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A Tale of Two Majors: Explaining the Gender Gap in STEM Employment among Computer Science and Engineering Degree Holders

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Abstract: We examine factors contributing to the gender gap in employment in science, technology, engineering, and math (STEM) among men and women with bachelor's degrees in computer science and engineering, the two largest and most male-dominated STEM fields. Data come from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT) from 1995 to 2008. Different factors are associated with persistence in STEM jobs among computer science and engineering degree holders. Conditional on receiving a degree in computer science, women are 14 percentage points less likely to work in STEM than their male counterparts. Controlling for demographic and family characteristics did little to change this gender gap. Women with degrees in engineering are approximately 8 percentage points less likely to work in STEM than men, although about half of this gap is explained by observed differences between men and women. We document a widening gender gap in STEM employment in computer science, but this gender gap narrows across college cohorts among those with degrees in engineering. Among recent computer science graduates, the gender gap in STEM employment for white, Hispanic, and black women relative to white men is even larger than for older graduates. Gender and race gaps in STEM employment for recent cohorts of engineering graduates are generally small, though younger Asian women and men no longer have an employment advantage relative to white men. Our results suggest that a one-size-fits-all approach to increasing women's representation in the most male-dominated STEM fields may not work.

Keywords: gender; scientists and engineers; STEM employment; gender inequality

1. Introduction

During the later third of the 20th century, the science and technology labor force diversified in important ways. Women's graduation rates in science, technology, engineering, and mathematics (STEM) increased between two and ten times since the 1970s (Committee on Maximizing the Potential of Women in Academic Science and Engineering (U.S.) and Committee on Science, Engineering, and Public Policy (U.S.) (2007)). However, even among women who held degrees in STEM fields, employment in STEM jobs continues to lag that of their male counterparts. Women who graduate with degrees in STEM majors are less likely than their male counterparts to enter STEM occupations, or remain in them (Glass et al. 2013; Ma and Savas 2014; Mann and DiPrete 2013; Sassler et al. 2017). Historically, women were often discouraged from pursuing employment outside the home, particularly in jobs—such as those in STEM—typically thought of as "masculine" (Robinson and McIlwee 1991).

Gender differences in human capital accumulation, occupational concentration, work history, and discrimination also differentiated the likelihood that women worked in STEM jobs. As women have increased their participation in the workforce and obtained college and advanced degrees, some of these explanations have faded in importance; others, such as differences in the working patterns of men and women, continue to have an impact on earnings differentials (Blau and Kahn 2006; Mandel and Semyonov 2014) and occupational attainment (Weeden et al. 2016).

Tremendous resources have been devoted to increasing women's representation in STEM employment (Committee on Maximizing the Potential of Women in Academic Science and Engineering (U.S.) and Committee on Science, Engineering, and Public Policy (U.S.) (2007)). Such efforts are based on the belief that increasing women's representation in STEM occupations will encourage more women to pursue such fields of study, and remain in the STEM work force (Fouad et al. 2011; Hill et al. 2010). The increased representation of women could also have the long-term effect of diversifying leadership in STEM jobs, and expanding women's access to mentoring and leadership positions (Preston 2004; Stephan and Levin 2005). In fact, among the most widely cited impediments to greater diversification of the STEM labor force are perceptions of being isolated, reported by many women who are employed in fields, such as engineering and computer science, where their representation is the smallest (Fouad et al. 2011; Gunter and Stambach 2005; Kanter 1977; Michelmore and Sassler 2016). Others attribute the dearth of women in some STEM fields, and disparities in wages, to discrimination, though the evidence suggests that discrimination has diminished as a contributor to the gender earnings gap, if not to the employment gap in particular fields (Mandel and Semyonov 2014; Michelmore and Sassler 2016). Despite a good deal of public discourse on the challenging climate facing women in computer science and engineering, additional empirical research is needed to better understand what factors contribute to the gender employment gap in these fields.

In the two largest and most male-dominated STEM fields, computer science and engineering, there have been opposing demographic shifts in the composition of degree holders over time. In computer science, the representation of women as a share of degree holders has fallen significantly even as the composition of female graduates has diversified. Women made up over one-third of graduates in the mid-1980s; in recent years, that share has fallen. By 2013, the share of bachelor's degrees in computer science that were being awarded to women was only half of what it had been in the 1980s (Corbett and Hill 2015). In engineering, in contrast, the opposite trend is seen. Although still heavily male-dominated, women have increased their representation in engineering ten-fold since 1970, going from 2% of majors in 1970, to 22% of majors in 2004 (Michelmore and Sassler 2016). However, degree receipt alone is not an adequate proxy of success in increasing shares of women in employment, as numerous studies make clear (e.g., Corbett and Hill 2015; Glass et al. 2013; Sassler et al. 2017). How these demographic shifts in the composition of STEM graduates have affected the gender gap in employment in STEM is an empirical question.

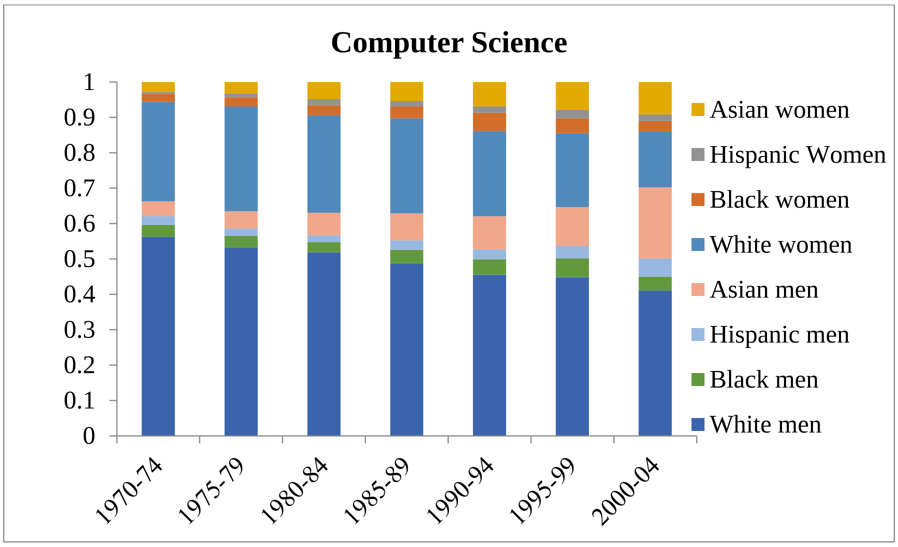
In this paper, we answer this question by examining the factors that contribute to the gender gap in STEM employment among those who received a bachelor's degree in computer science or engineering over the last four decades. We focus our analysis on these two fields because they represent the largest share of STEM jobs and are the two STEM fields in which women make up the smallest share of college majors. Using data from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT) from 1995 to 2008, we first illustrate the large demographic shifts that occurred in these two fields between 1970 and 2004—with computer science experiencing a large decline in the number of female degree holders, and engineering experiencing an increase in women degree holders. We then document the overall gender gap in persistence in STEM occupations among these individuals, testing to what extent gaps can be explained by differences in observable characteristics between men and women. Finally, we analyze how the large demographic shifts in the composition of computer science and engineering degree holders has influenced the gender gap in STEM employment over time through a cohort analysis.

Results from our analysis shed light on the factors associated with persistence in STEM occupations, and how the gender gap in persistence in STEM has changed over the last several decades. Our results reveal two distinct portraits of women's experiences in the two largest and most male-dominated STEM fields. Among recent cohorts, women's representation of computer science graduates has declined. Women who *do* obtain degrees in computer science are increasingly less likely to work in STEM occupations relative to their male peers. In contrast, as women have increased their representation in engineering over the last several decades, gender gaps in working in STEM appear to have stabilized. As a result, the share of women graduates who work in engineering is at near parity with men in recent cohorts. Our results suggest that the barriers to employment for women in computer science likely differ from those deterring even larger increases in women's representation in engineering. Such findings highlight the very real need to address roadblocks—such as a challenging and often unwelcoming work climate, gender bias and discriminatory treatment, and the negation of relationship and family responsibilities—that deter more women from majoring in and remaining in computer science jobs.

2. Understanding the Gender Gap in Women's Employment in STEM Occupations

Among one of the more frequent explanations for why women were underrepresented in STEM professions in the closing decades of the 20th century was one that drew on gender essentialism, namely that women were less interested in STEM topics, and therefore unlikely to pursue the training necessary to work in the STEM labor force. Historically, women who pursued bachelor's degrees have been far less likely than men to major in STEM, instead obtaining degrees in humanities or liberal arts subjects (Shauman 2006; Xie and Killewald 2012). A gender essentialist argument overlooks the social nature of gender, and the many barriers that prevented women's entrance into STEM studies and occupations (Charles and Grusky 2004). In fact, the gender composition of STEM fields varies a great deal across countries (Charles and Bradley 2006; Charles and Bradley 2009), suggesting cross-cultural variation in occupations that are considered "masculine" or "feminine." In recent years, there has been a substantial increase in the proportion of female STEM graduates in the United States. In the early years of the 21st century, women accounted for the majority of all college graduates with degrees in the life sciences, and approximately 40% of those graduating with degrees in the physical sciences (Michelmore and Sassler 2016).

