Explaining the Gender Wage Gap in STEM: Does Field Sex Composition Matter?

KATHERINE MICHELMORE AND SHARON SASSLER

Using the National Science Foundation's SESTAT data, we examine the gender wage gap by race among those working in computer science, life sciences, physical sciences, and engineering. We find that in fields with a greater representation of women (the life and physical sciences), the gender wage gap can largely be explained by differences in observed characteristics between men and women working in those fields. In the fields with the lowest concentration of women (computer science and engineering), gender wage gaps persist even after controlling for observed characteristics. In assessing how this gap changes over time, we find evidence of a narrowing for more recent cohorts of college graduates in the life sciences and engineering. The computer sciences and physical sciences, however, show no clear pattern in the gap across cohorts of graduates.

Keywords: scientists and engineers, gender wage gap, women in STEM

Enormous progress was made in narrowing the gender wage gap in the 1970s and 1980s, but since the 1990s relatively little movement has been made toward wage parity (Blau and Kahn 2006). The gender pay gap has persisted even though women now make up the majority of college graduates and have for a few decades (DiPrete and Buchmann 2013; Goldin, Katz, and Kuziemko 2006). Despite sizable increases in the likelihood that American women graduate with degrees in science, technology, engineering, and math (STEM) fields, women's representation in the STEM workforce lags behind their educational gains (Xie and Shauman 2003). Women who major in STEM fields 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. 2011). Proponents of diversifying the gender representation of STEM have long argued that having more women in STEM education and employment would help improve retention of women (Committee on Maximizing the Potential of Women 2006; Hill,

Katherine Michelmore is assistant professor in the Department of Public Administration and International Affairs at Syracuse University. **Sharon Sassler** is professor in the Department of Policy Analysis and Management at Cornell University.

This research was supported by Grant no. OSP #68979 from the National Science Foundation (NSF). Katherine Michelmore acknowledges the Institute of Education Sciences, U.S. Department of Education, which provided support through Grant no. R305B110001. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Science Foundation. The authors wish to thank Martha Bailey and Thomas DiPrete for helpful comments and suggestions. Any remaining errors are the authors'. Direct correspondence to: Katherine Michelmore at kmichelm@umich.edu, 935 S. State St. Ann Arbor, MI 48109; and Sharon Sassler at sharon.sassler@cornell.edu, Department of Policy Analysis and Management, Cornell University, 297 Martha Van Rennselaer Hall, Ithaca, NY 14850.

Corbett, and Rose 2010), which should also narrow the gender wage gap in the labor force overall. To date, however, research on occupations with large increases in the share of female workers has generally failed to find evidence of occupational or economic equality (Kogan and Kalter 2006; Roos and Reskin 1992).

Despite the large literature on the gender wage gap and how it has evolved over time (see, for example, Blau and Kahn 1994, 1997, 2006; Mandel and Semyonov 2014), these studies focus on the labor market as a whole, or broad sectors of the labor market. Two of the most common explanations for the gender pay gap are differences in human capital accumulation and occupational segregation. Such explanations should apply less well to the STEM labor force, given that individuals have already selected occupational concentrations and require the same minimum credentials. Yet findings reveal that the gender pay gap persists, whether among those concentrating in particular fields, or among those with a specific degree (see, for example, Bertrand, Goldin, and Katz 2009; Ginther 2003; Morgan 1998). Such disparities are generally attributed to differences in the working patterns of men and women.

In this paper, we assess the presence of and factors contributing to the gender wage gap in the STEM workforce. Building on previous work, this paper makes several contributions to the literature. First, we present a descriptive portrait of the gap in each of the four main STEM fields by racial-ethnic group. Causality is difficult to determine in this context, because individuals may positively (or negatively) select into STEM majors, and STEM occupations and any analysis based on survey data is likely to suffer from omitted variable bias. We can, however, assess the extent to which observed characteristics can explain the gap by field and racial and ethnic origin. Second, we investigate how a specific factor, change in the sex composition of the field, is associated with wages of all workers in a given field. For this analysis, we rely on within-occupation variation in the share of women working in a given field over time to estimate the relationship between sex composition and the wages of the men and women working in those fields. Although it is difficult to confidently argue that this relationship is causal, the data used in this analysis do allow for a rich set of demographic controls as well as occupation fixed effects to control for time-invariant unobservable characteristics that may affect wages. This is a significant improvement over previous work that relies solely on cross-sectional differences across fields, where omitted variable bias is likely to influence estimates. However, we are unable to control for time-varying unobserved factors specific to an occupation that may influence wages over time. Finally, using repeated cross-sectional data between 1995 and 2008, we estimate how the gender wage gap has evolved across the career span and by college cohort, estimating the extent to which it can be explained by a cohort effect or a glass-ceiling effect.

Results indicate a persistent gender pay gap in the two STEM fields with the smallest female representation—engineering and computer science—which also account for the largest share of STEM workers and have the rosiest growth projections for the future. These differences remain even after accounting for observed characteristics such as disparities in years of potential work experience. In the life sciences and physical sciences, the gender wage gap can be completely explained by observed characteristics for whites, African Americans, and Asians.

In assessing how overall wages change within a field as a function of female representation, we find a positive relationship (at least up to a point) between the lagged sex composition of the field and future wages for those working in computer science, life sciences, and engineering. We find no significant relationship between the share of women working in the physical sciences and wages in that field. In assessing whether the gender wage gap changes over the course of one's career (glass-ceiling effect) or across time (cohort effect), we find evidence of a narrowing across cohorts for women working in the life sciences and engineering, such that the most recent cohorts of women working in STEM earn on par with the men in those fields. In computer science and the physical sciences, we find no significant trend in the gender wage gap over time. Finally, we find some evidence that the gap widens over the careers of women in computer science, but we find no evidence of a glass-ceiling effect in any of the other three STEM fields.

