Sharon L. Sassler ${ }^{1}\left(\mathbb{D}\right.$, Kristin E. Smith ${ }^{2}$, and Katherine Michelmore ${ }^{3}$


#### Abstract

Although women's representation in science, technology, engineering, and mathematics (STEM) employment has increased significantly over the past few decades, their presence remains low in fields like computer science. Using the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT), this paper assesses the factors shaping employment in STEM and non-STEM occupations among men and women with bachelor's degrees in computer science. Our results reveal that women with degrees in computer science are far less likely than their male counterparts to be employed in STEM occupations, particularly in computer science jobs. But family factors do not have the expected association with employment in computer science jobs. Men who are parents and childless women are more likely to work in non-STEM jobs versus computer science jobs, relative to childless men. Furthermore, the gender gap in employment in computer science jobs is larger among those graduating in the new millennium, suggesting that other factors are at play.


## Keywords

family, science, knowledge, and technology, sex and gender

Considerable effort has been devoted in the United States to growing women's presence in science, technology, engineering, and mathematics (STEM) fields of study and work (National Academy of Sciences Engineering Medicine 2007). ${ }^{1}$ Women now account for over half of all bachelor's degree recipients in STEM fields (National Academy of Engineering 2014). Yet women's representation in the STEM work force lags their educational gains (Michelmore and Sassler 2016; Xie and Shauman 2003). Gender disparities in STEM occupational concentration are not equally distributed across fields. As of the early twenty-first century, women's presence in computer science remains low and has decreased over time (Corbett and Hill 2015; Michelmore and Sassler 2016).

Studies of women's occupational persistence in professional careers often focus on those who leave the paid labor force for the home front (Landivar 2017; Stone 2007). But most womenespecially the college educated-remain in the paid work force (Percheski 2008). That is

[^0]particularly the case for women trained in STEM fields. Jennifer Glass and colleagues (2013) found that women with STEM degrees who initially entered STEM occupations in the 1980s and 1990s were significantly more likely to leave STEM occupations than were women in other professions, such as law or business, but they left STEM occupations for other types of jobs. E. A. Cech and M. Blair-Loy (2019) find similar results in a more recent cohort of STEM professionals who became parents in the early twenty-first century; the majority remained working full-time work.

Women's underrepresentation in computer science is particularly notable, given broad demand for workers with such skills. About half of all STEM jobs are in computer science (Landivar 2013), and future job growth for those with such skills is projected to be robust (Bureau of Labor Statistics (BLS) 2019). Earlier research on women in technology found that marriage and family factors resulted in lower retention of women relative to men (Stephan and Levin 2005). More recent studies continue to document an association between childbearing and attrition from STEM fields more broadly (Cech and Blair-Loy 2019), though journalistic coverage of technology workers also suggests that the workplace climate pushes women out of jobs in computer science (Chang 2018; Mundy 2017). The association between working in computer science (and other STEM jobs) and higher wages is well documented (NCSES 2023), and researchers argue that increasing women's representation in STEM will improve STEM retention and in turn narrow the gender wage gap in the labor market (Committee on Maximizing the Potential of Women 2006; Hill, Corbett, and Rose 2010; Michelmore and Sassler 2016). Assessing what factors contribute to the composition of today's computer science workforce is exceedingly important for those seeking to understand the stubborn persistence of the gender wage gap and the underrepresentation of women in leadership roles.

Drawing upon data from the National Science Foundation's (NSF) restricted access Scientists and Engineers Statistical Data System (SESTAT), we evaluate the gender gap in employment in the computer science workforce and the role that family factors play in mitigating or exacerbating this gap. We pay particular attention to how gender disparities have evolved over time for cohorts of college graduates between 1980 and 2009. Our analyses explore how family factors predict working in a computer science occupation, a job within the broader STEM workforce, or a non-STEM occupation, and whether the relationship between family factors and employment in STEM has changed over time. We provide a descriptive portrait of the patterns of employment in STEM among men and women holding bachelors' degrees in computer science, rather than establishing a causal link between individual characteristics and STEM employment.

## Why Don't Women Work in STEM? Understanding the "Leaky Pipeline"

A great deal of effort is devoted to increasing women's pursuit of careers in STEM fields. Such efforts are based on the belief that growing women's representation in STEM occupations is important for the economic well-being of society (National Academy Engineering Medicine 2007). Although women's likelihood of majoring in STEM fields in college has increased (Morgan, Gelbgiser, and Weeden 2013), and their graduation rates in STEM fields have grown dramatically, their employment in STEM jobs lags their male counterparts (Michelmore and Sassler 2016; Xie and Shauman 2003).

Some of the gender gap in STEM employment results from differential transitions by field of study into STEM jobs. Those with degrees in engineering are more likely to transition into work in STEM jobs following degree receipt than are those whose degrees are in the life or physical sciences, for example (Sassler et al. 2017a; Xie and Shauman 2003). Evidence regarding whether there are gender differences in transitions from school to work within particular fields within STEM has been mixed. One study of those obtaining college degrees in the 1980s and early

1990s found that women and men did not differ significantly in their likelihood of working in STEM jobs within two years of receiving their degree (Sassler et al. 2017a). But studies utilizing data from more recent cohorts of college graduates suggest the emergence of gender disparities in transitions into the STEM workforce among those obtaining computer science degrees (Michelmore and Sassler 2016). Furthermore, even when women initially enter the STEM workforce, they are more likely than men to subsequently exit for non-STEM employment (Cech and Blair-Loy 2019; Glass et al. 2013; Sassler et al. 2017b).

Research exploring the factors shaping women's retention in the STEM workforce is of long standing (e.g., Glass et al. 2013; Gunter and Stambach 2005; Preston 1994; Xie and Shauman 2003). But such studies have focused heavily on the field of engineering (Fouad et al. 2016; J. Hunt 2016; Kahn and Ginther 2015). Some have examined women's retention in computer science jobs as the field has increased in importance in the labor market (Chang 2018; Sassler et al. 2017b; Stephan and Levin 2005; Wynn and Correll 2018), but these studies are either dated or do not rely on nationally representative data. One highly publicized report produced by the National Academies, which explored the challenges of retaining women in STEM occupations, attributed women's attrition to excessive workloads, unclear expectations, lack of work-life balance, and a "chilly climate" (National Academy of Engineering 2014), elements that are especially noted in computer science occupations (Sax et al. 2017; Wynn and Correll 2018). Yet the relatively small sample size of computer scientists in nationally representative, longitudinal surveys with detailed information on work conditions as well life cycle factors has made it difficult to find causal explanations for why women's attrition from computer science jobs exceeds men's exits. Absent such information, researchers have focused on information that is available in existing crosssectional data sets. Contemporary explanations for the leakage of women trained in STEM fields from related occupations have focused predominantly on factors that are ascertained in various data collections as demographic background variations-marital status and parenthood.