In computer science and engineering, women continue to make up a distinct minority of graduates: women account for approximately one-third of graduates in computer science, and one-fifth of graduates in engineering. Women's representation in computer science, however, has actually declined in recent years. We illustrate this in Figure 1, where we present the gender and race composition of computer science and engineering degree holders since 1970. Computer science has become more male-dominated in recent years, due in large part to an influx of Asian men into the computer science major. White women's representation in computer science, on the other hand, has declined substantially: from 28% during 1970–1974, to just 15% during 2000–2004. The decline in women's representation in computer science would be even more dramatic, were it not for the increase in representation among minority women, primarily black and Asian women. Engineering, on the other hand, has seen a very different pattern over the last several decades. Among graduates during 1970–1974, white men made up more than 80% of degree holders, and women as a whole accounted for just 2% of graduates. Over time, women have increased their representation, accounting for approximately 22% of graduates during 2000–2004. While the representation of white women among engineering graduates has grown, there have also been increases of other women, particularly Asian women. In addition to contributing to the gender wage gap, women's underrepresentation in engineering and computer science majors accounts for a sizable proportion of the gender employment gap in STEM occupations, as these two fields account for about three-quarters of jobs in STEM (Corbett and Hill 2015; Michelmore and Sassler 2016; Xie and Killewald 2012).



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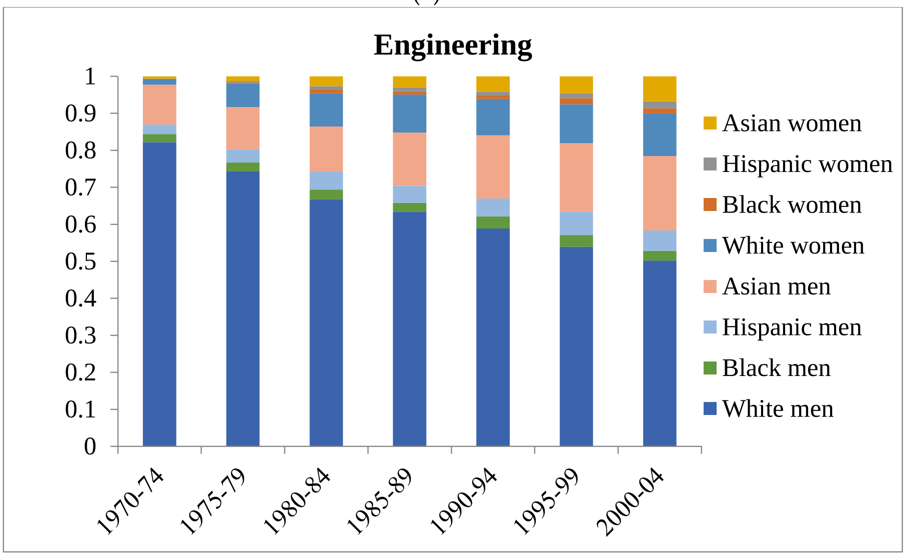

(**b**)

Figure 1. Race and gender distribution of computer science and engineering majors by college cohort: (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004.

In recent years, the evidence suggests that among those who complete degrees in STEM fields, the gender gap in transitions into STEM employment is minimal initially, and women appear as likely to transition into STEM jobs as their male counterparts, though computer science remains an exception (Smith-Doerr 2004). However, increasing the representation of women pursuing and obtaining STEM degrees is not enough to narrow the gender gap in STEM employment, as the pipeline continues to leak after degree receipt. The evidence suggests that retention of women in STEM professions is a challenge. Women in STEM occupations are significantly more likely to exit STEM employment than are women in other challenging fields, such as law or business (Glass et al. 2013), or men in STEM occupations (Fouad et al. 2011; Hunt 2016; Preston 2004).

The explanation most frequently proffered for gender discrepancies in professional job retention tend to revolve around challenges with balancing work and family life. Some scholars argue that persistent gender differences in labor market retention can be attributed to the discrepancy between women's and men's willingness to prioritize work demands over family obligations (Ceci and Williams 2011; Ferriman et al. 2009; Hakim 2000; Hakim 2002), though attributing differential behavior to preferences is strongly critiqued by feminist scholars as essentialist (Halrynjo and Lyng 2009; Stähli et al. 2009). The relational and family care obligations of marriage, for example, appear to be greater for women than men; perhaps as a result, women with STEM degrees are less likely than their male counterparts to be married (Mason et al. 2013).

Nonetheless, recent research has challenged the long-accepted belief that family constraints, such as the presence of children, contribute to differential retention of women in STEM occupations (Glass et al. 2013; Hunt 2016). Hunt (2016) showed that the gendered persistence gap in engineering was almost entirely due to dissatisfaction with pay and promotion, rather than resulting from family constraints. Glass and colleagues (2013) found that women exited STEM within a few years of college completion, often prior to marriage and having children. Nonetheless, among those who persisted in STEM jobs post marriage and childbearing, having a second or higher order child exacerbated women's odds of exiting from STEM jobs to a considerably greater extent than it did for other professional jobs (Glass et al. 2013). Research on how marriage and children influence men's attrition from the STEM labor force is non-existent, although descriptive evidence suggests that men are increasingly influenced by perceptions that STEM fields are not amenable to family life (Mason et al. 2013). There is also some evidence that the association between children and earnings—a central factor shaping retention (Hunt 2016)—has changed among more recent cohorts of women, at least for some segments; among professional women, the association between motherhood and wages has become positive (Buchmann and McDaniel 2016; Michelmore and Sassler 2016; Pal and Waldfogel 2016). This likely reflects, to some extent, selection issues into both motherhood and working among recent cohorts of professional women.

While family factors may matter less for attrition from the STEM labor force among more recent cohorts, particularly among women, the stock of STEM workers is shaped by the historical experiences of earlier graduates. In other words, gender gaps in STEM employment could be due to the labor force exits of earlier cohorts of women employed in STEM. Previous cohorts of women were more likely than men to have taken time out of the labor force, or to have reduced their hours of employment, to have and raise children (Bertrand et al. 2010; Budig and England 2001; Byker 2016; Goldin 2014). Older cohorts of women may also have exited the STEM work force due to frustration over lack of promotion or experiences with discrimination. The evidence suggests that the passage of equal employment legislation has reduced the impact of discrimination as a contributor to the gender earnings gap in the overall labor market between 1970 and 2010 (Mandel and Semyonov 2014), and perhaps in employment as well. Nonetheless, recent studies employing experimental designs have revealed how implicit bias and gendered stereotypes operate to privilege men over women in the hiring process, while also shaping pay and mentoring (Moss-Racusin et al. 2012). Still, female employment throughout the life course has become increasingly normative, leading us to expect the gender gap in employment to narrow among more recent graduates.

In this paper, we expand on prior work analyzing the gender gap in STEM employment. Our analysis uses a broad range of cohorts of college graduates, and we focus on the two STEM professions that account for the largest share of STEM workers. Our sample includes all men and women holding bachelor's degrees in either computer science or engineering, unlike some prior work that focused on PhD holders (e.g., Mason et al. 2013; Shauman 2017). We begin by illustrating the gender gap in retention in STEM occupations, separately for computer science and engineering degree holders. We next use regression analysis to illustrate how the gender gap in working in STEM changes with the addition of controls for race/ethnicity, immigrant status, college cohort, advanced degree holding, and family characteristics. Finally, given the large demographic shifts in these two fields over the last several decades, we examine how the gender gap in persistence in STEM has changed across college cohorts from 1970 to 2004.

3. Data and Method

Data come from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT). We incorporate data from six waves of the SESTAT data collection: 1995, 1997, 1999, 2003, 2006, and 2008. SESTAT is comprised of three ongoing surveys designed to create a nationally representative sample of science and engineering college degree holders. We utilize the integrated data, which include data from the National Survey of College Graduates Science and Engineering Panel, the National Survey of Recent College Graduates, and the Survey of Doctoral Recipients. SESTAT participants have all received at least a bachelor's degree and have at least one degree in science or engineering, or are individuals holding any college degree that work in a science or engineering occupation. The restricted SESTAT data include detailed information regarding labor force participation, occupation categories, educational attainment, and demographic characteristics.

We treat the data as repeated cross-sections, although some respondents appear in more than one wave of data. To reduce concerns of non-independent sampling, we restrict our analysis to one observation per person, choosing a survey wave at random for individuals represented in multiple waves. We further limit our analysis to men and women who received a bachelor's degree in either computer science or engineering between 1970 and 2004. Since data are collected between 1995 and 2008, this cohort restriction limits the sample to working-aged individuals (aged 22 to 60). We further limit our sample to individuals who are working, excluding individuals who are unemployed, in school, or out of the labor force. This restriction reflects our interest in understanding the factors that determine men and women's decisions to work in STEM occupations relative to other non-STEM occupations. Results from our analysis of the gender gap in STEM can therefore be interpreted as the difference in men and women's propensity to work in STEM compared to other employment outside of STEM occupations. Labor force participation is quite high among this sample: these restrictions omit 7% of men and 14% of women with degrees in computer science or engineering.[1] Our final sample consists of 55,895 men and women working (in any occupation) with bachelor's degrees in computer science or engineering.