EXPLANATIONS FOR THE PERSISTENT GENDER WAGE GAP

The gender wage gap has received much attention over the last several decades, particularly because progress in narrowing the gap has largely stalled. Gender pay disparities narrowed rapidly in the 1980s, but progress since then has been far more modest (Blau and Kahn 2006). Among the reasons women historically earned less than men are gender differences in occupational concentration, human capital accumulation, work history, and discrimination. Some of these explanations have become less relevant in the twenty-first century as women have increased their participation in the workforce and obtained college and advanced degrees; others, such as differences in the working patterns of men and women, continue to have an impact on earnings differentials (Weeden, Cha, and Bucca, this issue; Blau and Kahn 2006; Mandel and Semyonov 2014).

Women surpassed men in their college attendance and graduation as of the 1980s; by the early 2000s, 60 percent of all college degrees were granted to women (DiPrete and Buchmann 2013; Goldin, Katz, and Kuziemko 2006). The narrowing education gap has been credited with reducing some of the gender pay gap (Mandel and Semyonov 2014). In fact, as of 2012 there was virtually no difference in pay between men and women ages twenty-five to thirty-four working full time (Pew Research 2013). That is not to say that employed women may not experience what is often termed the glass ceiling in terms of earnings. Earnings differentials tend to emerge over the course of careers, given that women are more likely than men to take time out of the labor force, or to reduce the hours they work, to have and raise children (Bertrand, Goldin, and Katz 2009; Budig and England 2001; Byker, this issue; Goldin 2014), although recent studies have found a positive wage differential for some mothers (Buchmann and McDaniel, this issue; Pal and Waldfogel, this issue). This represents a shift in recent years, given that estimates from the late 1980s and early 1990s indicated a negative motherhood wage differential of about 6 percent (Budig and England 2001; Pal and Waldfogel, this issue) that narrowed to about 1 percent as of 2011 (Pal and Waldfogel, this issue). Among certain groups, a positive wage differential has been found in most recent years. Pal and Waldfogel (this issue) find a 2 percent positive wage differential for married mothers versus unmarried childless women in 2011, and Buchmann and McDaniel (this issue) find a similar wage differential for mothers versus nonmothers working in STEM and law in 2010. Recent studies have also shown that a significant share of the gender pay gap can be explained by differences in the number of hours men and women work (Bertrand, Goldin, and Katz 2009; Mandel and Semyonov 2014), as well as the overtime hours of professional workers (Weeden, Cha, and Bucca, this issue).

The presence of older cohorts in the workforce may account for a large portion of the remaining gender wage gap due to differences in working patterns and discrimination; we would expect this to narrow as these cohorts retire. The extent to which discrimination continues to account for the gap is hotly contested. Some assert that variations in employment patterns are the result of preferences (Hakim 2000), though such work has been met with fierce criticism, often focused on the structural barriers women with children face in the labor market (Halrynjo and Lyng 2009; Stähli et al. 2009). Results from Blinder-Oaxaca decompositions of the gap over time indicate that discrimination has diminished as a contributor to the gender earnings gap in the overall labor market between 1970 and 2010 (Mandel and Semyonov 2014).

Nonetheless, although women today may face fewer barriers to employment in challenging professions than they once did, their representation in various fields remains stubbornly low. Tremendous resources have been devoted to increasing women's representation in STEM study across the educational spectrum and into careers (Beede et al. 2011; Committee on Maximizing the Potential of Women 2006).[1] Such efforts are premised on the belief that increasing the presence of women will make women more comfortable pursuing such fields of study, and will also have the long-term effect of diversifying leadership in STEM jobs. Furthermore, an increasing proportion of women working in STEM occupations will signal other women that they can succeed in such positions. The success of such developments rests largely on the accumulation of women across cohorts. But some evidence indicates that when too many women enter into a particular occupation and jobs become feminized, earnings and occupational prestige decline for both women and men (Goldin 2002; Levanon, England, and Allison 2009; Mandel 2013). We test whether this phenomenon applies to the STEM labor force as well.

We expand on prior work analyzing the gender wage gap in STEM occupations. Our analysis uses a broad range of cohorts of college graduates and covers a broader range of STEM professionals than many studies. We pay particular attention to how the presence of women in the field is associated with wages in those fields. Because we have several years of data, we are able to control for time-constant occupation level factors that may affect wages, analyzing how the within-occupation changes in sex composition are associated with wages in the field. There are opposing theoretical views on how the presence of other women in the workplace may affect wages. One argument is that increasing the presence of women may tip the occupation to a predominantly female occupation and subsequently devalue (or pollute) the field, thereby resulting in lower wages for all individuals within the field. Some evidence of this phenomenon is indicated in specific (nonscientific) fields and the overall labor market (Huffman and Velasco 1997; Jacobsen 2007; Mandel 2013). Others have suggested, on the other hand, that increasing the presence of women in the field may increase wages for women specifically, particularly if women have more control over hiring decisions (Cohen and Huffman 2003, 2007; Cotter et al. 1997). The extent to which the presence of women in STEM occupations affects the wages of men and women who work in STEM is an open question.

We begin by illustrating trends in the STEM labor force over time, noting increases in the share of women majoring in, and working in, STEM fields. We next analyze the gender wage gap in each STEM field using ordinary least squares (OLS) regressions of logged wages on observed characteristics, noting how the gap changes with the addition of these controls. We describe differences in pay gaps for racial and ethnic groups and further distinguish between women with children and women without children in some analyses. To test the devaluation theory, we analyze how changes in the sex composition of the field are associated with wages of the men and women who work in those fields. We test our hypotheses regarding the cohort effect and the glass-ceiling effect by analyzing how the gender wage gap has evolved for more recent cohorts of college graduates and whether it grows over the course of the career.