## Gender, Family Obligations, and Employment

The explanation most frequently proffered to account for women's underrepresentation in STEM jobs centers on pervasive gender norms that assign primacy to women's obligations as wives and mothers (Blair-Loy 2003; Stone 2007). But both women's and men's family building processes have changed. The median age at first marriage increased from 23.0 in 1984 to 25.9 by 2009 (United States Census Bureau 2019) and continued to rise in the years following the Great Recession. The median age at first childbirth also increased (Guzzo and Payne 2018). Women with college degrees both marry and have children considerably later than do less educated women, on average. ${ }^{2}$ Men's role in childrearing has also grown over the past few decades (Bianchi et al. 2012; Sayer, Bianchi, and Robinson 2004; Smith 2015). A growing body of evidence increasingly suggests that the returns to marriage and parenthood have changed, especially for highly educated professionals, in terms of the gender wage gap (Beutel and Schleifer 2022; Buchmann and McDaniel 2016; Michelmore and Sassler 2016; Pal and Waldfogel 2016). Whether this can be attributable in part to differential levels of retention in particular occupations, however, requires additional study.

Labor force participation rates have, until relatively recently, been lower among married women and mothers than among their single or childless counterparts (Bianchi and Cohen 1999), and this has also been the case among STEM workers. In her influential study of the leakage of women out of the STEM pipeline, A. E. Preston (2004) conducted interviews with women engineers; she found that women often reported leaving engineering jobs because of difficulties with juggling family obligations and workplace demands. Utilizing more recent data, S. Kahn and D. K. Ginther (2015) also found that much of the gender difference in who remained in engineering jobs was due to women leaving the labor force following childbearing.

Other studies, utilizing a variety of data sources, have questioned the extent to which family factors are associated with exiting the STEM labor force. While finding that women were less likely than men to remain in technology jobs, Paula Stephan and Sharon Levin (2005) concluded that changing marital or parental status was not significantly associated with women's lower rates of retention. Two studies utilizing data from the National Longitudinal Study of Youth (NLSY79) also challenged common perceptions that women left STEM jobs due to marriage and parenthood. Looking at women with STEM degrees who worked in STEM in the 1980s and early 1990s, Glass and colleagues (2013) found that nearly half of such workers exited STEM occupations within the first five years of employment, generally prior to getting married and having children. Utilizing the same data set, Hunt (2016) found that the gendered persistence gap in engineering was almost entirely due to dissatisfaction with pay and promotion, rather than family factors such as marriage and childbearing.

The returns to employment have shifted in the early years of the twenty-first century, particularly for highly educated women (Beutel and Schleifer 2021; Buchmann and McDaniel 2016; Michelmore and Sassler 2016). Among more recent cohorts, for example, women have increasingly remained in the workforce after having children (Percheski 2008). Furthermore, a growing body of evidence has shown that recent cohorts of college-educated women, especially those who work in well-paying professions, are receiving marriage and motherhood wage bonuses instead of penalties, relative to their unmarried or childless counterparts (Buchmann and McDaniel 2016; Glauber 2018; Pal and Waldfogel 2016); this has also been found for women employed in STEM occupations (Beutel and Schleifer 2022; Michelmore and Sassler 2016). The ability of high-earning professional women to purchase services that make it easier for them to remain in the paid labor force, such as childcare and domestic help, may have shifted the association between marriage, parenthood, and retention in the STEM workforce over time, and increased their resemblance (in terms of job retention) to men. Furthermore, companies have expanded paid leave policies, mainly for highly paid professionals (Kaufman and Petts 2020), which may also allow women to combine work and family more easily than in the past.

Men are also playing a larger role in childrearing, highlighting the convergence of men's and women's work and family roles (Sayer et al. 2004; Smith 2015). Changes in expectations for fathers, especially growing support for men desiring to participate more fully in their children's lives (Coltrane 1996) and employed women's expectations that home obligations are shared (Sayer et al. 2004), may both decrease men's likelihood of remaining in computer science jobs and increase women's occupational retention. In fact, Cech and Blair-Loy (2019) report that nearly a quarter of new fathers left full-time STEM employment after the birth or adoption of a child. These trends suggest that the role of family factors in predicting STEM employment, for both men and women, may have shifted over time.

## Other Explanations for the Gender Gap in STEM Employment

STEM places of employment - especially in engineering and technology-have historically been dominated by men, resulting in workplaces that are highly gendered, with unsupportive workplace environments and practices (Williams 2019). Various authors suggest that the workplace climate contributes to women's attrition from the STEM workforce in general (Sassler et al. 2017b; Glass et al. 2013; Hunt 2016), and computer science jobs, in particular (Chang 2018; Mundy 2017). Women employed in STEM fields often report feeling isolated or unwelcome due to their scarcity (Fouad et al. 2016; Gunter and Stambach 2005). They may also feel misaligned with coworkers, as they exhibit significantly more liberal gender ideologies than their male STEM counterparts (Sassler et al. 2017a). Women who do not adhere to workplace success stereotypes are significantly more likely to consider switching career fields (Wynn and Correll 2018). ${ }^{3}$ To date, however, an absence of nationally representative data sets with regular collection of information on workplace environments precludes the ability to assess the causal impact of
gendered work organizations on retention in computer science jobs, or whether these associations have changed over time.

## The Current Study

We examine the gender gap in employment in the computer science workforce, how it has changed across cohorts, and how family factors such as marriage or parenthood are associated with working in a computer science occupation, another STEM occupation, or a non-STEM occupation. Assessing factors contributing to occupational retention is challenging, given cohort changes in women's labor force participation rates (especially following childbearing), shifts in the national economy and the technology workplace, and variability in the composition of the technology workforce. The demand for, and availability of, jobs in computer science has also fluctuated over time, in response to recessions, tech bubbles, and immigration bottlenecks (Chang 2018). ${ }^{4}$ Finally, the composition of the technology workforce has changed and is increasingly comprised of foreign-born workers but a smaller representation of women (Sana 2010). The evidence suggests that the association between factors such as marital status, parenthood, and retention in STEM and computer science jobs likely varies over time.

Based on this review of the literature, we propose the following hypotheses:

Hypothesis 1: We expect women to be less likely than their male counterparts with similar degrees to work in computer science jobs relative to jobs in non-STEM occupations.
Hypothesis 2: We hypothesize that marriage will be negatively associated with working in computer science relative to a non-STEM occupation; we expect the association to be stronger for women than for men.
Hypothesis 3: We anticipate that being a parent will be negatively associated with working in computer science, again to a larger extent for women than for men.
Hypothesis 4: Based on the research showing cohort change in the effects of family factors on STEM employment, we expect that the association between gender, marriage, children, and computer science employment will be weaker among more recent graduates than among older cohorts.

## Data and Methods

Our analysis relies on data from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT). We incorporate data from the following nine SESTAT data collection efforts: 1993, 1995, 1997, 1999, 2003, 2006, 2008, 2010, and 2013. 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 compiled by the National Center for Science and Engineering Statistics (NCSES), drawn 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 who 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.

Some respondents appear in the SESTAT data in more than one wave and are linked across waves by a common identifier. To reduce concerns of non-independent sampling, we treat the data as repeated cross-sections, restricting 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 computer science between 1980 and
2009. ${ }^{5}$ The data are collected between 1993 and 2013, resulting in a sample that is aged 22 to 65 . Since the data are cross-sectional, we can only observe employment at one point in time, rather than longitudinally. However, as we have data over a 20 -year time period, we observe employment trends over time for a given cohort of computer science degree holders.