4. Measurement

Dependent variable: Our dependent variable of interest is a binary indicator for whether the individual was working in a STEM occupation at the time of the interview. The SESTAT data contain detailed occupation codes for all employed individuals in the survey. Individuals working in one of the four main STEM fields were considered working in STEM (computer science, engineering, life sciences, or physical sciences), while individuals who were employed outside of the STEM fields were considered not working in STEM. While we analyze results separately for computer science and engineering majors, we do not restrict STEM majors to work in the occupation they majored in. That is, respondents who majored in computer science and work as life scientists are considered working in STEM, just as computer science majors working in computer science are also considered working in STEM. A list of STEM occupations can be found in Table A1, along with the share of STEM workers working in each of the occupations. Table A1 also lists the top occupation categories for individuals not working in STEM.

Approximately 90% of computer science majors who work in STEM are working in computer science or math-related occupations. Among engineering majors, 74% of those who are working in a STEM occupation are working in an engineering occupation. Another 16% of engineering majors are working in computer science. Among those not working in a traditional STEM field, the top occupations were science and engineering managers, science and engineering pre-college teachers,

[1] Our main findings are consistent if we include individuals who are unemployed, in school, or out of the labor force and consider them "not working in STEM". Gender gaps are slightly larger, reflecting the fact that women are more likely to be out of the labor force relative to men (6% compared to 2% of men).

and science and engineering technicians.[2] These three fields accounted for roughly 40–45% of the occupations of non-STEM employed computer science and engineering degree holders in our sample.

As a sensitivity analysis, we also present results using a more restrictive definition of working in STEM (we refer to this as the "restricted" definition). In particular, we present results restricting the definition of working in STEM to include only the occupations that are in the respondent's major degree of study (i.e., computer science occupations for computer science majors and engineering occupations for engineering majors). These results reveal whether there is gender or racial variation in the propensity to work in STEM fields outside of the major field of study.

Independent variables: Our key independent variable of interest is the gender of the respondent. As a sensitivity check, we also estimate separate gender gaps in STEM employment for whites, blacks, Hispanics, and Asians by running regressions separately by race/ethnic group. Given the large foreign-born representation in the STEM work force (Sana 2010) we also include a dummy variable indicating whether respondents were born outside of the United States.

A number of controls are incorporated to account for the age and cohort structure of our sample. For starters, a linear control for the survey year of the SESTAT data is included in order to account for the variations in the propensity to work in STEM over time. We also utilized a linear control for age, to allow the propensity to work in STEM to vary by age. Last, we construct five-year college cohort indicators to account for the fact that the propensity to work in STEM may differ across college cohorts between 1970 and 2004; the 1970–1974 cohort serves as the comparison group.

We also include controls for whether the respondent obtained an advanced degree, differentiating among those with a master's degree in a STEM field, a PhD in a STEM field, and a non-STEM advanced degree. We expect that individuals with graduate degrees in STEM will be more likely to work in STEM compared to individuals with only a bachelor's degree or an advanced degree in a non-STEM field. Finally, we incorporate various controls for family characteristics. Separate indicators are constructed indicating whether the respondent is married or cohabiting, given that cohabitors espouse less traditional views regarding gender roles than do marrieds (Clarkberg et al. 1995). We also include a control for whether the respondent has any children, or any children under the age of six, the most time-intensive years. We also include interactions of all family characteristics with gender, to allow the association between family characteristics and propensity to work in STEM to differ for men and women. We expect family characteristics to be negatively associated with women's propensity to work in STEM, but to have no association with men's propensity to work in STEM.

Our analysis proceeds as follows. First, we describe differences in observed characteristics between men and women graduating with bachelor's degrees in computer science and engineering. We then turn to our multivariate analyses, using linear probability models to test whether differences between men and women in background characteristics, educational attainment, and family formation can account for the gender gap in persistence in STEM. A linear probability model has the advantage of allowing a straightforward interpretation of regression coefficients, particularly in evaluating how coefficients change across models. We test the sensitivity of our results using our restricted definition of what is considered a STEM occupation. Finally, we examine how the large demographic shifts in the composition of computer science and engineering degree recipients may have affected the gender gap in working in STEM by examining how the gender gap has evolved according to college cohort. This analysis will provide insight into whether the large demographic shifts in the race and gender composition of computer science and engineering graduates over the last several decades has correlated with shifts in the gender gap in persisting in STEM occupations. Since computer science and engineering have experienced very different demographic shifts over the last several decades, we present all results separately for these two fields.

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[2] Results including these occupations as STEM occupations revealed largely similar gender and race gaps in working in STEM.

5. Results

Descriptive statistics of those who majored in computer science or engineering are presented in Table 1, separately by major and gender. Underlined coefficients indicate significant differences in characteristics between men and women. The gender gap in working in STEM is much wider among computer science majors than among engineering majors. While 56% of male computer science majors in our sample were working in STEM at the time of the survey, the equivalent share of women was just 42% for female computer science majors, a gap of 14 percentage points. The gap is slightly narrower if we restrict our definition of "working in STEM" to include only working in computer science-related occupations (52% vs. 40%), reflecting the fact that male computer science majors are slightly more likely to be working in STEM occupations outside of the main computer science field.

Table 1. Descriptive Statistics of those who majored in Computer Science or Engineering, by Gender.

	Computer Science				**Engineering**			
	Men		**Women**		**Men**		**Women**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Working in STEM	0.56	0.50	<u>0.42</u>	0.49	0.64	0.48	<u>0.61</u>	0.49
Working in STEM (restricted) *	0.52	0.50	<u>0.40</u>	0.49	0.49	0.50	<u>0.45</u>	0.50
Survey year	2002.8	4.39	<u>2002.5</u>	4.38	2002.5	4.48	<u>2002.8</u>	4.33
Age	37.80	9.40	37.60	9.23	39.20	9.50	<u>35.02</u>	8.11
Race/Ethnicity								
White	0.75	0.43	<u>0.68</u>	0.47	0.74	0.44	<u>0.62</u>	0.49
Black	0.06	0.24	<u>0.10</u>	0.30	0.03	0.17	<u>0.07</u>	0.26
Hispanic	0.05	0.21	<u>0.05</u>	0.22	0.06	0.23	<u>0.07</u>	0.25
Asian	0.15	0.35	<u>0.17</u>	0.37	0.17	0.38	<u>0.24</u>	0.43
Foreign born	0.20	0.40	<u>0.23</u>	0.42	0.25	0.44	<u>0.30</u>	0.46
College (BA) cohort								
1970–1974	0.09	0.29	0.09	0.28	0.12	0.32	<u>0.02</u>	0.12
1975–1979	0.08	0.28	0.09	0.28	0.12	0.32	<u>0.06</u>	0.24
1980–1984	0.13	0.34	0.13	0.34	0.18	0.38	<u>0.17</u>	0.38
1985–1989	0.19	0.39	0.20	0.40	0.18	0.39	<u>0.20</u>	0.40
1990–1994	0.19	0.39	<u>0.20</u>	0.40	0.18	0.38	<u>0.21</u>	0.41
1995–1999	0.16	0.37	0.17	0.37	0.14	0.35	<u>0.20</u>	0.40
2000–2004	0.15	0.36	<u>0.12</u>	0.33	0.08	0.27	<u>0.14</u>	0.35
Graduate Degrees								
Has a master's in STEM	0.17	0.38	<u>0.16</u>	0.36	0.25	0.43	<u>0.27</u>	0.44
Has a PhD in STEM	0.02	0.15	<u>0.02</u>	0.13	0.04	0.18	0.03	0.18
Has an advanced degree in non-STEM	0.11	0.32	<u>0.14</u>	0.35	0.14	0.34	<u>0.12</u>	0.33
Family Characteristics								
Married	0.67	0.47	<u>0.65</u>	0.48	0.75	0.44	<u>0.63</u>	0.48
Cohabiting	0.03	0.16	0.03	0.16	0.02	0.13	<u>0.03</u>	0.16
Has any kids	0.46	0.50	<u>0.48</u>	0.50	0.52	0.50	<u>0.44</u>	0.50
Has any kids <6	0.24	0.43	0.23	0.42	0.25	0.44	0.25	0.43
Number of Observations	10,229		5666		35,377		7889	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Underlined cells indicate significantly different from men at $p < 0.05$ level; * Restricted definition: working in a STEM occupation of same field as college degree.

While male and female computer science majors are of similar age (on average, 37 years old at the time of the survey), the racial composition of computer science majors is quite different for men and women. Three-quarters of male computer science majors are white, compared to just two-thirds of female computer science majors. Female computer science majors are more likely to be black or Asian, and are also more likely to be foreign-born, compared to male computer science majors. Aside from differences in the racial composition between male and female computer science majors, other observable characteristics are quite similar between the two groups. Female computer science majors are slightly less likely to have an advanced degree in STEM, but more likely to have an advanced degree in a non-STEM field compared to men (14% versus 11%, respectively). Somewhat surprisingly, male and female computer science majors have similar family characteristics: about two-thirds are married, about half have any children, and just under a quarter have any children under the age of six.