DATA AND MEASUREMENT

Data come from pooling six waves of the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT), covering 1995 through 2008. SESTAT comprises three ongoing surveys designed to create a nationally representative sample of science and engineering college degree holders. The integrated data are 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 in-

1. For example, the report produced by David Beede and his colleagues for the U.S. Department of Commerce included the following conclusion: "The findings provide definitive evidence of a need to encourage and support women in STEM with a goal of gender parity" (2011, 8).

formation regarding labor-force participation, occupation categories, educational attainment, and demographic characteristics.

Only those who received their bachelor's degrees between 1970 and 2004 are considered, and only those who majored in STEM and worked in STEM occupations at the time of the interview are included for the analysis. We further restrict our sample to individuals who work at least thirty-five hours per week, although results including part-time workers are quite similar and are available on request. This results in a sample of 61,417 individuals. We then run OLS regressions of the logged hourly wage on gender, adding controls to see whether background characteristics and workforce experience can explain the gender wage gap. Regressions are run separately by racial-ethnic group and for each of the four main STEM occupation categories: computer science and mathematics, life sciences, physical sciences, and engineering. All regressions are weighted by the person weights provided.

Measurement

Our dependent variable of interest is the logged hourly wage for individuals working in STEM occupations. The SESTAT data provide information on annual earnings from the main occupation, as well as average weekly hours spent on the main job, and the number of weeks worked at the main job in the last year. Using these variables, we construct an hourly wage by dividing annual salary by weeks worked per year and by hours worked per week. We then calculate the log of the wage, as is customary in this literature. All wages are converted to year 2014 dollars using the consumer price index.

Our key independent variable of interest is the gender of the respondent. We estimate separate gender wage gaps for whites, blacks, Hispanics, and Asians by running separate regressions for each group. Given the large foreign-born representation in the STEM workforce (Sana 2010), we also include a dummy variable indicating whether respondents were born outside the United States to noncitizen parents.

We also account for a number of other workforce and demographic characteristics that might explain differences in hourly wages between men and women. We include these controls in stages to test the roles of human capital accumulation, family characteristics, and gender composition in contributing to the gender wage gap. Our measures of human capital accumulation include a quadratic specification of potential years of work experience, measured by the number of years since receiving a college degree; college degree cohort, measured in five-year intervals; and graduate school experience, measured by indicators for having a master's degree in a STEM field, a doctorate in a STEM field, or a higher degree in a non-STEM field.[2]

Controls for family characteristics include indicators for respondent's union status and parental status. We construct dummy variables measuring whether the respondent is married or cohabiting with a partner. Our measure of parental status captures whether respondents have any children, and whether respondents have any children under the age of six specifically. We allow the effects of family characteristics to differ for men and women by interacting an indicator for female with each family characteristic.

Finally, to test the devaluation theory that increasing the share of women in a field results in a decline in prestige (and therefore wages) of the field, we analyze how the gender composition of the STEM workforce is associated with wages in those fields. We construct a measure of the lagged share of women working in each specific STEM occupation and model the relationship between the share of women working in STEM on wages of the men and women who work in those fields. This measure is intended to proxy for the gender composition of the work environment, so it is constructed separately for each STEM occupation

2. We use potential work experience to avoid issues of endogeneity of labor-force participation, but this also does not account for any time spent out of the labor force. Women are historically more likely to take time out of the labor force for childrearing, so this measure of potential work experience will likely overestimate total years of experience for women.

and varies by survey year. We construct the lag based on the concentration of women working in each specific STEM occupation in the SESTAT wave prior to the current wave. A list of occupations included in each STEM field is presented in table A1. For example, in the 1995 SESTAT, the lagged share of women working in STEM is measured based on the men and women working in each STEM occupation in the 1993 SESTAT survey. This term is updated for each SESTAT wave, such that the gender composition of the field changes with each survey year. Similar to the approach used by Asaf Levanon and his colleagues (2009), in all analyses we include fixed effects for each specific STEM occupation to control for time-invariant differences in unobservable characteristics that might affect wages in each field. Variation in this term is generated by within-occupation changes in the gender composition over time. Although we cannot control for time-varying characteristics within occupations that might be correlated with wages, this strategy does improve upon prior work that relies on cross-sectional variation in sex composition across occupations, which likely suffers from omitted variable bias. To make a causal statement about the relationship between sex composition within an occupation and the gender wage gap with this analysis, we must assume that any unobserved characteristics correlated with wages are time-constant within occupations and can therefore be controlled for with occupation fixed effects.

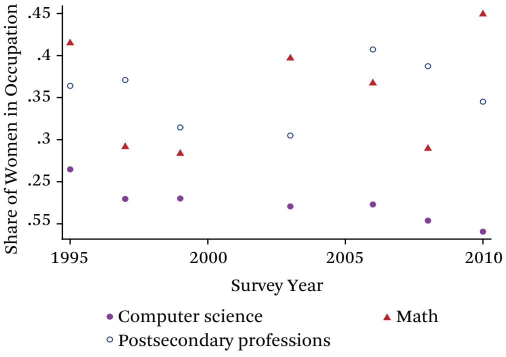
Scatter plots depicting the variation in the share of women working in each STEM field by SESTAT wave are presented in figures 1 through 4, with separate scatter plots for each of the four main STEM fields. These scatter plots illustrate the variation across occupations as well as within occupations over time. In computer and mathematical sciences, for instance, women make up approximately 40 percent of mathematicians in the 1995 SESTAT wave but only about 25 percent of computer scientists. The share of women working as mathematicians declines substantially over this period to approximately 30 percent of workers in 2008; the proportions were even lower among women in computer science in recent years, at just 20 percent. In many other STEM occupations, women have increased their representation over time, though the extent of this increase varies by occupation. The share of women working as biological scientists increases from about 45 to 55 percent, and that of those in chemical engineering fluctuates between 20 and 25 percent.