This analysis focuses on individuals who are working full time, excluding individuals who are unemployed, in school, out of the labor force, or working less than 35 hours per week. ${ }^{6}$ We exclude 198 individuals who are in school ( 136 men, 62 women), 467 individuals who are unemployed ( 276 men, 191 women), and 573 who are out of the labor force ( 147 men, 426 women). ${ }^{7}$ The exclusion of 1,238 individuals represents 8 percent of the respondents who hold a computer science bachelor's degree attained between 1980 and 2009. Previous research suggests that the share of STEM degree holders not in the labor force is quite small (Glass et al. 2013; Landivar 2013), which our results confirm, as only 3.6 percent of computer science degree holders are out of the labor force. Furthermore, only 5 percent or 789 respondents report working less than 35 hours per week ( 374 men, 415 women). A larger share of women report working part time than men ( 9 percent compared with 4 percent, respectively, $p$-value $<.000$ ). Our analyses exclude the 789 part-time workers and those who are unemployed as our intention is to test whether an elite group of workers-computer science majors employed full time-experience gender differences in occupational retention. Multinomial regression robustness tests including full-time and parttime workers show that part-time workers are more likely to work in non-STEM occupations ( $p$ $<.001)$ and the remaining results are not sensitive to work hours and the results are consistent with the models including full-time workers only.

Results from our analysis of the gender gap in computer science can therefore be interpreted as the difference in men and women's propensity to work in computer science compared to employment in other STEM fields (such as engineering) or employed outside of STEM occupations, among those receiving at least a bachelor's degree in computer science. ${ }^{8}$ Our final sample consists of 13,682 men and women working full time (in any occupation) with bachelor's degrees in computer science.

## Dependent Variable

Our dependent variable of interest is a three-category indicator for whether an individual worked in a computer science occupation, another STEM occupation, or in a non-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 computer science occupations were distinguished from those working in other STEM occupations (math, engineering, life sciences, or physical sciences). We separate computer science and math because the employment trajectory for math majors differs substantially from those of computer science majors. Respondents who majored in computer science but were working as engineers or life scientists were classified as working in another STEM occupation. Those who obtained their degree in computer science but worked outside of all STEM fields were classified as not working in STEM; jobs in management, sales, and as teachers accounted for the largest share of occupations outside of computer science or STEM.

## Key Independent Variables

Our key independent variables of interest are gender, marital status, and parental status, as well as indicators of age and year of degree attainment. SESTAT categorization limit us to examining gender only in terms of women and men. We also explore family characteristics, distinguishing between respondents who are married, cohabiting, and single (the reference group), ${ }^{9}$ and include measures for whether the respondent has any children. ${ }^{10}$

Because the propensity to work in STEM may differ across graduation cohorts and by lifestage, we also account for respondent's age and year of degree receipt. We construct five-year college graduation cohort indicators, with the earliest cohort (those graduating between 1980 and 1984) serving as the reference group. We also make use of a linear control for age, as well as a quadratic to allow the propensity to work in STEM or outside STEM to vary and change across the life course.

## Control Variables

We control for several other factors that may shape retention in computer science occupations. Racial minorities are underrepresented in STEM occupations, especially in computer science (Corbett and Hill 2015; National Academy of Engineering 2014). Initial models include dummy variables denoting whether respondents identified as White, Black, Hispanic, or Asian. Given the large foreign-born representation in computer science (Sana 2010), we also include a dummy variable indicating whether respondents were born outside of the United States. Other controls account for measures of human capital, such as educational attainment. We note 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; those with only a bachelor's degree in computer science serve as the reference. We also control for whether the individual obtained their bachelor's degree outside of the United States.

## Analytical Strategy

Our analysis proceeds as follows. First, we describe differences in observed characteristics between men and women who hold at least a bachelor's degree in computer science. We then examine how respondents who majored in computer science are arrayed in occupations, differentiating by gender and exploring various factors associated with transitions out of computer science occupations. Next, we turn to multivariate analyses, using multinomial logistic regression models to test whether differences between men and women in background characteristics, educational attainment, and family formation can account for disparities in employment in computer science occupations compared with employment in other STEM occupations and nonSTEM occupations. Our tables present both the coefficients and the relative risk ratios (or the exponentiated coefficients of the parameter estimates, referred to as RRR), which can be interpreted as the change in the relative risk of working in another STEM occupation or a non-STEM occupation, relative to a computer science occupation.

Next, we examine how the influence of these family measures has changed over BA cohorts by predicting the probability of working in a non-STEM occupation over 1980 to 2009. We interact all family characteristics with gender, to allow the association between family characteristics and work propensities to differ for men and women. ${ }^{11}$ Finally, we consider the factors contributing to the gender employment gap in computer science, and how that has changed over time using a modification of the Blinder-Oaxaca regression decomposition, the Fairlie decomposition, which is appropriate for nonlinear models (Fairlie 2005). The Fairlie decomposition does not allow for a dependent variable with three outcomes, thus we combine non-STEM with other STEM employment for these analyses. ${ }^{12}$ This model allows us to assess the extent to which gender differences in employment in computer science jobs can be explained by differences in the attributes of women and men. The traditional Blinder-Oaxaca decomposition separates the portion of the gap that is due to differences in the observed characteristics between two groups. The portion, due to "unexplained" differences, is generally attributed to differences in the returns to these characteristics, or discrimination (Blinder 1973; Oaxaca 1973). Our analyses assess changes in the amount of variation across the entire time span 1980-2009 and also across three graduation
cohorts-those obtaining their degrees between 1980-1989, 1990-1999, and 2000-2009-to evaluate the changes in differential treatment over time. We use 10 -year cohorts to ensure large enough sample size for analyses.

## Results

Descriptive statistics of those who majored in computer science and are working full time are presented in Table 1, separately by gender, with asterisks indicating significant differences in characteristics between men and women. Consistent with other studies of STEM professionals (Beutel and Schleifer 2022; Michelmore and Sassler 2016), men's earnings significantly exceed their female counterparts, on the order of $\$ 15,000$ per year. Variations in when male and female respondents obtained degrees in computer science are also evident. Over a third of women who obtained computer science degrees ( 35 percent) had graduated in the 1980s, a larger proportion than had obtained their degrees in the first decade of the twenty-first century. Men were significantly better represented among graduates finishing between 2005 and 2009. This pattern is not surprising, given the downward trend in the share of women obtaining degrees in computer science (Michelmore and Sassler 2016). Other important distinctions are evident regarding family factors. Women with computer science degrees were significantly less likely to be married than men with computer science degrees. Greater proportions of women with computer science degrees are Black and Asian; they are also more likely than their male counterparts to be foreignborn. Finally, women are more likely than men with computer science degrees to have obtained a PhD in a non-STEM field.