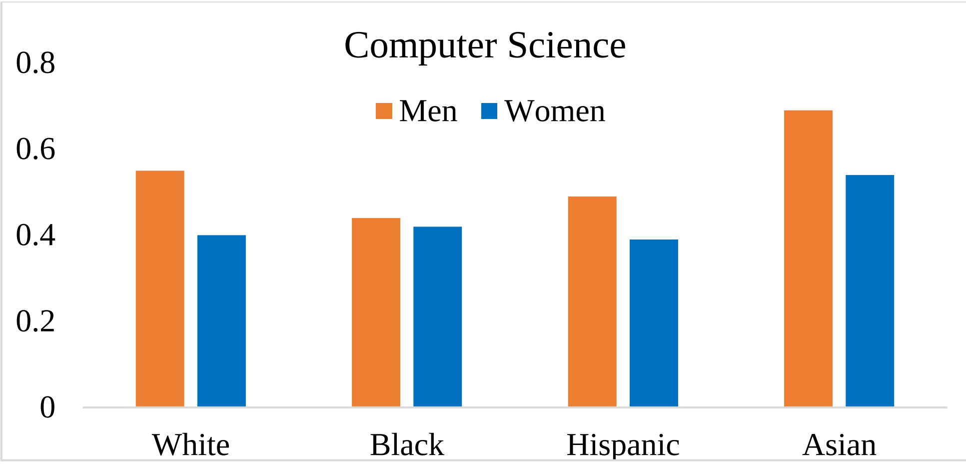
A different story emerges in engineering, where the gender gaps in working in STEM are much smaller, but the observable characteristics are quite different for men and women. The gender gap in working in STEM is just 3 percentage points when considering working in any STEM occupation in the four main STEM fields (64% of men compared to 61% of women), though this difference is statistically significant. Using our restricted definition of working in STEM, only 49% of men and 45% of women were working in STEM engineering occupations at the time of the interview. This lower retention reflects the migration of engineering majors into computer science-related fields (16%).

Despite the smaller gender gap in working in STEM, male and female engineering majors look quite different from each other. Male engineering majors are older than their female counterparts, indicating an influx of female engineers in more recent cohorts (39 years compared to 35 years on average, respectively). Similar to computer science, female engineering majors are more racially diverse than are male engineering majors, as three-quarters of male engineering majors are white, compared to just 62% of female engineering majors. Female engineering majors are more likely to be black than male engineering majors (7% versus 3%, respectively), and more likely to be Asian (24% versus 17%, respectively). Female engineering majors are also more likely than their male counterparts to be foreign-born (30% compared to 25%). Reflecting the age difference between male and female engineering majors, female engineering majors are more likely to have graduated from college (bachelor's degree) in 1995 or later. Less than 2% of the sample of female engineering majors graduated during 1970–1974, compared to 12% of male engineering majors. This reflects the large increase in female representation in engineering that has occurred over the last several decades.

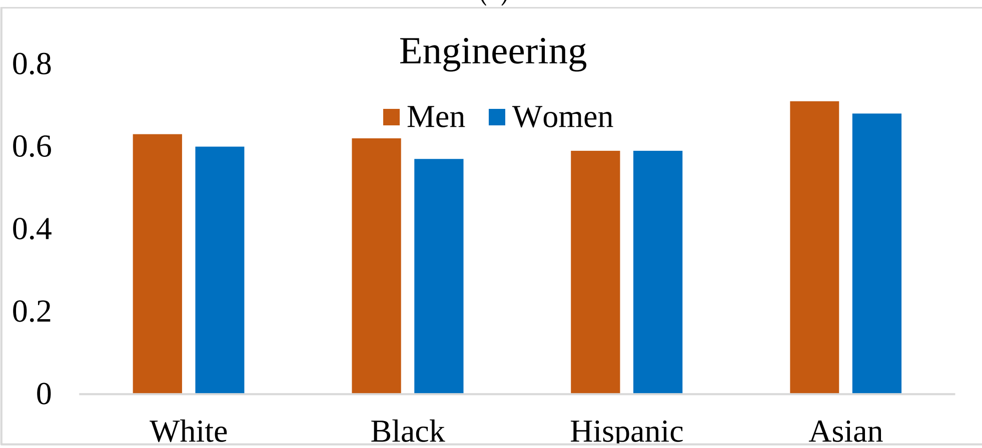
We also find significant differences in the family characteristics between male and female engineering graduates. Approximately three-quarters of male engineering degree holders were married, compared to just 63% of women. Women engineers were also somewhat more likely than their male counterparts to be cohabiting (3% versus 2%, though the difference is statistically significant), perhaps reflecting a desire to defer or avoid normative gender expectations that come with marriage. Male engineering majors were also more likely than their female counterparts in engineering to have any children (52% versus 44%). Still, women and men engineering graduates were equally likely to have young children (under age six) (25% of the sample). Some of these differences may be attributed to the younger average age of the female engineers, though others suggest the greater challenges to relationships for women committed to being professionals in demanding fields.

Among both computer science and engineering majors, women are less likely to be working in STEM occupations than men. These gender gaps are not uniform across racial groups, however. Figure 2 presents the share of men and women working in STEM for each of the four main race-ethnic groups in our sample, separately for computer science and engineering degree holders. In computer science, gender gaps in working in STEM are largest among whites and Asians; women are approximately 15 percentage points less likely to be working in STEM than their male counterparts in both of these groups. Gender gaps are much smaller among black and Hispanic computer science degree-holders. The gender gap for Hispanics is approximately 10 percentage points, while for blacks it is just 2 percentage points. For both men and women, black and Hispanic computer science degree holders are significantly less likely to be working in STEM compared to their white and Asian peers.

Among engineering degree holders, gender gaps in working in STEM are much narrower for all racial groups than in computer science. In engineering, the gender gap is actually widest between black men and women; black women are approximately 5 percentage points less likely to be working in STEM compared to black men. Among whites and Asians, women are approximately 3 percentage points less likely to be working in STEM relative to men. Among Hispanics, we find virtually no gender gap in working in STEM.



(**a**)



(**b**)

Figure 2. Share of men and women working in STEM among computer science and engineering degree holders, by race. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004.

6. Multivariate Results

We next turn to regression analyses to test whether background characteristics can explain some of the gender gap in the likelihood of working in STEM. Results for computer science graduates are presented in Table 2, while results for engineering graduates are presented in Table 3. We present models sequentially, first estimating the overall gender gap in the likelihood of working in STEM, then estimating gaps separately for each race/gender group, and subsequently adding controls for educational attainment and family characteristics to test whether differences in observable characteristics can explain part of the gender gap in STEM employment.

Table 2. Linear probability models predicting working in any STEM occupation: Computer science degree holders.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Survey Year			0.008	***	0.007	***	0.007	***	0.001		0.0003		0.001		0.001	
Age			−0.007	***	−0.007	***	−0.007	***	0.0001		0.001		0.001		0.001	
Gender and race																
Female	−0.136	***	−0.136	***												
White female					−0.148	***	−0.149	***	−0.147	***	−0.136	***	−0.134	***	−0.123	***
Black female					−0.146	***	−0.149	***	−0.16	***	−0.145	***	−0.139	***	−0.128	***
Hispanic female					−0.172	***	−0.200	***	−0.211	***	−0.179	***	−0.176	***	−0.165	***
Asian female					−0.038	**	−0.092	***	−0.082	***	−0.07	***	−0.069	***	−0.058	**
White male (ref)																
Black male					−0.114	***	−0.122	***	−0.133	***	−0.113	***	−0.111	***	−0.111	***
Hispanic male					−0.069	***	−0.087	***	−0.094	***	−0.066	***	−0.064	***	−0.064	***
Asian male					0.108	***	0.056	***	0.065	***	0.043	***	0.042	**	0.042	**
Foreign-born							0.069	***	0.058	***	0.009		0.008		0.008	
BA cohort (ref: 1970–1974)																
1975–1979									0.106	***	0.101	***	0.109	***	0.109	***
1980–1984									0.196	***	0.184	***	0.192	***	0.192	***
1985–1989									0.226	***	0.222	***	0.226	***	0.226	***
1990–1994									0.224	***	0.228	***	0.228	***	0.228	***
1995–1999									0.291	***	0.297	***	0.297	***	0.297	***
2000–2004									0.283	***	0.287	***	0.289	***	0.29	***
Advanced degrees (ref: BA only)																
STEM master’s											0.197	***	0.195	***	0.194	***
STEM PhD											0.219	***	0.217	***	0.217	***
Non-STEM advanced degree											−0.229	***	−0.23	***	−0.231	***
Marriage and family																
Married													0.024	**	0.024	*
Cohabiting													−0.055	**	−0.033	
Has kids													−0.047	***	−0.042	***
Has kids under 6													0.033	***	0.037	***
FemaleXMarried															0	
FemaleXCohabiting															−0.065	
FemaleXHas kids															−0.014	
FemaleXHas kids under 6															−0.012	
R-squared	0.016		0.036		0.044		0.046		0.057		0.111		0.1125		0.1125	
N	15,895		15,895		15,895		15,895		15,895		15,895		15,895		15,895	