We then model the association between logged wages and the lagged share of women working in each field. Because this relationship may not be linear (for instance, wages may rise as the share of women working in STEM increases only up to a threshold, also thought of as a tipping point), we model the share of women working in STEM using a quartile specification. Specifically, we look at the distribution of the concentration of women working in STEM, labeling those with the lowest concentration of women in the bottom quartile and those with the greatest concentration of women working in an occupation in the top quartile. Because variation in the share of women working in an occupation across STEM fields is substantial, we construct these quartiles separately for each of the four broad STEM fields. For instance, the distribution of women working in engineering ranged from 5 to 25 percent. Whereas the mean share of women engineers in the lowest quartile was 7.1 percent, in the highest quartile it was only 18.7 percent—less than the lowest quartile for women in computer science or in the life sciences. Further, because wages might be lower in certain STEM occupations than in others (mathematics versus computer science, for instance) and this is correlated with the share of women working in those fields, we include controls for specific occupations in all models, such that we measure the impact of increasing the share of women within a specific STEM occupation on wages in those fields. This approach enables us to determine, for example, how wages for biological scientists change when the share of female biological scientists increases from 45 to 55 percent.

RESULTS

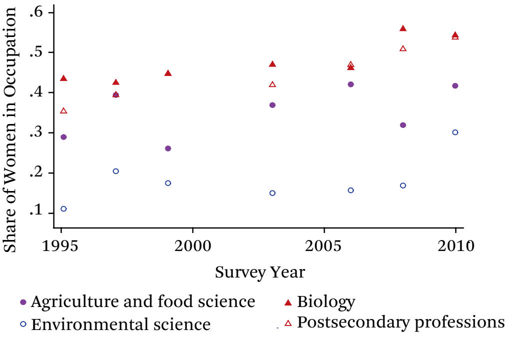
Figure 5 illustrates the trends in the share of women majoring in and working in STEM for each STEM field by college cohort. The solid lines represent the share of women majoring

Figure 1. Scatter Plots of Women in STEM Occupations, Computer and Mathematical Sciences



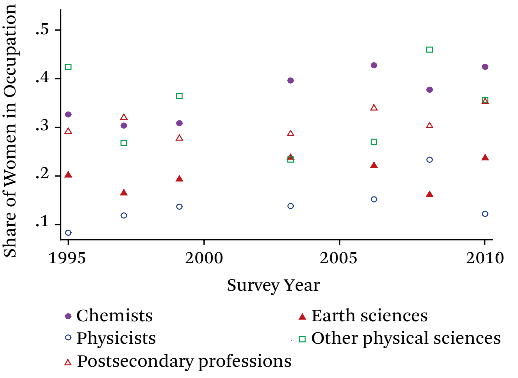
Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Note: All men and women working in STEM.

Figure 2. Scatter Plots of Women in STEM Occupations, Life Sciences



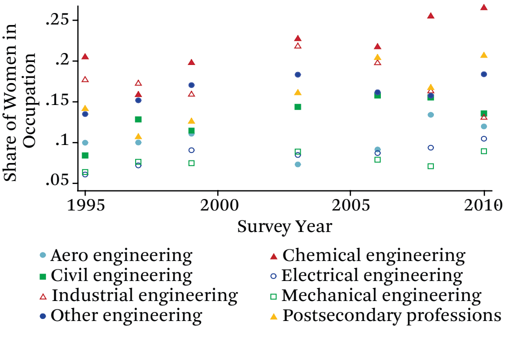
Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Note: All men and women working in STEM.

Figure 3. Scatter Plots of Women in STEM Occupations, Physical Sciences



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Note: All men and women working in STEM.

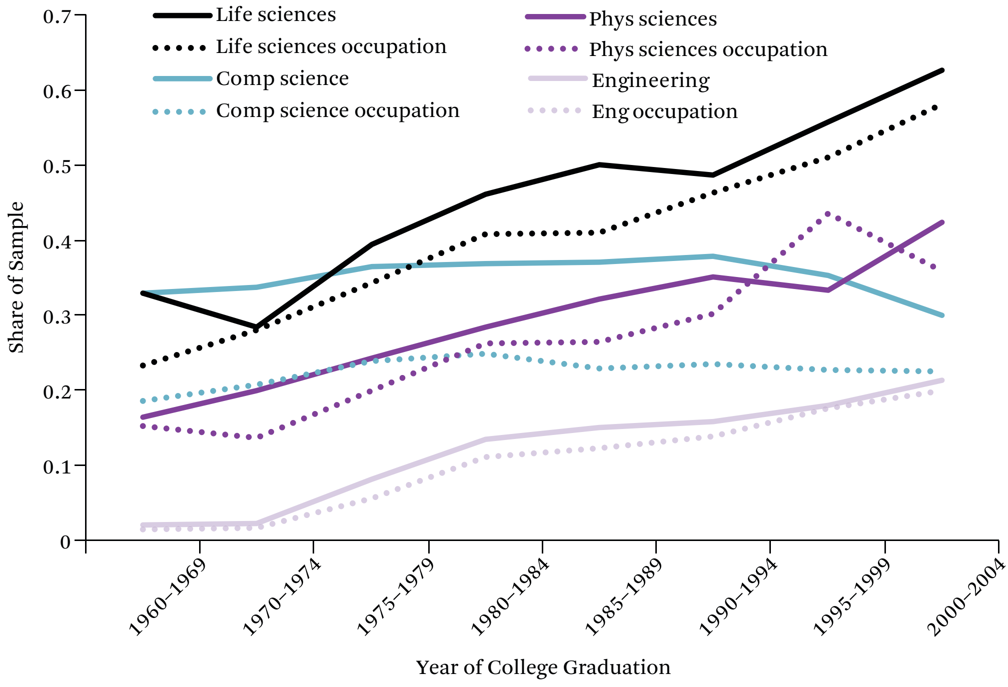
Figure 4. Scatter Plots of Women in STEM Occupations, Engineering