Overall, nearly six in ten of those who obtained degrees in computer science worked in a computer science occupation (see Table 2). This average, however, masks considerable gender differences. Only half of all women with degrees in computer science worked in computer science occupations, compared with 62 percent of men. In fact, women holding degrees in computer science are nearly as likely to be working in non-STEM occupations (48 percent) and far more likely to be doing so than their male counterparts.

## Multivariate Results

The multivariate results further confirm this pattern: Women are significantly more likely to work in a non-STEM occupation, relative to a computer science occupation, compared with men, which supports Hypothesis 1 (see Table 3). The odds of women working in a non-STEM job relative to a computer science job are 1.58 times that of men who obtained a degree in computer science. Women also exhibited significantly greater odds of working in a non-STEM job relative to a job in another STEM field, like engineering, than men ( $R R R=1.84$ times greater). We find no evidence that women are any more likely than men to work in another STEM occupation relative to computer science jobs, perhaps because the flow is in the reverse direction (those trained in other STEM fields work in computer science; Sassler et al. 2017b).

Consistent with popular perceptions of technology workers, our findings suggest that working in computer science jobs is the domain of the young. As computer science degree holders age, the likelihood of working in non-computer science occupations increases. With each additional year, the odds of working in non-STEM jobs (vs. computer science ones) increases by 9.2 percent. While the annual increase is smaller, each additional year of age is also associated with a 1.0 percent increase in the odds of working in other STEM jobs relative to a computer science one.

We also observe a time trend in how respondents with degrees in computer science utilize their credentials. Compared with those graduating in the early 1980s, all successive cohorts have a lower likelihood of "opting out" of computer science for work in non-STEM occupations. Those graduating in the late 1980s, for example, have odds of working in non-STEM jobs that

Table I. Descriptive Statistics of Full-Time Workers Who Majored in Computer Science, by Gender.

| Descriptive Statistics | Men |  | Women |  | Sig. diff. |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | M | SD | M | SD |  |
| Annual earnings (mean) 2018US\$ | \$96,515 | \$55,855 | \$80,781 | \$41,966 | *** |
| Age | 36.3 | 8.80 | 37.7 | 9.20 |  |
| Age squared | I,403.1 | 693.30 | 1,507.9 | 733.35 |  |
| BA cohort |  |  |  |  |  |
| 1980-1984 | 0.12 | 0.32 | 0.13 | 0.34 |  |
| 1985-1989 | 0.19 | 0.39 | 0.22 | 0.42 |  |
| 1990-1994 | 0.16 | 0.37 | 0.17 | 0.38 |  |
| 1995-1999 | 0.17 | 0.37 | 0.15 | 0.36 |  |
| 2000-2004 | 0.20 | 0.40 | 0.22 | 0.41 | ** |
| 2005-2009 | 0.15 | 0.36 | 0.10 | 0.30 | *** |
| Family indicators |  |  |  |  |  |
| Married | 0.66 | 0.47 | 0.59 | 0.49 | *** |
| Cohabiting | 0.04 | 0.19 | 0.04 | 0.21 |  |
| Single | 0.30 | 0.46 | 0.37 | 0.48 | *** |
| Has children | 0.48 | 0.50 | 0.45 | 0.50 |  |
| No minor coresident children | 0.52 | 0.50 | 0.55 | 0.50 |  |
| Race |  |  |  |  |  |
| White | 0.69 | 0.46 | 0.56 | 0.50 | *** |
| Black | 0.07 | 0.25 | 0.16 | 0.37 | *** |
| Hispanic | 0.06 | 0.23 | 0.06 | 0.24 |  |
| Asian | 0.19 | 0.39 | 0.22 | 0.41 | *** |
| Nativity |  |  |  |  |  |
| Foreign-born | 0.25 | 0.43 | 0.28 | 0.45 | *** |
| Level/area of degree attainment |  |  |  |  |  |
| BA only | 0.78 | 0.41 | 0.76 | 0.43 |  |
| STEM Master's | 0.13 | 0.34 | 0.11 | 0.32 |  |
| STEM PhD | 0.01 | 0.09 | 0.01 | 0.08 |  |
| Non-STEM advanced degree | 0.08 | 0.27 | 0.12 | 0.33 | *** |
| Where obtained degree: Foreign BA | 0.11 | 0.31 | 0.11 | 0.32 |  |
| $N$ | 9,599 |  | 4,083 |  |  |

Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1993-2013.
Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full-time at the time of survey. STEM = science, technology, engineering, and mathematics.
Notation indicates statistical significance: ${ }^{*} p<.05$. ${ }^{* *} p<.01 .{ }^{* * *} p<.00$ I.
are 21 percent lower than those graduating in the early 1980s. We do not see evidence that the bursting of the tech bubble (2001) and the Great Recession of 2008 increased employment in non-STEM jobs; those who obtained their computer science degree in the new millennium (2000-2004, and 2005-2009) remain significantly more likely to work in computer science jobs than in non-STEM ones, consistent with the age results. It is not clear, however, whether this trend operates for both men and women, a topic we further explore below.

The results also provide little support for the argument that employment in computer science is not compatible with adult roles of partner and parent. Being married is not associated with elevated odds of working in non-STEM jobs at conventional levels of significance. Whereas those who are cohabiting are more likely to work in non-STEM jobs relative to their unpartnered

Table 2. Employment Type, Full-Time Workers Who Majored in Computer Science, by Gender.

| Employment Field | Men |  | Women |  | Sig. diff. |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | M | SD | M | SD |  |
| Percent employed in |  |  |  |  |  |
| Computer science | 0.62 | 0.48 | 0.50 | 0.50 | *** |
| Other STEM, including math | 0.03 | 0.18 | 0.03 | 0.16 | * |
| Non-STEM | 0.34 | 0.47 | 0.48 | 0.50 | *** |
| $N$ | 9,599 |  | 4,083 |  |  |

Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013.
Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full-time at the time of survey. STEM = science, technology, engineering, and mathematics.
Notation indicates statistical significance: ${ }^{*} p<.05$; ${ }^{* *} p<.01$; ***p $<.001$ (two-tailed test).
peers, they are less likely to be working in occupations in STEM fields outside of computer science, and most of our sample members in coresidential unions are married rather than cohabiting. We do not find much support for Hypothesis 2 for the overall sample. Furthermore, respondents with any children $(0-18)$ are more likely to be working outside of STEM compared with their childless counterparts, ${ }^{13}$ providing support for Hypothesis 3.

In terms of our other controls, we find substantial variation in non-STEM employment by race and ethnic group. Black computer science degree holders have odds of working in non-STEM jobs relative to computer science jobs that are 38 percent greater than White computer science degree holders, while the odds of working outside of computer science are 60 percent greater for Hispanics relative to Whites. Hispanics are also more likely to leave computer science for another STEM job. Asians are no more (or less) likely than their White counterparts to work in computer science, and the foreign-born do not differ at conventional levels of significance from the nativeborn. Attaining post-graduate education (whether a Master's or PhD) in a STEM field significantly reduced the likelihood of working in a non-STEM occupation over computer science jobs but obtaining a doctoral degree in a STEM field substantially elevated the likelihood of working in another STEM field over computer science. Investing in a non-STEM degree, such as an MBA, also elevated the odds of working in other STEM as well as non-STEM jobs relative to computer science.