Source: National Science Foundation’s Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor’s degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 3. Linear probability models predicting working in any STEM occupation: Engineering degree holders.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Survey Year			0.0003		−0.0001		0		−0.009	***	−0.007	***	−0.006	***	−0.006	***
Age			−0.011	***	−0.011	***	−0.011	***	−0.003	***	−0.002	***	−0.002	***	−0.002	***
Gender and race																
Female	−0.028	***	−0.074	***												
White female					−0.083	***	−0.082	***	−0.080	***	−0.079	***	−0.080	***	−0.030	**
Black female					−0.120	***	−0.118	***	−0.118	***	−0.091	***	−0.093	***	−0.052	**
Hispanic female					−0.098	***	−0.088	***	−0.092	***	−0.091	***	−0.092	***	−0.044	*
Asian female					−0.012		0.010		0.015		−0.013		−0.014		0.041	**
White male (ref)																
Black male					−0.026	*	−0.02		−0.028	**	−0.029	**	−0.029	**	−0.028	**
Hispanic male					−0.059	***	−0.049	***	−0.056	***	−0.043	***	−0.043	***	−0.043	***
Asian male					0.045	***	0.068	***	0.071	***	0.045	***	0.044	***	0.043	**
Foreign-born							−0.029	***	−0.028	***	−0.062	***	−0.061	***	−0.060	***
BA cohort (ref: 1970–1974)																
1975–1979									0.057	***	0.051	***	0.057	***	0.056	***
1980–1984									0.068	***	0.069	***	0.078	***	0.077	***
1985–1989									0.096	***	0.089	***	0.095	***	0.094	***
1990–1994									0.153	***	0.148	***	0.150	***	0.149	***
1995–1999									0.206	***	0.190	***	0.188	***	0.186	***
2000–2004									0.285	***	0.253	***	0.247	***	0.244	***
Advanced degrees (ref: BA only)																
STEM master's											0.154	***	0.153	***	0.154	***
STEM PhD											0.111	***	0.111	***	0.110	***
Non-STEM advanced degree											−0.278	***	−0.277	***	−0.278	***
Marriage and family																
Married													−0.0004		0.006	
Cohabiting													−0.059	***	−0.049	**
Has kids													−0.030	***	−0.026	***
Has kids under 6													0.009		0.012	*
FemaleXMarried															−0.042	**
FemaleXCohabiting															−0.056	
FemaleXHas kids															−0.040	**
FemaleXHas kids under 6															−0.017	
R-squared	0.0004		0.045		0.0479		0.048		0.054		0.119		0.12		0.121	
N	43,266		43,266		43,266		43,266		43,266		43,266		43,266		43,266	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

7. Computer Science Majors

With no other controls in the model, Model 1 shows that women who majored in computer science are 14 percentage points less likely to work in STEM compared to men who majored in computer science. In Model 2, we add controls for age and survey year. These controls do not mediate the relationship between gender and working in any STEM occupation.

Adding race to the model (Model 3) shows some heterogeneity in the gender/race gap among computer science majors in working in STEM. White, black, and Hispanic women are much less likely to work in STEM compared to white men (between 15 and 17 percentage points), while Asian women are only 4 percentage points less likely to work in STEM. Minority men are also less likely to work in STEM: black men are approximately 11 percentage points less likely to work in STEM and Hispanic men are 7 percentage points less likely to work in STEM compared to white men. Asian men, on the other hand, are significantly more likely to work in STEM than their white counterparts (11 percentage points). Including a control for whether the respondent is foreign-born (Model 4) explains some of the race gaps in working in STEM. Foreign-born computer science majors are 7 percentage points more likely to work in STEM compared to native-born respondents. This foreign-born advantage is explained by differences in the likelihood of obtaining higher degrees in STEM between native-born and foreign-born respondents, as the effect of being foreign-born is fully mediated (the coefficient is reduced and becomes statistically insignificant) (Model 6). Having a masters or a Ph.D. in STEM increases the propensity to be working in STEM by approximately 20 percentage points, while having an advanced degree in a non-STEM field reduces the likelihood of working in STEM by more than 20 percentage points. A cohort pattern emerges for computer science majors, with the most recent college cohorts being the most likely to work in STEM. Controlling for college cohort and advanced degree holding, however, has little impact on the gender/race gaps for computer science graduates working in STEM, as these coefficients remain relatively unchanged across models.

Adding controls for family characteristics (Model 8) does partially mediate the gender/race gaps among computer science majors in working in STEM. However, with all controls in the model, white women remain 12 percentage points less likely to work in STEM compared to white men. Black and Hispanic women are even less likely to work in STEM compared to their white, male counterparts, and Asian women remain 6 percentage points less likely to work in STEM. Including controls for family characteristics have virtually no impact on the likelihood of working in STEM for black, Hispanic, or Asian men relative to white men.

For both men and women, being married is positively associated with persisting in STEM, though cohabiting is negatively associated with persevering in STEM. Having children is also negatively associated with persisting in STEM, particularly when children are older (over the age of six). Interestingly, we find no gender differences in propensity to work in STEM associated with family characteristics among computer science graduates. Married and cohabiting women are equally likely to work in STEM as married men, as are women with children, although coefficients of the interaction among gender, cohabitation, and having children are slightly negative (though insignificant). This implies that among computer science degree holders, family characteristics do not appear to influence persistence in STEM differentially by gender.

8. Engineering Majors

The engineering story is quite different (Table 3). Among engineering degree-holders, women are approximately 3 percentage points less likely to work in STEM compared to men. As shown in Table 1, the female engineering degree holders were younger on average than the male engineering degree holders. Controlling for differences in age and the survey year actually *widens* the gender gap in STEM employment, since age is negatively correlated with persisting in STEM. Differentiating by race (Model 3), white, black, and Hispanic women are least likely to work in STEM compared to their white male counterparts. The gap for white women is 8 percentage points, while black women are 12 percentage points and Hispanic women are 10 percentage points less likely to work in STEM relative to white men. Asian women are no less likely to work in STEM relative to white men. Among the men, black and Hispanic men are less likely to work in STEM relative to white men, but Asian men are approximately 5 percentage points more likely to work in STEM.

In contrast to the story in computer science, foreign-born engineering majors are *less* likely to be working in STEM relative to native-born majors. Controlling for advanced degrees exacerbates the native-foreign born gap, suggesting that foreign-born engineering majors are less likely to obtain higher degrees in STEM. Again, a cohort pattern emerges for engineering majors, with the most recent college cohorts being the most likely to work in STEM.

Similar to the findings for computer science, we see little change in the gender/race gap in working in STEM with the inclusion of controls for college cohort, advanced degree holding in STEM, and the main effects for family characteristics. Only once we include interactions of our family characteristics with an indicator for female, allowing the family characteristics to have a different effect on the likelihood of working in STEM for men compared to women, do we see any change in the gender gaps in working in STEM (Model 8). Including controls for whether the women are married or cohabiting and have any children substantially reduces the gender gap in working in STEM among engineering majors. For white women, the gap shrinks from 8 to 3 percentage points, while reductions were quite similar in magnitude for the other racial groups as well. For white, black, and Hispanic women, observable characteristics can explain between 55% and 64% of the gender gap in persistence in STEM. For Asian women, controlling for observable characteristics actually reverses the gender gap in persistence in STEM: Asian women are 4 percentage points *more* likely to be working in STEM relative to white men.

In contrast to computer science, family characteristics *do* appear to have different associations with working in STEM for men and women engineering graduates. While we find no association between marriage and working in STEM for men (coefficient: 0.006 and insignificant), married women are 4 percentage points less likely to work in STEM compared to married men. Cohabiting women, however, are more likely to be working in STEM than cohabiting men, though the difference is not significant. Having any children is negatively associated with working in STEM for both men and women, but women with children are 4 percentage points less likely to work in STEM compared to men with children. This implies that married female engineers with children face substantially more barriers to working in STEM than do married male engineers who are parents.

These analyses reveal two distinct portraits of the gender gap in persistence in STEM for those majoring in computer science and engineering. Among computer science majors, women are substantially less likely to work in STEM compared to men, and observable characteristics do little to explain this gap. In contrast, among engineering majors, the gender gap in working in STEM is much smaller, and approximately half of the gender gap can be explained by observable characteristics: namely, family characteristics.

8.1. How Does Our Restricted Definition of "STEM" Affect Results?

To test the sensitivity of our results to the definition of "working in STEM", we also ran models where we restrict the definition of working in STEM to be "working in STEM occupation of same major". For instance, if the respondent obtained a bachelor's degree in computer science, then they will be considered "working in STEM" only if they also work in a computer science occupation. Among computer science degree holders, approximately 90% of those working in any STEM field were working in computer science. In contrast, engineering degree holders were less likely to be working in engineering occupations: 75% of engineering degree holders working in any STEM field were working in engineering occupations. An additional 15% of those working in any STEM field were working in computer science (see Table A1).

