although the GSS does not include a measure for sexual orientation, I assume most if not all marriages in the GSS are heterosexual given that the sample is representative of U.S. demographics. From this, the gender sign should flip, as women would marry STEM-employed men. Blacks continue to marry into STEM less frequently and Asians more frequently. According to column (2), there is no special influence in spousal occupation for women. Column (3) shows that, while neither parent appears to be a significant source of influence, mothers again matter most. Finally, column (5) shows that these trends continue at the margin of being a woman.

These results indicate that assortative matching may not be the operating mechanism in STEM occupation. However, as evident from the main findings, these results can be masked by stark generational differences. I next conduct the same analyses, conditioning on generation.

Table 1.17 provides the regression results for spousal occupation analyses among Baby Boomers. In terms of statistical significance, the results in each column are identical to those in Table 1.12. The magnitude of the coefficient in column (1) is smaller. In columns (3) and (4), the coefficient on $STEMocc^M$ exceeds that of $STEMocc^F$, although both are imprecisely measured. The similarity to Table 1.12 implies that Boomers may once again be driving the baseline results. Table 1.18 gives the estimates among Generation-Xers. The main difference between these results and those of the Baby Boomers is that the coefficient on $STEMocc^M$ becomes significant when the interaction term is included.

Table 1.19 gives the results for Millennials. Column (1) shows a negative association between parental occupation and spousal STEM occupation, significant at the 5% level. Column (2) shows that this trend does not persist at the margin of gender. When separating parental occupation by parent, the negative, significant association continues for both parents. Again, the effect from mothers is nearly twice that of fathers. Both tend to significantly decrease the likelihood of having a STEM spouse. Column (5) shows that these patterns may not be driven by daughters specifically.

These results can be interpreted together along with the baseline results. In the spouse setting, Baby Boomers continue to drive the main results. The multi-generational analyses show that there may be a trade-off in the source of influence respondents have in their occupation. Specifically, Baby Boomers appear to more likely follow their parents' occupational choices when deciding their own. On the other hand, Millennials seem to prefer spouses that do not match their parent's occupations. This may be driven by Millennials not following their parent's occupational cues in general. There may be preferences among this birth cohort to pursue jobs not yet pursued in the family. On that basis, there may still exist assortative matching effects, but they are not evident in the context of STEM.

Table 1.16: Differential Effects of Parental Influence on Spouse STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0114	0.00507			
	(0.0169)	(0.0180)			
STEMocc^P * Fem		0.0137			
		(0.0343)			
STEMocc^F			0.0147	0.0110	0.000136
			(0.0173)	(0.0172)	(0.0181)
STEMocc^M			0.0345	0.0364	0.0107
			(0.0561)	(0.0561)	(0.0696)
STEMocc^F * Fem					0.0238
					(0.0360)
STEMocc^M * Fem					0.0349
					(0.101)
Working Mom				0.00455	0.00466
				(0.0115)	(0.0115)
Female	0.0909***	0.0894***	0.0907***	0.0906***	0.0879***
	(0.0101)	(0.0106)	(0.0101)	(0.0102)	(0.0106)
Constant	0.0150	0.0133	0.0128	0.0136	0.0109
	(0.0558)	(0.0563)	(0.0559)	(0.0556)	(0.0563)
N	3299	3299	3299	3253	3253

Heteroskedasticity-robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all respondents in the sample. In columns (1)-(5), the dependent variable is whether the respondent's spouse's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators and generation indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.17: Baby Boomers – Differential Effects of Parental Influence on Spouse STEM Occupation

	(1)	(2)	(3)	(4)	(5)
STEMocc^P	0.0267	0.00543			
	(0.0259)	(0.0260)			
STEMocc^P * Fem		0.0463			
		(0.0535)			
STEMocc^F			0.0152	0.0145	-0.00513
			(0.0255)	(0.0256)	(0.0253)
STEMocc^M			0.186	0.186	0.108
			(0.114)	(0.114)	(0.155)
STEMocc^F * Fem					0.0409
					(0.0540)
STEMocc^M * Fem					0.118
					(0.218)
Working Mom				-0.000977	-0.000790
				(0.0144)	(0.0145)
Female	0.0964***	0.0922***	0.0954***	0.0955***	0.0911***
	(0.0136)	(0.0141)	(0.0136)	(0.0137)	(0.0141)
Constant	-0.00200	0.000617	-0.00773	-0.00741	-0.00327
	(0.0467)	(0.0462)	(0.0463)	(0.0484)	(0.0478)
N	1836	1836	1836	1822	1822