## Variations by Gender

Our starting premise was that something unique about gender differentiated the experiences of women and men trained in computer science. We now turn to examining whether the overall patterns discussed above operate differently for men and women. We interact the variables described in Table 3 with gender to assess whether differences in the effects of these variables of interest (e.g., family factors such as marital and parental status, vintage of degree receipt) are statistically significantly different for men and women. Mize (2019) argues that using predicted probabilities is the best practice to estimate and present nonlinear interaction effects. The predicted values are based on interaction models (not shown) from Table 3. We present predicted probabilities of working in non-STEM occupations, as generated by the sum of these interaction terms. We highlight gender variations in the associations when appropriate. ${ }^{14}$

Women exhibit higher predicted probabilities of working in non-STEM jobs compared with men, consistent with Hypothesis 1. However, we find little support for Hypothesis 2, even after allowing marital status to operate differently by gender. Married women are actually less likely to work in non-STEM jobs compared with cohabiting women (Figure 1). Married women are,

Table 3. Multinomial Models Predicting STEM Employment Among Computer Science Majors Employed Full Time.

| Variables | Other STEM versus computer science |  | Non-STEM versus computer science |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Coef. | RRR | Coef. | RRR |
| Female | -0.155 | 0.856 | 0.456 | $1.578 * * *$ |
| Age and graduation cohort |  |  |  |  |
| Age | 0.022 | 1.022 | -0.088 | 0.916** |
| Age squared | 0.001 | 1.001 | 0.001 | I.001** |
| BA cohort (1980-1984 = Reference) |  |  |  |  |
| 1985-1989 | -0.267 | 0.766 | -0.235 | 0.791* |
| 1990-1994 | 0.113 | 1.120 | -0.243 | 0.784* |
| 1995-1999 | 0.057 | 1.059 | -0.352 | 0.703** |
| 2000-2004 | 0.021 | 1.021 | -0.450 | $0.638^{* * *}$ |
| 2005-2009 | -0.202 | 0.817 | -0.476 | $0.621^{* *}$ |
| Family measures |  |  |  |  |
| Partnership status (Single $=$ Reference) |  |  |  |  |
| Married | -0.233 | 0.792 | -0.148 | 0.862 |
| Cohabiting | -0.650 | 0.522* | 0.486 | 1.626** |
| Parental Status (No minor coresident children $=$ Reference) |  |  |  |  |
| Has children | 0.147 | I.158 | 0.324 | 1.383*** |
| Race/Ethnicity (NH White $=$ Reference $)$ |  |  |  |  |
| Black | 0.130 | 1.139 | 0.322 | 1.380* |
| Hispanic | 0.504 | 1.655* | 0.469 | 1.598** |
| Asian | -0.052 | 0.949 | -0.099 | 0.906 |
| Foreign-born | -0.143 | 0.867 | 0.078 | 1.081 |
| Advanced degree (Bachelor's only = Reference) |  |  |  |  |
| STEM Master's | 0.066 | 1.068 | -0.687 | 0.503*** |
| STEM PhD | 1.577 | 4.840*** | -0.880 | 0.415* |
| Non-STEM advanced degree | 0.808 | 2.243* | 1.101 | 3.007 *** |
| Foreign BA | 0.054 | 1.055 | -0.112 | 0.894 |
| Constant | -2.941* |  | -0.927 |  |
| N | 13,682 |  |  |  |

Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013.
Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Underlined coefficients indicate statistically significant difference between employment in non-STEM versus Other STEM at $p<.05$. STEM $=$ science, technology, engineering, and mathematics. RRR refers to relative risk ratios, or the exponentiated coefficients of the parameter estimates. Notation indicates statistical significance: ${ }^{*} p<.05 .{ }^{* *} p<.01 .{ }^{* * *} p<.00 \mathrm{I}$ (two-tailed test).
however, substantially more likely to work in non-STEM compared with married men. ${ }^{15}$ Although cohabiting men have a higher probability of working in non-STEM than married or single men, this difference is not statistically significant at conventional levels, and we find no difference in the propensity to work in non-STEM between married and single men. ${ }^{16}$ We can therefore reject the argument that union formation, particularly marriage, distinguishes women's attrition to a greater extent than it does for men. It is not married women who opt out of computer science. Rather, employment in computer science jobs seems to be particularly low among unmarried women (especially when compared with married or single men).


Figure I. Predicted probability of working in non-STEM, men and women by marital status.
Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013. Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Figure presents predicted probabilities of working in non-STEM jobs with interactions of gender and marital status, controlling for all variables in the multinomial model in Table 3 and holding these covariates at their means. Bars portray 95 percent confidence intervals. STEM = science, technology, engineering, and mathematics.

Our interaction results reveal that being a father reduces men's likelihood of working in computer science relative to a non-STEM job, consistent with the findings of Cech and Blair-Loy for STEM occupations overall (2019). For women, the association between having any children and the likelihood of working in a non-STEM job is not significant (Figure 2). In fact, men and women with children have similar rates of employment in non-STEM, which does not support Hypothesis 3. In fact, it is the childless men who stand apart from all other groups: Childless men are substantially less likely to work in non-STEM compared with men with children ( 29.9 percent compared with 39.5 percent), as well as women, regardless of whether they have children. ${ }^{17}$

We next test whether the gender difference in propensity to work in computer science and non-STEM has changed over time. We do this through an interaction term of graduation cohort and gender (see Figure 3). ${ }^{18}$ Consistent with the results from Table 3, we see that men with computer science degrees are more likely than their female counterparts to work in computer science jobs across all graduation cohorts, but the pattern is particularly notable among more recent cohorts. Among graduates from the latter half of the 1990s, the patterns among men and women began to diverge. Men became increasingly likely to work in computer science occupations over time; the probabilities for women working in computer science jobs decreased. Looking at the cohorts graduating between 1990 to 1994 and 2005 to 2009, the predicted share of men working in computer science increased from about 60 percent to nearly 70 percent, whereas the predicted share of women working in computer science decreased from 55 percent to less than half. By the 2005 to 2009 cohort, women with computer science degrees were roughly equally likely to work in computer science as they were to work in a non-STEM occupation.

## Variations by Cohort

Does the impact of marriage or parenthood on employment in computer science vary across graduation cohorts, given changes over time in normative expectations for women and men? To


Figure 2. Predicted probability of working in non-STEM, men and women by presence of children. Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013. Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Figure presents predicted probabilities of working in non-STEM jobs with interactions of gender and parental status, controlling for all variables in the multinomial model in Table 3 and holding these covariates at their means. Bars portray 95 percent confidence intervals. STEM = science, technology, engineering, and mathematics.


Figure 3. Predicted probability of working in computer science and non-STEM jobs, men and women by BA cohort.
Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013. Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Figure presents predicted probabilities of working in non-STEM jobs with interactions of gender and college cohort, controlling for all variables in the multinomial model in Table 3 and holding these covariates at their means. STEM = science, technology, engineering, and mathematics.