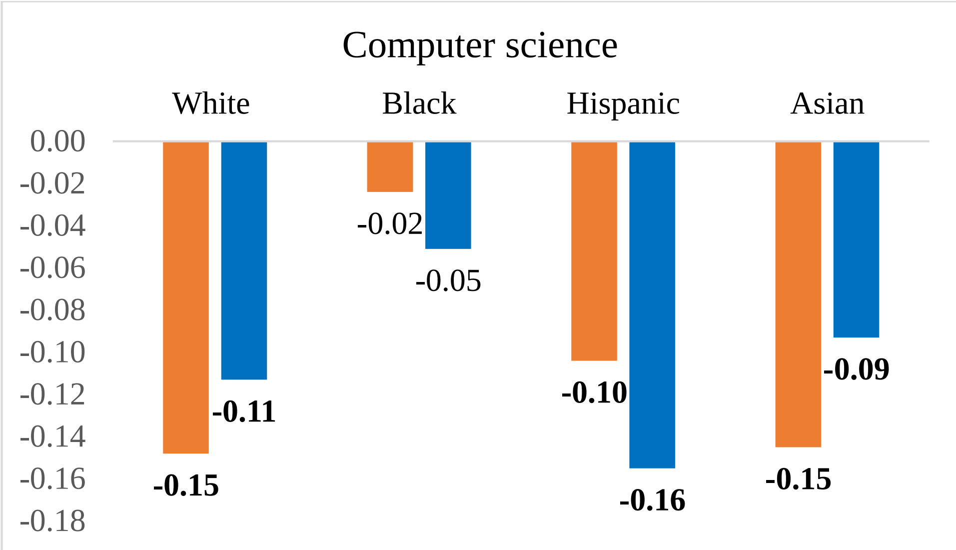
Using our restricted definition of working in STEM does not alter results much among computer science degree holders (see Table A2). This is not surprising, since 90% of those working in any STEM occupation were working within their field of major. Gaps are slightly smaller for all racial groups aside from Asian women, and, once again, controls do very little to alter the gender gap in persistence in STEM.

The gender gap in persisting in STEM among engineering degree holders also does not change upon using a more restricted definition of working in STEM, except for Asian men and women. While Asian men and women were actually *more* likely to work in STEM compared to white men using a traditional definition of working in STEM (including any STEM occupation in the four main fields of STEM), restricting the definition to only include engineering occupations reverses the direction of the relationship. In the fully-controlled model, both Asian men and women were 8 percentage points *less* likely to work in engineering compared to white men. Upon further exploration, this result is due to Asian men and women with engineering degrees having a higher propensity to work in computer science compared to non-Asian engineering degree holders.

There is considerable heterogeneity among engineering graduates. Because it remains among the engineering fields with the lowest representation of women (Michelmore and Sassler 2016), some have suggested that electrical engineers are more similar to computer science majors than to many other engineering fields (like mechanical or civil engineering). We therefore explored whether grouping electrical engineers with computer science graduates altered our results substantively. Analyses run on our new, expanded group (computer science and electrical engineering graduates) reveal more similarities between electrical engineers and computer science graduates than other engineering specializations. For this new expanded category the gender and race gaps in STEM employment are accentuated, and family characteristics now largely do not mediate the gender/race gaps evident for those working in STEM. In contrast, the omission of electrical engineering majors from the engineering models results in smaller gaps in STEM employment among our more constrained group of engineers, and family characteristics now fully mediate the gender and race gaps in STEM employment. Our results indicate that not all engineers are alike; the barriers facing women engineering graduates who specialized in electrical engineering—an area with relatively few women—are more similar to those experienced by women in computer science than they are to women in other engineering disciplines.

8.2. Differences by Race/Ethnic Group

Our analyses in Tables 2 and 3 measure gender and race gaps relative to white men; estimating within-race gender gaps in likelihood of working in STEM separately for each of the four main race/ethnic groups presents a similar story (see Figure 3). Figure 3 presents results from regressing an indicator for working in STEM on an indicator for whether the respondent is female for each of the four main race/ethnic groups, measuring how gender gaps change with the addition of the full set of controls from Model 8 in Tables 2 and 3 (the dark bar represents the coefficient without controls, while the light bar represents coefficients with controls). In computer science, we find evidence that observed characteristics explain more of the gender gap in working in STEM for white and Asian computer science degree holders than for black and Hispanic degree-holders. With no other controls in the model, white women are approximately 15 percentage points less likely to work in STEM relative to white men. This gap narrows to 11 percentage points with the addition of controls for educational attainment, college cohort, and family characteristics. Similarly, Asian women are approximately 15 percentage points less likely to work in STEM relative to Asian men. Including the full set of controls, this gap narrows to 9 percentage points. The story is quite different for black and Hispanic computer science degree-holders. Among black computer science degree-holders, we find no statistically significant differences in the likelihood of working in STEM between men and women in either model. Among Hispanic degree-holders, we find evidence that including controls for demographic characteristics *exacerbates* the gender gap in persisting in STEM occupations—increasing the gap from 10 to 16 percentage points with the inclusion of controls.



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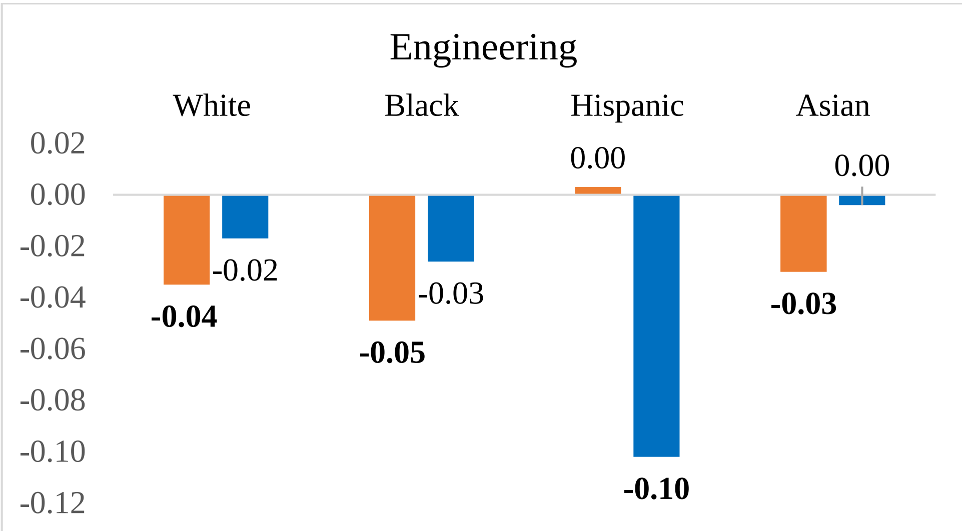


(**b**)

Figure 3. Differences in likelihood of working in STEM for women relative to men by race, coefficient on indicator for women from LPM regressions predicting likelihood of working in STEM, separate regressions by race/ethnic group and STEM major. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, and employed at the time of survey. Bolded coefficients indicate statistically significant at $p < 0.05$ level.

Among white, black, and Asian engineering degree-holders, the race-specific gender gaps in STEM persistence are consistent with the overall results. For these three groups, women are between 3 and 5 percentage points less likely to work in STEM relative to their male counterparts, not including any controls in the model aside from age and survey year. Including the full set of controls presented in Model 8 in Table 3, fully mediates the gender gaps in likelihood of working in STEM for these groups. This implies that among engineering graduates, the majority of the gender gap in propensity to work in STEM is explained by difference in observable characteristics between men and women. Among Hispanics, we see a different pattern. Similar to Hispanic computer science degree holders, we find that including controls for observable characteristics actually exacerbates the gender gap in propensity to work in STEM, increasing from virtually no gap in the uncontrolled model, to 10 percentage points in the fully-controlled model.

8.3. How Has the Gender Gap in Employment in STEM Changed over Time?

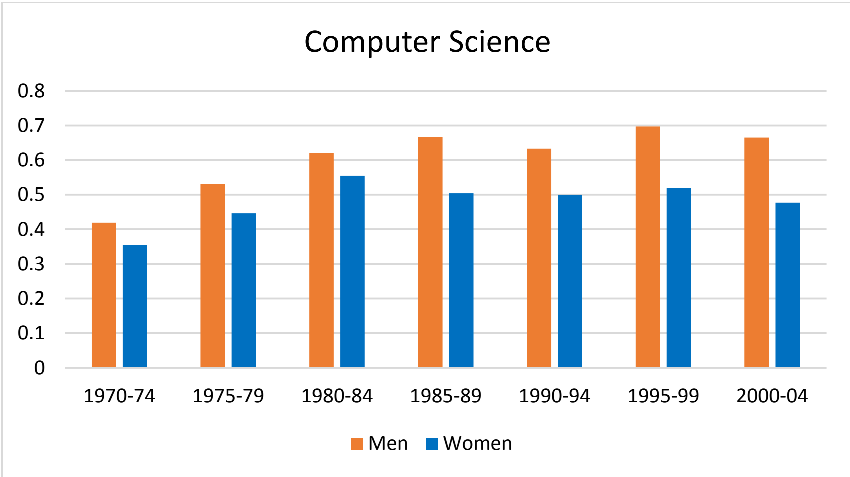
The gender and racial composition of computer science and engineering majors have shifted dramatically over the last several decades (see Figure 1). Since the 1970s, white women have exhibited a retreat from computer science, accounting for 28% of computer science majors during 1970–1974, to just 16% of majors among the 2000–2004 graduating cohort. The decline of women's representation in computer science would be more dramatic, were it not for the increase in representation among minority women. In engineering, women have increased both their representation and become more diverse. With these large demographic shifts in computer science and engineering, it raises the question of how the gender gap in working in STEM has changed over time.