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Baby Boomers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's spouse's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.18: Generation-X – Differential Effects of Parental Influence on Spouse STEM Occupation

	(1)	(2)	(3)	(4)	(5)
$STEMocc^P$	0.0128	0.00856			
	(0.0274)	(0.0302)			
$STEMocc^P$ * Fem		0.00951			
		(0.0567)			
$STEMocc^F$			0.0247	0.0181	0.00647
			(0.0293)	(0.0286)	(0.0307)
$STEMocc^M$			-0.0459	-0.0418	-0.0875***
			(0.0595)	(0.0593)	(0.0336)
$STEMocc^F$ * Fem					0.0277
					(0.0635)
$STEMocc^M$ * Fem					0.0556
					(0.0774)
Working Mom				0.0145	0.0146
				(0.0205)	(0.0204)
Female	0.0864***	0.0853***	0.0883***	0.0867***	0.0833***
	(0.0172)	(0.0180)	(0.0173)	(0.0173)	(0.0180)
Constant	-0.0169	-0.0183	-0.0235	-0.0220	-0.0255
	(0.0836)	(0.0848)	(0.0827)	(0.0835)	(0.0847)
N	1215	1215	1215	1192	1192

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Generation-Xers in the sample. In columns (1)-(5), the dependent variable is whether the respondent's spouse's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

Table 1.19: Millennials – Differential Effects of Parental Influence on Spouse STEM Occupation

	(1)	(2)	(3)	(4)	(5)
$STEMocc^P$	-0.0919**	-0.0585			
	(0.0356)	(0.0548)			
$STEMocc^P$ * Fem		-0.0595			
		(0.0732)			
$STEMocc^F$			-0.0848**	-0.0962**	-0.0768
			(0.0353)	(0.0371)	(0.0661)
$STEMocc^M$			-0.157*	-0.164*	-0.0871
			(0.0932)	(0.0961)	(0.0682)
$STEMocc^F$ * Fem					-0.0344
					(0.0852)
$STEMocc^M$ * Fem					-0.310
					(0.202)
Working Mom				0.0272	0.0280
				(0.0510)	(0.0510)
Female	0.0344	0.0434	0.0328	0.0341	0.0426
	(0.0360)	(0.0425)	(0.0365)	(0.0377)	(0.0430)
Constant	0.186	0.186	0.190	0.193	0.205
	(0.132)	(0.132)	(0.132)	(0.158)	(0.160)
Observations	248	248	248	239	239

Heteroskedasticity-robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports regression results for all Millennials in the sample. In columns (1)-(5), the dependent variable is whether the respondent's spouse's occupation classifies as STEM. Age and adolescent regional effects are omitted from the table, which have been controlled for with dummy variables. Year-of-survey indicators are also included. "Other Race" refers to non-white and non-black respondents. White is omitted to avoid multicollinearity. In columns (1) and (2), the regressor of interest is whether either parent has a STEM job. In columns (3) and (4), the regressors of interest are both separated parent job measurements. Column (5) has the same two regressors of interest, now with a female indicator.

1.7 Conclusion

The gender gap in STEM has been studied for decades, yet no consensus exists on the determinants of this gap. Much of the previous literature looks at various sources within schools and within jobs to explain the gap. Class composition, teacher and professor gender, industry gender composition, and reinforced ability measurements have all been found to explain, in part, the current disparity between men and women in the STEM industry. What remains unclear, however, is the role parents play as role models for their children's careers.