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Note: All men and women working in STEM.

in STEM, and the dotted lines indicate the share of women working in STEM by college cohort. In all fields except for computer science, the increase in the representation of women in STEM majors since the 1960s has been substantial. Whereas women accounted for approximately 30 percent of the 1960 to 1969 cohort of life science majors, they made up more than 60 percent of those graduating between 2000 and 2004. A similar increase occurred in the physical sciences, where the share of women rose from 16 percent to 40 percent over the period. Although still a small proportion, women majoring in engineering increased tenfold between 1960 and 2004, from 2 to 20 percent. In all three of these fields, the share of women majoring in STEM also coincides closely with the share working in STEM.

Figure 5. Female STEM Majors and Workers



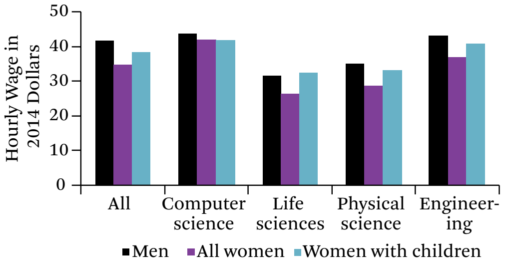
Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Note: All men and women graduating with a STEM bachelor's degree between 1960 and 2004.

This implies that, conditional on receiving a degree in a STEM field, women appear equally likely to work in STEM as their male counterparts.

Computer science is the exception to the trend of increasing representation of women in STEM. There, women's representation has been stagnant over the last several decades and shown evidence of a decline in computer science majors for the most recent cohorts of college graduates. Women also account for a considerably lower share of the computer science workforce than computer science majors, on the order of 5 to 10 percentage points, indicating that women are less likely to work in computer science than to major in it. For the 1980 to 1984 college cohort, for instance, women made up approximately 30 percent of all computer science majors, but only 20 percent of all computer science workers. This implies that conditional on completing a degree in computer science, women are still less likely to work in the field than men. For more recent graduates, the gap between majoring and working in computer science has converged, but this is primarily due to a decline in the share of women majoring in the field in recent decades. This trend is of particular concern given that computer science accounts for more than 30 percent of the STEM workforce. In fact, the two fields with the fewest women, computer science and engineering, represent approximately 75 percent of STEM workers. So, although women make up more than 50 percent of workers in the life sciences for recent college cohorts, their overall share working in STEM is just 20 percent.

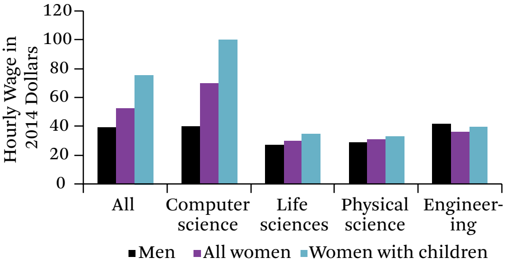
Figures 6 through 9 show descriptive statistics on wages for men and women by STEM occupation, which is our dependent variable. We show wages for all men and women who work in STEM, as well as the women with children who work in STEM to illustrate the wage differential for mothers. For the whole STEM

Figure 6. Average Hourly Wages, Whites



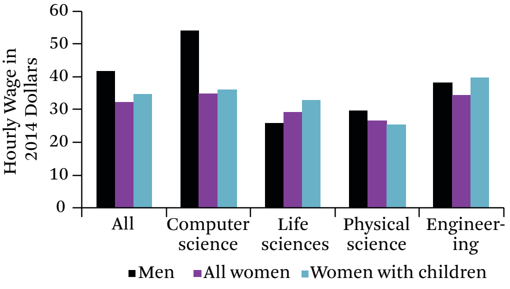
Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. Wages are calculated by dividing annual salary by number of weeks worked.

Figure 7. Average Hourly Wages, Blacks



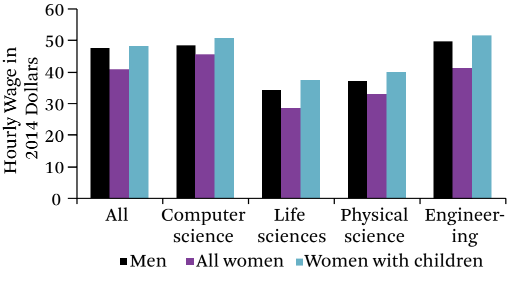
Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: See notes to figure 6.

Figure 8. Average Hourly Wages, Hispanics



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: See notes to figure 6.