Figure 4. Predicted probability of working in non-STEM by BA cohort, men and women by marital status.
Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1993-2013.
Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Figure presents predicted probabilities of working in non-STEM jobs with interactions of gender, college cohort, and marital status controlling for all variables in the multinomial model in Table 3 and holding these covariates at their means. STEM = science, technology, engineering, and mathematics.
explore this question, we present the results of our predicted probabilities for three-way interactions of gender, college cohort, and marital status, as well as gender, college cohort, and parenthood status. ${ }^{19}$ We depict the probability of working in non-STEM occupations (relative to jobs in computer science).

Family demands imposed by marriage do not seem to account for the probability that women with degrees in computer science have lower probabilities of working in computer science jobs (Figure 4). Since the mid-1980s cohorts of college graduates, single women have had higher probabilities of working in non-STEM jobs than married women. Similarly, single women are more likely to work outside of STEM compared with both single and married men. This gender employment gap is most pronounced among the more recent college cohorts, with under 30 percent of single men working outside of STEM compared with 53 percent of single women. Married women also have higher probabilities of working in non-STEM than their married male counterparts, and these differences are also most striking in the millennium cohorts, as married women's probabilities of working outside of STEM resemble unmarried women's probabilities. In the most recent college cohort (2005-2009), gender is associated with non-STEM employment more than is marital status.

A closer examination of how the association between children and employment in computer science jobs has changed across graduation cohorts and by gender suggests that the impact of parenthood changed for both men and women. In the 1980 to 1984 college cohort, we find no statistically significant difference in the probability of working in non-STEM jobs among women and men with and without children (all probabilities hover between . 42 and .49) (see Figure 5). But in the intervening years, there is increasing divergence between childless men and both fathers and women (regardless of parental status). Among graduates of the late 1980s through the


Figure 5. Predicted probability of working in non-STEM by BA cohort, men and women by children. Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013. Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. Figure presents predicted probabilities of working in non-STEM jobs with interactions of gender, college cohort, and parental status controlling for all variables in the multinomial model in Table 3 and holding these covariates at their means. STEM = science, technology, engineering, and mathematics.

1990s, fathers and childless women have similar probabilities of working in non-STEM jobs. The probability of working in non-STEM jobs declines over time for childless men; among those in the college graduation cohort of 2005 to 2009 , the predicted probability of working in nonSTEM jobs is only 20.7 percent. For those who are parents, an inflection occurs among both women and men with children who graduated in 2005 to 2009, consistent with Cech and BlairLoy's (2019) finding of higher transition rates among both new mothers and new fathers out of STEM jobs early in the new millennium. Among those obtaining their degree in computer science between 2005 and 2009, the predicted probability of working in non-STEM jobs was more than two times greater among fathers and childless women and three times greater among mothers than it was for childless men of that graduation vintage (0.207). Our results do not support Hypothesis 4, as we anticipated a weaker association between gender and marriage (Figure 4) and gender and children (Figure 5) among more recent cohorts; instead, we found stronger associations.

## Comparing Women's and Men's Retention in Computer Science Jobs: Decomposition Results

Our final analysis of the gender employment gap in computer science, and how the factors contributing to that gap have changed over time, presents results from regression decompositions to assess the extent to which gender differences in employment in computer science jobs can be explained by differences in the attributes of women and men (Table 4). Over the entire sample of college graduates between 1980 and 2009, the total gender difference in the probability of working in computer science was 7.2 percentage points, reflecting the higher concentration of men working in computer science than women. That difference varies greatly, however, depending on vintage of BA degree receipt. For the early cohort of 1980 to 1989 , the difference is 3.8 percentage points, but the gender gap in computer science employment increases in subsequent cohorts
Table 4. Decomposition of Components of Gender Difference in the Expected Log Odds of CS Employment by BA Cohort.

|  | Computer science majors |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1980-2009 |  |  | 1980-1989 |  | 1990-1999 |  | 2000-2009 |  |
|  | Model A |  | Model B | Model A | Model B | Model A | Model B | Model A | Model B |
|  | Women as standard |  | Men as standard | Women as standard | Men as standard | Women as standard | Men as standard | Women as standard | Men as standard |
| Total gender difference in probability of working in CS |  | 0.072 |  |  |  |  |  |  |  |
| Percent of total gender difference in CS employment due to |  |  |  |  |  |  |  |  |  |
| Compositional difference | 28.6\% |  | 30.6\% | 43.8\% | 36.2\% | 43.1\% | 44.9\% | 13.3\% | 25.6\% |
| Unexplained differences | 71.4\% |  | 69.4\% | 56.2\% | 63.8\% | 56.9\% | 55.1\% | 86.7\% | 74.4\% |

[^1]to 5.5 percentage points among the 1990 to 1999 cohort, and then more than doubles for the most recent cohort, those graduating from 2000 to 2009 , to 13 percentage points.

Of note is that compositional differences explain more of the probability of working in computer science occupations in the earlier cohorts than in the most recent cohort. Among those receiving their degrees in the 1980s, compositional differences between women and men accounted for 43.8 percent of the gender difference when women's attributes are used as the standard, and 36.2 percent when men's attributes are used. Among those graduating since 2000, compositional differences make up only 13.3 percent of the difference, though this percent nearly doubles - to 25.6 percent - when men's attributes are the standard. Differences in racial composition and other demographics explain more of the gender employment gap in computer science occupations, while differences in family factors contribute a minimal amount (if using women as the standard, 9.3 percent in the 1990s, and 2.6 percent in the 2000s, see Appendix Tables A1 and A2). For all three cohorts, over half of the gender difference in employment in computer science is due to unexplained characteristics. While we do not have measures used by employers in hiring that may vary by gender, such as college grades or referral networks, unexplained differences in decomposition models are often used as a proxy for discrimination (Mandel and Semyonov 2014).

In summary, we highlight four main conclusions from our analyses. First, women with computer science degrees are more likely to work outside of STEM compared with men. Second, the role of family factors has decreased for more recent cohorts such that married men and women are no more likely to work outside of STEM relative to their single counterparts, and parenthood does not appear to increase the likelihood of working outside of STEM, at least for women. However, fathers are more likely to be working outside of STEM relative to childless men. Third, the gender gap in employment in computer science is widening, rather than narrowing for more recent cohorts of college graduates. Finally, discrimination or unmeasured characteristics, rather than family factors, appears to account for more of the gender gap in computer science employment.

## Discussion and Conclusions

This paper examined the occupational placement of those who obtained college degrees in computer science, a relatively young and evolving field that provides considerable returns to investment in terms of pay and employment opportunities. In recent years, the challenges of retaining women in computer science positions have garnered considerable attention. Our results indicate that increasing women's representation in computer science jobs will be a challenge. Not only are women underrepresented among those receiving degrees in computer science or accepting jobs in computer science; women with computer science degrees are significantly more likely than their male counterparts to work outside of the field of computer science, in non-STEM jobs.