To answer this question, we predict the probability of working in STEM separately for men and women for each cohort using a regression similar to Model 8 in Tables 2 and 3, but adding an interaction term of college cohort and gender, to allow for the gender gap in STEM employment to change over cohort (see Figure 4). We hold all other characteristics at their mean value. The predicted probabilities indicate how the gender gap in working in STEM has changed by college degree cohort. In computer science, we find that the decline of white female majors over the last several decades coincides with a retreat of women from working in STEM as well. Relative to their male counterparts, women who have graduated from college since 1985 have a much lower predicted probability of working in STEM than men who graduated from college during the same time period (ranging from a 12 to 19 percentage point difference). This analysis is conditional on obtaining a college degree in computer science, and implies that on top of being less likely to major in computer science to begin with, women who graduated with degrees in computer science over the last two decades are also less likely to work in STEM.

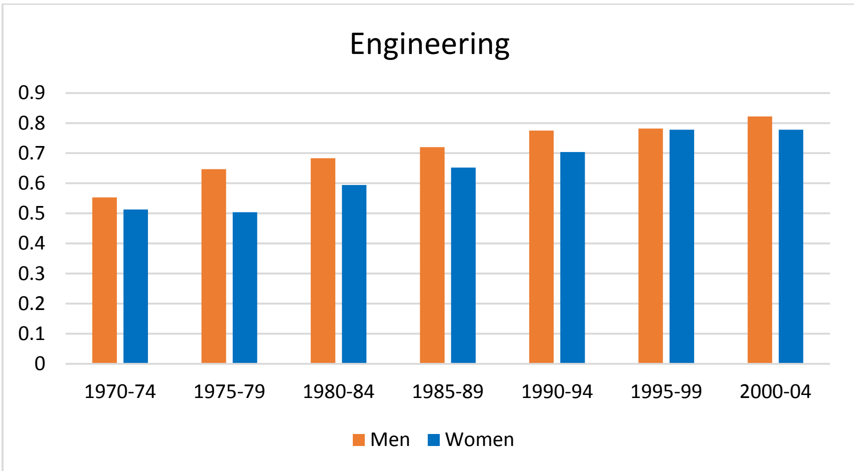
In engineering, on the other hand, we find the opposite pattern by college cohort. Since 1975–1979, the gap in working in STEM between women and men who graduated with an engineering degree has narrowed such that, for the college cohort 1995–1999, the predicted probabilities of working in STEM are identical. This narrowing of the gender gap in STEM employment has occurred at the same time that more women have obtained engineering degrees.

Finally, we also examined whether major non-demographic factors influencing the likelihood of working in STEM persist among the most recent cohorts. To do that, we ran our linear probability models, but limited our sample to the two most recent cohorts—those who graduated between 1995 and 1999, and those finishing their degree between 2000 and 2004. The general patterns shown in Table 2 for computer science remained, but the gender and race gaps were considerably larger (results not shown). Among the most recent cohorts, female computer science graduates were considerably less likely to be working in STEM jobs than their male counterparts, and the gaps between white and Hispanic females and white males had expanded, though Asian women who had completed a degree in computer science were no less likely than their White male counterparts to be working in STEM jobs. Our measures of family status (married and had any minor children) was also not significant among the most recent cohorts of computer science graduates, perhaps due to delayed marriage and parenting among both women and men.

Among engineering graduates, on the other hand, gender disparities in employment were far narrower among more recent cohorts. Nonetheless, we do observe some widening of disparities among racial minorities (results not shown). The gender gap between white women and men remains largely the same magnitude, even as their representation in engineering grew. The gap between Black and Hispanic women and men, relative to white men, is greater among the two most recent cohorts of engineering graduates. Furthermore, the employment advantage demonstrated by Asians is no longer significant among the two most recent cohorts, though in the full sample both Asian women and men had exhibited a greater probability of working in STEM jobs than had white males. However, our family covariates do not explain the gender and race gaps in employment among the most recent cohorts, as the race gaps persist upon including our family controls.



(**a**)



(**b**)

Figure 4. Predicted Probabilities of Working in STEM by College Cohort for Women and Men. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, and employed at the time of survey.

9. Discussion and Conclusions

Much progress has been made in diversifying the STEM labor force over the last several decades (Xie and Killewald 2012), but women continue to remain underrepresented in science and engineering occupations. Numerous studies have examined the source of the gender gap in women's STEM presence, noting differences in major field of study, transitions into STEM occupations, as well as differential retention in STEM occupations, working patterns, and the challenging experience of being a minority. Restricting our sample to STEM degree holders in computer science and engineering eliminates some potential factors, such as differences in human capital accumulation or employment opportunities that contribute to women's underrepresentation. We use SESTAT data and assess the factors that influence the gender gap in persistence in STEM employment in computer science and engineering occupations, assessing differences by race as well as changes in the gender gap across cohorts.

We find sizable and significant gender and race gaps in STEM employment for both computer science and engineering degree holders. Disparities were greater, however, in computer science than in engineering. Women who received degrees in computer science were approximately 14 percentage points less likely to work in STEM occupations than white men, while women in engineering were 7 percentage points less likely to do so. Black and Hispanic men were also significantly less likely to be working in STEM occupations than their white male counterparts in both fields, but the gap was generally smaller than it was for women. Contrary to our expectations, we find no evidence that the gender gap in employment is narrowing among more recent college graduates, at least when it comes to employment in computer science occupations. Even though female employment throughout the life course has become increasingly normative in American society, and computer science jobs have proliferated and generally provide good wages, the occupation is not succeeding in drawing women. Instead, the evidence suggests that something about the field of computer science is repelling rather than attracting women.

However, it is difficult to account for the factors associated with these employment disparities. We found little evidence that differences in observable characteristics between men and women could explain the gender gap in persisting in STEM among computer science degree holders, contrary to our hypotheses. After controlling for college cohort, advanced degree holding, and marriage and family formation, white women with computer science degrees remained 12 percentage points less likely to work in STEM compared to white men. This suggests that there remain unobserved barriers to working in STEM for female computer science majors relative to male computer science majors. Empirical evidence suggests that computer science education is less welcoming to female students (Cheryan et al. 2013; Master et al. 2016) and that the field is often viewed as a quintessentially masculine subject (DuBow and James-Hawkins 2016), especially by men (Corbett and Hill 2015; Smyth and Nosek 2015). Furthermore, anecdotal evidence suggests that such barriers persist, or are even exacerbated, among those working in computer science occupations (Margolis and Fisher 2001; Mundy 2017), resulting in high attrition of women from jobs in computer science.

In engineering, we find a different story. Gender gaps in persisting in STEM were smaller than in computer science, and about half of the gap could be attributed to differences in the characteristics of male and female engineering degree holders. This is consistent with the changing demographic patterns that have occurred in these two fields over time. Women have historically obtained a greater proportion of degrees in computer science but are less likely to major in computer science today than they were forty years ago. In computer science, therefore, the demographic characteristics of men and women are quite similar. Engineering, in contrast, has seen a dramatic increase in women's their representation among degree holders in recent years, and therefore differ more in terms of their demographic characteristics: the female engineering degree holders are much younger, much less likely to be married, and much less likely to have children compared to the male engineering majors. Over time, then, as older engineering degree holders, who are predominantly male, retire, gender disparities in demographic characteristics—as well as retention in STEM occupations associated with engineering—should narrow.

Many attribute the dearth of women in STEM occupations to the challenges women (but not men) face in attempting to balance what are often rigid employment expectations with family life. Our findings suggest that the associations between family life and employment are more nuanced than one would expect. Among computer science degree holders, men and women were equally (un)likely to be married and have minor children. Our regression analysis suggests that both men and women were *more* likely to be working in STEM if they were married, relative to those who were single. Similarly, the presence of children reduced the propensity to work in STEM among both men and women equally, although having young children (under the age of six) was not significantly associated with working in STEM relative to childless individuals. In computer science, therefore, family characteristics do not appear to be an obstacle for women more so than men. That is the case, at least, among those who remained in computer science jobs. Evidence from other studies have suggested that those for whom children are not a deterrent in the work force, and who can maintain employment and even earn higher wages when they are parents of young children, are highly selective (e.g., Michelmore and Sassler 2016; Pal and Waldfogel 2016; Buchmann and McDaniel 2016). Furthermore, given that these women are better represented among those graduating in the 1980s than the 1990s and into the 21st century, they are older, may be more likely to be divorced or to have older children.

Family life, however, appears more challenging to adjudicate for women engineers than for their male counterparts. Among engineering majors, observed differences in the propensity to be married (75% of men were married compared to only 63% of women) and to have minor children (52% versus 44%, respectively) translate into differences in the likelihood of working in STEM. While married men in engineering were no less likely to be working in STEM compared to single men, married women were 4 percentage points less likely to be working in STEM relative to married men. Furthermore, having children further exacerbated this gender gap. Even though having minor children reduced the likelihood of working in STEM for both men and women, women with minor children were significantly less likely to work in STEM compared to men with children (by 4 percentage points). These results are consistent with the idea that women in engineering face barriers in balancing work and family that do not prevent men from combining marriage and family with working in STEM. Of note is that those with preschool aged children were slightly more likely to be working in engineering jobs, and that this effect does not differ for men and women. Perhaps it is not the presence of children, per se, that challenges employment among those in STEM jobs, but differences in the availability of full-day and full-year care for children of differing ages. Finally, there appears to be heterogeneity among engineering occupations, with electrical engineering looking more akin to computer science in its gender representation and the gender employment gap than to other engineering specialties. Such findings reveal the challenges that remain to making STEM fields where women are highly underrepresented welcoming workplaces.