Figure 9. Average Hourly Wages, Asians



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: See notes to figure 6.

workforce, wages are $42 for white men and $35 for white women. That is, white women earn about 84 cents for every dollar that white men earn, slightly higher than the 77 cents in the overall labor force. However, differences across STEM occupations are substantial. The gap is narrowest in computer science, where white women earn 96 cents for every dollar that white men earn. The biggest gap is in the physical sciences, 82 cents for every dollar. Differences are substantial by race as well—Asian women experience similar wage gaps as white women relative to their male peers in all of the STEM occupations. There is evidence of positive selection into the STEM workforce for black women, where black women earn 32 percent higher wages than black men. Figures 6 through 9 also show wages of the women with children under the age of eighteen who work in STEM. Consistent with other work showing that women with children earn higher wages in some professional fields (Buchmann and McDaniel, this issue), we also find higher hourly wages for women with children than among women as a whole in all STEM fields and for most racial groups. This is likely due at least in part to selection factors. Only the women with the highest earning potential may be able to combine motherhood and work in STEM.

Multivariate Results

To what extent do these patterns of wage gaps change upon including controls for human capital characteristics or family measures? Table 1 shows regression results pooling all racial groups and the four main STEM fields. Model 1 includes an indicator for whether the respondent is female, representing the overall male-female wage gap in STEM occupations. Model 2 differentiates the gender wage gap by race and ethnicity, with white men serving as the reference category. Model 3 adds an indicator for whether the respondent is foreign born. Model 4 adds the human capital controls: years of potential experience, college cohort, STEM field, and higher degrees. Model 5 adds measures of family characteristics.

In model 1, which includes no other controls, we estimate an overall male-female gender wage gap of 0.18 log points, indicating that women who work in STEM earn about 18 percent lower hourly wages than men. Differentiating by race (model 2) reveals that all women earn significantly lower wages than white men. Black and Hispanic men also earn significantly lower wages than white men, while Asian men earn 6 percent higher wages than white men. Adding an indicator for whether the respondent is foreign born (model 3) reveals that the Asian male advantage is driven entirely by foreign-born workers. On the other hand, accounting for nativity widens the wage disparity between Asian women and white men, as well as between Hispanic women and men and white men.

The gender wage gap narrows dramatically when including controls for occupation sector and human capital experience (model 4). Including these controls reduces the white male-female wage gap from 0.20 log points to 0.06 log points, which suggests that the women who work in STEM tend to have less potential work experience than the men and are more likely to work in lower-paying sectors of the STEM workforce (such as the life sciences). Those working in computer science and engineering earn the highest hourly wages, whereas those in the life sciences earn significantly less than those in the physical sciences. Not surprisingly, having additional credentials is also associated with higher wages. Individuals with master's degrees in STEM earn approximately 4 percent more, and those with doctorates and non-STEM graduate degrees about 5 to 6 percent more.

Model 5 adds controls for current family characteristics interacted with gender. Of note is that the inclusion of family characteristics shifts the coefficients on race-ethnicity only for women. Our results indicate that being partnered (both married and cohabiting) elevates earnings over being single, which may be important given differences in the experiences of men and women; descriptive results (shown in table A2) reveal that men are considerably more likely to be married than women. Having preschool-age children is associated with higher wages. This effect is concentrated equally between men and women, corroborating evidence from other papers in this volume indicating a positive association between motherhood and wages in recent years (Buchmann and McDaniel, this issue; Pal and Waldfogel, this issue).[3] This positive association between motherhood and wages likely reflects, at least to some extent, selection issues into both motherhood and working in STEM—only those with the highest earning potential are able to balance family life and work life.

We next present results running separate models for each of the four main STEM fields and each of the four main race groups. Figures 10 through 13 show the gender wage gap experienced by women, the dark bars indicating the gap with no other controls in the model (model 1 in table 1), and the light bars indicating the gender wage gap once all controls are included (model 5 in table 1). Italicized coefficients are

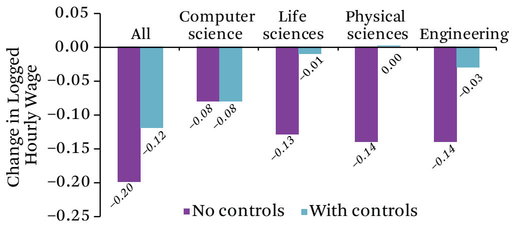
3. We also examine how the motherhood wage differential has changed over time in table A3, where we interact an indicator for being a woman with a child under the age of eighteen with college cohort.

Table 1. Linear Regressions Predicting Log Hourly Wage

	(1)	(2)	(3)	(4)	(5)
Gender and race					
Female	−0.18***				
White female		−0.20***	−0.20***	−0.06***	−0.04*
Black female		−0.12***	−0.12***	−0.02	−0.01
Hispanic female		−0.26***	−0.28***	−0.10***	−0.08**
Asian female		−0.08***	−0.15***	−0.02	−0.01
White male (reference)					
Black male		−0.09***	−0.10***	−0.06***	−0.06***
Hispanic male		−0.09***	−0.11***	−0.05***	−0.05***
Asian male		0.06***	0.00	0.04***	0.05***
Foreign born			0.08***	0.00	−0.01
Years since degree				0.06***	0.05***
Years since degree squared				0.00***	0.00***
College cohort (reference = 1970–1974)					
1975–1979				0.11***	0.08***
1980–1984				0.20***	0.16***
1985–1989				0.24***	0.19***
1990–1994				0.21***	0.17***
1995–1999				0.22***	0.19***
2000–2004				0.16***	0.14***
STEM occupation (reference = physical sciences)					
Computer and math sciences				0.32***	0.32***
Life sciences				−0.16***	−0.15***
Engineering				0.27***	0.27***
Advanced degrees (reference = bachelor's degree)					
STEM master's				0.03***	0.03***
STEM PhD				0.05***	0.05***
Non-STEM advanced degree				0.06***	0.05***
Marriage and family					
Married					0.06***
Cohabiting					0.01
Has children					0.02*
Has children under six years old					0.04***
Female*married					−0.01
Female*cohabiting					0.09***
Female*has children					−0.01
Female*has children under six years old					0.03
R-squared	0.02	0.02	0.02	0.23	0.23
Number of observations	61,417	61,417	61,417	61,417	61,417

Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. Results from OLS regressions of logged wages on indicator for female and demographic characteristics. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. Women with children are defined as those who have at least one child under the age of eighteen living in the household. Marriage and cohabitation evaluated at the time of the survey. All wages reported in 2014 dollars. Regressions weighted by person weights.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

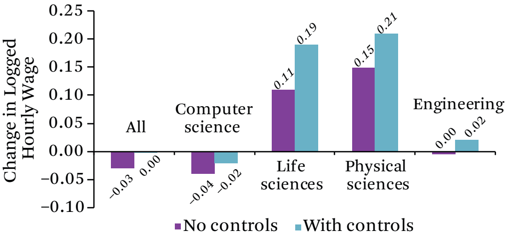
Figure 10. Wage Differentials for Women Relative to Men, Whites



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. Results from OLS regressions of logged hourly wages on indicator for female. Dark bar represents coefficient on female in OLS regression with no other controls (model 1 from table 1). Light shaded bar represents coefficient on female in OLS regression with full set of controls (model 5 from table 1). Each bar represents a different regression. Regressions run separately by race and STEM field. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. All wages reported in 2014 dollars. Regressions weighted by person weights. Italicized terms indicate significantly different from zero at the $p < 0.05$ level.

Figure 11. Wage Differentials for Women Relative to Men, Blacks



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

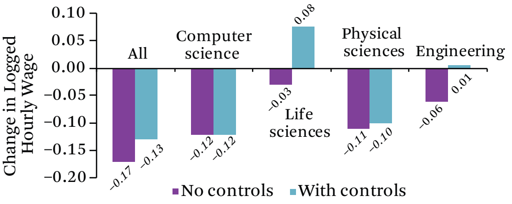
Notes: See notes to figure 10.

significant at the $p < 0.05$ level. For the life sciences and physical sciences, the gender wage gap for white women is reduced to nearly zero and is insignificant once all controls have been added to the models. Before including controls, white women in the life sciences, physical sciences, and engineering earned about 14 percent lower wages than white men, but differences in wages once controls are included in the model are not significant. These patterns are similar for Asian women and Asian men. Black women exhibit a different pattern, earning higher wages than black men in the life sciences and the physical sciences, and no significantly different wages in computer science or engineering even before controlling for human capital and family characteristics. For all other racial groups, we find persistent wage gaps in computer science, even after controlling for human capital and family characteristics, ranging from 8 to 12 percent lower wages compared to their male counterparts.

We next analyze the extent to which the representation of women in each of the four main STEM fields is associated with wages in these fields. For simplicity, we pool all race groups for this analysis, but models were run separately for each of the four main STEM fields. Results of this exercise are shown in table 2. As discussed, we use a measure for the lagged share of women working in each STEM occupation using the prior SESTAT survey information. The share of women working in STEM are evaluated at the specific occupation level for up to ten occupations within each of the four main STEM fields. We categorize these measures into quartiles separately for each of the four main STEM fields. We regress the logged hourly wages on a full set of controls (model 5 from table 1 along with indicators for each specific STEM occupation), including indicators for the top three quartiles of the lagged share of women working in STEM. The coefficients on these terms indicate the change in the logged hourly wage for all workers in those fields relative to the lowest concentration of women in each STEM field. Variation in this term is generated by changes within each STEM occupation over time.

For the life sciences and engineering, we

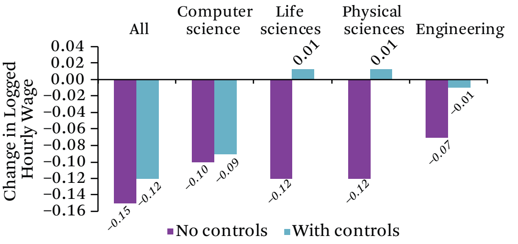
Figure 12. Wage Differentials for Women Relative to Men, Hispanics



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. Results from OLS regressions of logged hourly wages on indicator for female. Dark bar represents coefficient on female in OLS regression with no other controls (model 1 from table 1). Light shaded bar represents coefficient on female in OLS regression with full set of controls (model 5 from table 1). Each bar represents a different regression. Regressions run separately by race and STEM field. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. All wages reported in 2014 dollars. Regressions weighted by person weights. Italicized terms indicate significantly different from zero at the $p < 0.05$ level.

Figure 13. Wage Differentials for Women Relative to Men, Asians



Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

Notes: See notes to figure 12.

find significant increases in wages associated with increasing the concentration of women working in these occupations. Increasing the concentration of women to 51 percent of the life science workforce is associated with 19 percent higher wages for all workers in the field compared with when women made up 33 percent of the that workforce. Similarly for engineering, increasing the concentration of women from 7 percent to 19 percent is associated with 11 percent higher wages for all workers. In these two fields, we find no evidence that increasing the share of women in a field devalues or feminizes the field to the extent that all workers in those fields earn less. In contrast, we find a negative, but not always significant, association between the concentration of women working in the physical sciences and the wages in those fields. We also find evidence of a slight decline in wages in computer science once women make up a significant share of the workforce. In both physical sciences and computer and mathematical sciences, therefore, we find some evidence in support of the devaluation theory that increasing the share of women in the field is associated with lower wages for all workers in those fields, though our estimates are not always significant at conventional levels.

How has the gender wage gap changed over time?