Why has it been so challenging to retain women in computer science occupations? Among the prime explanations used to account for the dearth of women in computer science jobs are reasons related to family factors and women's perceptions that they do not fit in (Cech and Blair-Loy 2019; Mundy 2017). While our cross-sectional data and the lack of variables measuring workplace climate in our dataset make it difficult to fully explore all explanations, our findings challenge the primacy of family reasons as explanations for the low retention of women in computer science. We find little difference in the impact of marriage on men's and women's probabilities of working in computer science jobs. Married men are no less likely to work in computer science (vs. non-STEM jobs) than are single men, while married women are more likely to work in computer science jobs than their unmarried (both single and cohabiting) counterparts. Delayed marriage may contribute to this development, as both men and women accrue additional work experience prior to union formation. Other studies have noted that there is a wage premium for
married professionals (Beutel and Schleifer 2022; Buchmann and McDaniel 2016). In fact, Beutel and Schleifer (2022) find that among men employed in STEM occupations, the earnings premium derives primarily from being married (rather than parenthood). For women computer scientists, marriage may increasingly signal to employers that they are responsible workers.

The impact of children on retention in computer science jobs, on the other hand, does suggest that family factors are important - but they are increasingly important for men as well as women. Consistent with recent studies (Cech and Blair-Loy 2019), we find that both men and women with degrees in computer science have lower probabilities of working in their field when they are parents-though for men this outcome is limited to those graduating in the new millennium. Our findings indicate the strains men increasingly face with combining parenthood and employment in demanding professions, further evidence that the behaviors of men and women are converging on the parenting front as well as in employment (Smith 2015). It is not only women with degrees in computer science who are voting with their feet by finding employment in other STEM or non-STEM workplaces that may have greater job flexibility or a more welcoming climate for parents. The most recent cohorts of fathers with degrees in computer science are doing so as well.

Our results also reveal that factors shaping retention in STEM occupations have changed over time. We have already noted the findings regarding the association between parenthood and employment in computer science among the most recent cohorts of college graduates with degrees in computer science, but our results suggest that there is more at play than observable factors like parenthood. Evidence from other research suggests that discrimination and adverse work climate conditions-demands for long work hours and continued gender disparities in pay and promotion-persist (and may account for a more of the gender employment gap) among more recent cohorts of computer science graduates (Hunt 2016; Quadlin 2018). Notwithstanding efforts encouraging women to take coding classes and major in STEM, women - especially single women - continue to drop out of the computer science workforce or obtain a degree and never enter the field. This loss is particularly notable among women graduating with computer science degrees since 2000. Single women with degrees in computer science have the highest probabilities of working outside of jobs in their field of training, whereas single men are least likely to exit the computer science labor force for non-STEM jobs. The portion of the gender difference in employment in computer science that is due to unexplained factors is greater among the younger, more recent graduates than for those earning their computer science degrees in the 1980s.

Why are young, single women who most recently obtained their degrees in computer science degrees less likely to work in computer science jobs than their older counterparts? Previous research suggests several explanations, though the nature of the SESTAT data precludes us from empirically testing them. Young women may initially work in emergent areas that have more of a "wild west" feel (detailed in E. Chang's (2018) book Brotopia), such as tech start-ups or very male-dominant professions, that may push women out (Chang 2018; Mundy 2017). Job turnover may also be higher in these new industries, as employers compete for workers with specific technological skills and young workers seek to maximize their earnings; younger workers may be more flexible, especially if they are not "tied" to one location or job due to family obligations. Some research has also found that there is a "specter of motherhood" that encourages young women to opt out of STEM positions in anticipation of family demands (Thebaud and Taylor 2021), though that work was limited to academic professions rather than computer science. In fact, a growing body of evidence suggesting that professional married mothers with children earn more than single or married childless women (Beutel and Schleifer 2022; Buchmann and McDaniel 2016; Michelmore and Sassler 2016; Pal and Waldfogel 2016). Future research must examine the selection of both women and men who persist in computer science occupations, and the returns to doing so across the life course.

Our study is not without limitations. We rely on cross-sectional results from a relatively large sample of men and women who have degrees in computer science and assume individuals select majors that are linked with subsequent occupations. College degrees, however, may serve as more than simply a vocational credential, though why that should differ so significantly by gender is unclear. Longitudinal data would better enable us to address when in their employment career individuals left computer science, or if, in fact, they ever worked in the field. It would also allow us to assess if transitions resulted in higher (or lower) earnings, or if these varied by gender, as well as other selection mechanisms, such as the timing of marriage or parenthood, shaping retention in computer science jobs. Those becoming parents among the most recent graduates may also be more selective than previous graduation cohorts. Furthermore, there is limited information in the SESTAT data about reasons for leaving a job, but it is retrospective. Such challenges aside, there are few data sets that contain an adequate sample of women STEM degree recipients in computer science, over a considerable span of time.

Despite considerable advances in the past few decades that have resulted in increases in women's representation in STEM fields, computer science is one area where persistent barriers to women's participation remain. Our decomposition results, in fact, reveal that such barriers have increased among those graduating in the new Millennium. Additional attention relying on diverse methodological approaches that explore the mechanisms that account for women's underrepresentation in computer science jobs is required to better understand how gender inequality is both persistent and changing in the United States into the twenty-first century.

## Appendix

Table AI. Decomposition of Components of Gender Difference in the Expected Log Odds of CS Employment.

| \% of total gender difference due to differences in key covariate means | CS majors only |  |
| :---: | :---: | :---: |
|  | Model A | Model B |
|  | Women as standard | Men as standard |
| Black (ref: White non-Hispanic) | 17.5\% | 17.8\% |
| Hispanic | 1.0\% | 1.8\% |
| Asian | 3.5\% | -0.1\% |
| Foreign-born | -1.3\% | 2.4\% |
| Foreign BA | -0.6\% | -0.6\% |
| BA cohort 1990-1999 (ref: BA 1980-1989) | 0.1\% | 0.6\% |
| BA cohort 2000-2009 | 0.0\% | 0.3\% |
| Age | 21.5\% | 26.4\% |
| Age squared | -19.9\% | -25.6\% |
| STEM Master's degree (ref: Bachelor's only) | I.1\% | 0.0\% |
| STEM PhD | -0.7\% | -0.4\% |
| Non-STEM adv degree | 4.4\% | 5.8\% |
| Married (ref: Single) | 2.9\% | 3.6\% |
| Cohabiting | 0.3\% | -0.1\% |
| Has children (ref: no coresident children) | -1.4\% | -1.4\% |
| Total compositional difference | 28.6\% | 30.6\% |
| Total unexplained differences | 71.4\% | 69.4\% |
| Total difference in probability of working in CS |  |  |

Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013.
Note. All men and women graduating with a bachelor's degree in computer science between 1980 and employed full time at the time of survey. STEM = science, technology, engineering, and mathematics; CS = computer science.
Table A2. Decomposition of Components of Gender Difference in the Expected Log Odds of CS Employment by BA Cohort.