In examining how these patterns have changed over time, computer science appears to be the exception to increasing female representation, as recent cohorts of female computer science majors are increasingly *less* likely to work in STEM jobs than their counterparts who graduated three decades ago. Women and men are equally likely to work in STEM jobs if they graduated in the 1970s and 1980s. We document an emerging gender gap in employment in computer science in the late 1980s, rising to between 10 and 15 percentage points in the more recent cohorts. The declining share of women and minority computer science workers has been well canvassed in the popular media (Dewey 2014; Mundy 2017; Stross 2008). Our findings shed additional light on the need to better understand the factors contributing to women's diminishing representation in this field, given that computer science is of considerable importance to the American and global economy. While our findings do not provide much purchase on *why* women find computer science an unwelcome field, our results are consistent with several recent studies detailing persistent wage gaps between men and women in computer science (Michelmore and Sassler 2016). Increasing the representation of women in computer science employment, then, appears to be very challenging, and additional research is needed to best determine effective ways of addressing gender barriers to retention.

Our study is not without limitations. The nature of our data does not allow us to determine the factors that push or pull men or women out of the STEM labor force and into other occupations, or whether this process differs for men and women. Recent research has suggested that women exit particular STEM fields as a result of frustration with working conditions (e.g., Glass et al. 2013; Hunt 2016), such as dissatisfaction with pay and promotion opportunities. Despite the increasing presence of women in STEM fields of study, the evidence indicates that women are significantly less likely to be retained in the STEM labor force (Glass et al. 2013). In engineering, however, we find no evidence of an expanding gender gap in employment over time, coinciding with an increase in women majoring in engineering. Nonetheless, family responsibilities more adversely shape women engineering graduates' odds of retention than they do for men, suggesting the need to further explore how spousal and parental roles play out differentially in the spheres of work and home.

Over the past few decades, remarkable progress has been made in narrowing the gender gap in STEM employment, but considerable work remains. While the engineering field presents a reason for optimism that women's persistence in STEM will increase as their representation among majors continues to rise, the story in computer science is just the opposite. Increasing women's representation in the two largest STEM fields has important implications for gender equity in the labor force, as well as the overall gender wage gap. Computer science and engineering are among the highest-paying fields for college graduates; expanding women's presence in these fields would go a long way towards reducing gender inequality in pay.

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Appendix A

Table A1. List of STEM occupations and the fraction of computer science and engineering STEM workers working in each occupation.

STEM Occupations	Percent of Computer Science STEM Workers	Percent of Engineering STEM Workers
Computer and information scientists	66.7%	15.7%
Mathematical scientists	7.0%	<1%
Postsecondary teachers—computer and math sciences	16.0%	<1%
Agricultural and food scientists	<1%	<1%
Biological and medical scientists	1.0%	1.0%
Environmental life scientists	<1%	<1%
Postsecondary teachers—life and related sciences	<1%	<1%
Chemists, except biochemists	<1%	<1%
Earth scientists, geologists and oceanographers	<1%	<1%
Physicists and astronomers	<1%	<1%
Other physical and related scientists	<1%	<1%
Postsecondary teachers—physical and related sciences	<1%	<1%
Aerospace, aeronautical, or astronautical engineers	<1%	5.9%
Chemical engineers	<1%	6.2%
Civil, architectural, or sanitary engineers	<1%	12.0%
Electrical or computer hardware engineers	2.5%	17.7%
Industrial engineers	<1%	5.1%
Mechanical engineers	<1%	15.2%
Other engineers	1.4%	13.4%
Postsecondary teachers—engineering	<1%	3.9%
Percent working in STEM occupation of same major	89.7%	73.6%
Top occupations for individuals not working in STEM		
Science and Engineering Managers	14.0%	26.1%
Science and Engineering pre-college teachers	13.6%	1.7%
Science and Engineering technicians	19.1%	11.9%
Sales and marketing occupations	8.6%	11.3%
Other non S&E occupations	16.8%	22.7%

Table A2. Linear probability models predicting working in a computer or math science occupation: Computer science degree holders.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Survey Year			0.009	***	0.008	***	0.008	***	0.001		0.002		0.002	*	0.002	*
Age			−0.007	***	−0.007	***	−0.007	***	−0.001		0.0002		0.0002		0.0002	
Gender and race																
Female	−0.123	***	−0.123	***												
White female					−0.131	***	−0.132	***	−0.130	***	−0.120	***	−0.119	***	−0.110	***
Black female					−0.133	***	−0.136	***	−0.145	***	−0.130	***	−0.125	***	−0.115	***
Hispanic female					−0.162	***	−0.186	***	−0.200	***	−0.172	***	−0.169	***	−0.161	***
Asian female					−0.046	***	−0.099	***	−0.090	***	−0.080	***	−0.080	***	−0.070	***
White male (ref)																
Black male					−0.105	***	−0.114	***	−0.123	***	−0.106	***	−0.104	***	−0.104	***
Hispanic male					−0.074	***	−0.092	***	−0.098	***	−0.073	***	−0.071	***	−0.072	***
Asian male					0.099	***	0.047	***	0.056	***	0.0356	**	0.035	**	0.035	**
Foreign-born							0.068	***	0.057	***	0.017		0.016		0.016	
BA cohort (ref: 1970–1974)																
1975–1979									0.098	***	0.093	***	0.100	***	0.100	***
1980–1984									0.184	***	0.169	***	0.177	***	0.176	***
1985–1989									0.216	***	0.208	***	0.212	***	0.212	***
1990–1994									0.205	***	0.203	***	0.204	***	0.203	***
1995–1999									0.264	***	0.262	***	0.620	***	0.262	***
2000–2004									0.264	***	0.258	***	0.259	***	0.259	***
Advanced degrees (ref: BA only)																
STEM master's											0.174	***	0.172	***	0.172	***
STEM PhD											0.132	***	0.131	***	0.132	***
Non-STEM advanced degree											−0.222	***	−0.223	***	−0.224	***
Marriage and family																
Married													0.020	**	0.014	
Cohabiting													−0.043	*	−0.019	
Has kids													−0.041	***	−0.036	***
Has kids under 6													0.025	**	0.039	***
FemaleXMarried															0.013	
FemaleXCohabiting															−0.073	
FemaleXHas kids															−0.013	
FemaleXHas kids under 6															−0.042	*
R-squared	0.013		0.033		0.04		0.042		0.051		0.094		0.095		0.095	
N	15,895		15,895		15,895		15,895		15,895		15,895		15,895		15,895	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table A3. Linear probability models predicting working in an engineering occupation: Engineering degree holders.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Survey Year			−0.006	***	−0.005	***	−0.004	***	−0.015	***	−0.014	***	−0.013	***	−0.013	***
Age			−0.007	***	−0.008	***	−0.007	***	0.002	***	0.002	***	0.002	***	0.002	***
Gender and race																
Female	−0.039	***	−0.065	***												
White female					−0.057	***	−0.055	***	−0.052	***	−0.051	***	−0.050	***	0.005	
Black female					−0.115	***	−0.108	***	−0.108	***	−0.087	***	−0.086	***	−0.043	
Hispanic female					−0.087	***	−0.056	**	−0.063	**	−0.063	***	−0.064	**	−0.011	
Asian female					−0.193	***	−0.129	***	−0.124	***	−0.140	***	−0.143	***	−0.080	***
White male (ref)																
Black male					−0.041	***	−0.023		−0.032	**	−0.035	**	−0.034	**	−0.033	**
Hispanic male					−0.043	***	−0.010		−0.019	*	−0.011		−0.010		−0.010	
Asian male					−0.137	***	−0.068	***	−0.065	***	−0.082	***	−0.083	***	−0.083	***
Foreign-born							−0.086	***	−0.082	***	−0.106	***	−0.105	***	−0.105	***
BA cohort (ref: 1970–1974)																
1975–1979									0.064	***	0.056	***	0.058	***	0.058	***
1980–1984									0.074	***	0.069	***	0.073	***	0.073	***
1985–1989									0.097	***	0.084	***	0.088	***	0.088	***
1990–1994									0.165	***	0.150	***	0.153	***	0.152	***
1995–1999									0.238	***	0.210	***	0.211	***	0.210	***
2000–2004									0.376	***	0.334	***	0.335	***	0.331	***
Advanced degrees (ref: BA only)																
STEM master's											0.090	***	0.090	***	0.090	***
STEM PhD											0.113	***	0.113	***	0.112	***
Non-STEM advanced degree											−0.242	***	−0.241	***	−0.243	***
Marriage and family																
Married													0.008		0.019	***
Cohabiting													−0.058	***	−0.055	***
Has kids													−0.012	*	−0.009	
Has kids under 6													−0.005		−0.004	
FemaleXMarried															−0.067	***
FemaleXCohabiting															−0.018	
FemaleXHas kids															−0.026	
FemaleXHas kids under 6															−0.003	
R-squared	0.006		0.024		0.034		0.037		0.047		0.0855		0.086		0.0864	
N	43,266		43,266		43,266		43,266		43,266		43,266		43,266		43,266	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

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