Separating role-modeling effects from other ways parents influence their children is challenging. For one, ability is at least partially transmitted genetically between parents and children matters. Many STEM jobs require high cognitive ability, measures of which remain unobservable in many data sets. My analysis of the effects of growing up in a household with a parent working in a STEM occupation will inevitably represent some mixture of their influence as professional role models and their genetic legacy. Secondly, separately identifying paternal and maternal transmission requires variation that effectively eliminates one parent entirely. In addition, household variation may have its own direct effect on occupational choice. For agents that grew up with both parents, both of whom work in STEM, it may be impossible to identify which parent matters most in the child's decision to also work in STEM or to pivot out of STEM.

I first estimate baseline levels of influence among a multi-generational sample and find that parents positively influence their children to enter STEM if they too work in it. I find the impact to be greater among mothers that work in STEM. These results are driven by generational differences. Baby Boomers, representing 50% of my sample, follow these trends exactly while Millennials seem to take negligible influence from their parents as role models.

I then test for differential role modeling effects in different household structures. I do this in three distinct settings: two-parent households, single-mother households, and one-parent households resulting from divorce. I find the results from two-parent households to largely match those of the main analysis, with the other two household types suggesting that daughters negatively associate their mother's career when deciding on their own.

In the education space, the results point towards daughters interacting strongly with their parents. Across generations, parents in general and mothers working in STEM have a negative effect on daughters' propensities to enter STEM in college. Among Millennials especially, daughters and mother demonstrate a negative relationship. Future research can improve on this analysis by instead using data on parental college major.

I finally consider a separate mechanism, spousal influence, in conjunction with parental influence. Among the multi-generational sample, little evidence suggests the existence of spousal influence; however, after considering each generation in isolation, it seems that Millennials do derive influence from sources other than their parents. The combination of parent effects and potential spouse effects suggest a trade-off in influence source. Older respondents seem to look to their parents for occupational guidance; younger respondents do not.

While the results of this paper cannot be interpreted causally due to data limitations, they do shed novel light on a particularly unusual source of explanation for the gender gap in STEM. Future research can improve on this design by utilizing panel data and tracking respondents from adolescence to adulthood. Additionally, within-family variation could be accounted for by having information on both a respondent's parents and grandparents. Having exact timing on household shocks would also provide crucial information to better understand the exact dosages of either parent's influence a child receives.

In doing so, future scholars may be able to determine the causal effect of parental occupation on their child's decision to enter STEM. The results from this research may provide clarity in the main cause of the gender gap in STEM.

Appendix A

Full List of STEM Jobs

The full list of STEM jobs: sales engineers, miscellaneous life, physical, and social science technicians, nuclear technicians, geological and petroleum technicians, chemical technicians, biological technicians, agricultural and food science technicians, physical scientists, all other, environmental scientists and geoscientists, chemists and materials scientists, atmospheric and space scientists, astronomers and physicists, life scientists, all other, medical scientists, conservation scientists and foresters, biological scientists, agricultural and food scientists, surveying and mapping technicians, engineering technicians, except drafters, drafters, engineers, all other, petroleum engineers, nuclear engineers, mining and geological engineers, including mining safety engineers, mechanical engineers, materials engineers, marine engineers and naval architects, industrial engineers, including health and safety, environmental engineers, electrical and electronics engineers, computer hardware engineers, civil engineers, chemical engineers, biomedical engineers, agricultural engineers, aerospace engineers, surveyors, cartographers, and photogrammetrists, architects, except naval, miscellaneous mathematical science occupations, statisticians, operations research analysts, mathematicians, actuaries, computer occupations, all other, computer network architects, network and computer systems administrators, database administrators, computer support specialists, web developers, software developers, applications and systems software, computer programmers, information security analysts, computer systems analysts, computer and information research scientists, natural sciences managers, architectural and engineering managers, and computer and information systems managers.

Appendix B

Full List of STEM Majors

The full list of STEM majors: information technology, electronics, statistics/biostatistics, aviation/aeronautics, environmental science/ecology, food science/nutrition/culinary arts, health, general sciences, veterinary medicine, psychology, physics, pharmacy, mathematics, industry & technology, forestry, engineering, computer science, chemistry, biology, architecture, and agriculture/horticulture.

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