| \% of total gender difference due to differences in key covariate means | CS majors only |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1980-1989 |  | 1990-1999 |  | 2000-2009 |  |
|  | Model A | Model B | Model A | Model B | Model A | Model B |
|  | Women as standard | Men as standard | Women as standard | Men as standard | Women as standard | Men as standard |
| Black (ref: White non-Hispanic) | 21.3\% | 15.2\% | 26.7\% | 25.8\% | 8.5\% | 12.6\% |
| Hispanic | 1.9\% | 1.3\% | 3.6\% | 3.5\% | 0.0\% | 0.8\% |
| Asian | 15.4\% | -2.4\% | 3.6\% | 0.2\% | 0.6\% | 0.2\% |
| Foreign-born | -3.7\% | 6.9\% | -6.2\% | -0.2\% | 0.7\% | 1.2\% |
| Foreign BA | 1.1\% | 1.3\% | 0.5\% | 0.2\% | -1.7\% | -1.0\% |
| Age | 145.5\% | 149.2\% | 27.8\% | 43.8\% | -9.5\% | -3.0\% |
| Age squared | -147.3\% | -148.4\% | -25.5\% | -41.1\% | 12.8\% | 9.9\% |
| STEM Master's degree (ref: Bachelor's only) | 10.1\% | 6.6\% | 3.3\% | 1.8\% | -4.8\% | -3.4\% |
| STEM PhD | -0.2\% | -0.8\% | -4.4\% | -1.8\% | -0.1\% | -0.5\% |
| Non-STEM adv degree | 4.8\% | 5.9\% | 4.2\% | 4.5\% | 4.2\% | 7.6\% |
| Married (ref: Single) | 2.4\% | 4.3\% | 10.2\% | 11.3\% | 0.8\% | 1.2\% |
| Cohabiting | -0.5\% | 0.1\% | 0.0\% | -1.5\% | 0.7\% | 0.2\% |
| Has children (ref: no coresident children) | -7.2\% | -2.9\% | -0.9\% | -1.6\% | 1.1\% | -0.2\% |
| Total compositional difference | 43.8\% | 36.2\% | 43.1\% | 44.9\% | 13.3\% | 25.6\% |
| Total unexplained differences | 56.2\% | 63.8\% | 56.9\% | 55.1\% | 86.7\% | 74.4\% |
| Total difference in probability of working in CS | 0.038 |  | 0.055 |  | 0.130 |  |

[^2]
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## ORCID iD

Sharon L. Sassler id https://orcid.org/0000-0002-5287-8398

## Notes

1. While some designations of science, technology, engineering, and mathematics (STEM) incorporate the social sciences, and other variants include the arts (STEAM), we refer here to the more limited definition of STEM that encompasses science, technology, engineering, and mathematics fields (Landivar 2013).
2. In 2016, for example, the average age of a mother without a college degree at her first birth was 23.8 , but for women with a college degree or more the average age was 30.3 (Bui and Miller 2018). This gap has widened between 1980 and the present.
3. Cech et al. (2011) also find similar outcomes among women enrolled in engineering colleges.
4. This is reflected in dramatic shifts in the numbers as well as the gender composition of those receiving bachelor's degrees (or more) in computer science (National Science Foundation, National Center for Science and Engineering Statistics 2015).
5. Individuals with at least a bachelor's degree make up the majority (about 70 percent) of STEM workers (Landivar 2013).
6. Data from the Current Population Survey Annual Social and Economic Supplement (2003-2020) reveal that the proportions of college-educated women who work part time is considerably smaller among those working in STEM versus non-STEM occupations (Beutel and Schliefer 2022).
7. Chi-square results show men were significantly more likely than women to be in school and unemployed, while women were significantly more likely to be out of the labor force.
8. Only about a third of all those employed in computer science have a degree in computer science. The next most common degree held by those working in computer science was engineering (Sassler et al. 2017b).
9. Cohabitors may have different family obligations than do marrieds, or different access to resources (Sassler and Lichter 2020).
10. Additional analyses disaggregating children by age-having children under age 6 or children under age 18 , or mutually exclusive combinations of young $(<6)$ and older (ages 6-18) children-revealed that the effect of children on employment has more to do with just having children than their specific age, when compared with those who do not have any minor children (results available from the authors). We therefore utilize one measure that captures the presence of any children under age 18 (any children $=1$ ) relative to those who have no children under age 18.
11. We are unable to run a three-way interaction of marital status, presence of children, and gender in our analysis due to the small sample size of cohabiters in the data set: only 2 percent ( $N=35$ ) of female cohabiters have children and 1 percent $(N=45)$ of male cohabiters have children.
12. Robustness tests were conducted combining computer science and other-STEM versus non-STEM and the overall trends and patterns were consistent with those presented in Table 4 and Appendix Tables A1 and A2.
13. Robustness tests were conducted including part-time workers and the overall results remained consistent. Full-time workers have a lower probability of working in non-STEM occupations compared with CS occupations.
14. Full results for these analyses are available upon request.
15. When single and cohabiting women are combined (due to the small number of cohabiting women) into one category, this new unmarried group is significantly more likely than married women to be working in non-STEM jobs.
16. It is unlikely that cohabitors have greater family responsibilities than their married or single counterparts, such as parenting might impose; among the college educated, pre-marital childbearing is far less common than it is among the less educated, though cohabitation following divorce has become more normative (Sassler and Lichter 2020).
17. All analyses were run with separate indicators for children under 6 and children 6-18 to test whether child's age differentially determined propensity to work in non-STEM. The results (not shown) were inconsistent and muted compared with the results for having any children under 18 , which we present in this paper.
18. The probability of working in Other STEM jobs is very small and does not vary much over BA Cohort or by gender (range is from .028 to .044 for men and from .016 to .031 for women).
19. Due to the small cell size of cohabiting women in the earlier college cohorts, we grouped single and cohabiting women in the subsequent analyses.

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## Author Biographies

Sharon Sassler received her PhD in Sociology from Brown University in 1995, and joined the Cornell faculty in 2005. A social demographer, her research examines factors shaping young adult's transitions into school and work, relationships, and parenthood, and how these transitions vary by gender, race/ethnicity, and social class.

Kristin Smith (PhD University of Maryland, 2006) is Visiting Research Associate Professor of Sociology at Dartmouth College. Her research focuses on gender inequality, employment and earnings, and work and family policy. Her expertise lies in examining gender differences in how work and family life interconnect and developing workplace policy recommendations.

Katherine Michelmore is an associate professor of public policy at the University of Michigan's Gerald R. Ford School of Public Policy. Michelmore is a leading scholar and educator on the social safety net, education policy, labor economics, and economic demography. Previously, she was assistant professor of public administration and international affairs at Syracuse University's Maxwell School; she completed her PhD in policy analysis and management at Cornell University.


[^0]:    'Cornell University, Ithaca, NY, USA
    ${ }^{2}$ Dartmouth College, Hanover, NH, USA
    ${ }^{3}$ University of Michigan Institute for Social Research, Ann Arbor, MI, USA
    Corresponding Author:
    Sharon L. Sassler, The Brooks School of Public Policy, Cornell University, Ithaca, NY I4853, USA.
    Email: ss589@cornell.edu

[^1]:    Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) I993-2013.
    Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. CS $=$ computer science.

[^2]:    Source. National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1993-2013. Note. All men and women graduating with a bachelor's degree in computer science between 1980 and 2009 and employed full time at the time of survey. STEM = science, technology, engineering, and mathematics; CS $=$ computer science.