Results from table 1 suggest that one of the biggest contributors to the gender wage gap in STEM is in the human capital accumulation differences between men and women. In most of the STEM fields, the share of women majoring in and working in STEM since the 1970s has increased, which suggests that the women who work in STEM are likely younger and less experienced than the men in the field. This result may portend an optimistic assessment of the future of gender wage equality in the STEM workforce. If women continue to increase their representation in STEM and accumulate similar levels of experience, we would expect to see a continued narrowing of the gender wage gap. On the other hand, we could also see a glass-ceiling effect, where women begin their careers earning wages on par with men, but begin to

Table 2. OLS Regressions of Logged Wages

	Computer Science		Life Sciences		Physical Sciences		Engineering	
	Mean Percent Female	Regression Coefficient	Mean Percent Female	Regression Coefficient	Mean Percent Female	Regression Coefficient	Mean Percent Female	Regression Coefficient
Quartiles								
1st (reference)	20.4	0	33.4	0	14.9	0	7.1	0
2nd	22.2	0.03*	42.5	0.10*	24.8	−0.04*	9.1	0.03***
3rd	24	0.06**	45.2	0.13**	30.9	−0.03	14.3	0.11***
4th	35	−0.04	51.1	0.19***	38.2	−0.04	18.7	0.11***

Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

Note: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. All regressions include controls from model (5) in table 1, weighted by person weights. Each column represents a different regression—regressions run separately for each main STEM field. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. All wages reported in 2014 dollars. Percent female quartile calculated at the specific occupation level, lagged by one SESTAT survey year. Regressions also include controls for specific occupation so changes in percentage female represent changes within specific occupation over time (such as impact of increasing share of women in electrical engineering over time).

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

fall behind as they progress through their careers. To test this premise, we examine how the gender wage gap has evolved by college cohort, and whether we find evidence that these gaps increase over the career, regardless of cohort. We are able to disentangle this cohort versus glass-ceiling effect because we have multiple years of observation for the same cohorts of college graduates, allowing us to observe wage gaps at several points over the course of the career.

Table 3 shows results of interacting college cohort with gender, and separately, interacting years of potential experience with gender. For the first test, we regress logged wages on an indicator for female and a set of interactions of female with college cohort. In this exercise, women who completed their bachelor's degrees between 1970 and 1974 are the reference category; each interaction of female with subsequent cohorts represents the relative gender wage gap of that cohort compared with the gender wage gap for those who graduated between 1970 and 1974. To estimate the overall gender wage gap for each cohort, we add the coefficient on the female indicator with that on the interaction of the female indicator with college cohort. For instance, the overall gender wage gap for women who graduated in the life sciences between 1975 and 1979 is 0.08 log points (0.18 minus 0.098). The overall gap for those who graduated between 1970 and 1974 is merely the coefficient on the indicator for female in each field. Each column represents a separate regression and all regressions include the full set of controls represented in model 5 of table 1.

In the fields where the share of women increased the most—life sciences and engineering—we also see significant trends in the gender wage gap over time. Despite an overall gap in wages between men and women in these fields (women earn 0.18 and 0.23 log points less than men, respectively), we see positive effects of the interaction of female with degree cohort. This suggests that the wage gap is narrowing among more recent cohorts of college graduates in these fields.

In contrast, we see very little difference in the gap by college cohort for those working in computer science or the physical sciences. In computer science, we find an overall gap of 0.11

Table 3. Trends in Gender Wage Gap

	Computer Science	Life Sciences	Physical Sciences	Engineering
Trends over time				
Female	−0.11	−0.18***	−0.099	−0.225***
Female*1970–1974				
Female*1975–1979	−0.09	0.10	−0.03	0.21**
Female*1980–1984	0.03	0.11*	−0.07	0.15*
Female*1985–1989	0.07	0.06	0.07	0.23**
Female*1990–1994	0.01	0.22***	0.01	0.20**
Female*1995–1999	−0.03	0.16**	0.01	0.20**
Female*2000–2004	0.09	0.09	0.03	0.20**
Trends over career				
Female	−0.069***	−0.035	−0.087	−0.02
Female*years since degree	−0.002*	−0.001	−0.002	−0.002

Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation.All regressions include controls from model (5) in table 1, weighted by person weights. Each column represents a different regression—regressions run separately for each main STEM field. Trends over time represents regressions of logged wages on interaction of indicator for female and college cohort, along with full set of controls. Trends over career represents separate regressions of logged wages on interaction of indicator for female and years since college degree, along with full set of controls. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. All wages reported in 2014 dollars.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

log points but no indication of a narrowing for more recent cohorts of college graduates. That is, none of the coefficients on the interaction of gender with college cohort are significantly positive. Some are actually negative, indicating that the gender wage gap is wider for some more recent cohorts than for those graduating between 1970 and 1974. In the physical sciences, we find no significant gap for any of the college cohorts.

Although these results imply a somewhat positive story that discrimination against women may be declining for recent cohorts of college graduates (at least in the life sciences and engineering), this trend of a declining gender wage gap for more recent college cohorts could also reflect differences in the gap across the career span. Previous work has shown that gender wage gaps are fairly narrow among workers age twenty-five to thirty-four but tend to emerge over the course of the career. If this were the case in STEM, we should expect to find a widening over time since graduation. Because we have data from 1995 to 2008, we are able to test this hypothesis by observing wage differences at different times for each college cohort. We do so by interacting an indicator for female with the number of years since college graduation, holding college cohort fixed. For computer science, we find some evidence of a widening of the gap over the course of the career. We estimate a 7 percent wage gap overall, and a 0.2 percent increase with each year since graduation. In all other STEM fields, we find no evidence that wage gaps grow over the course of the career, though coefficients are close in magnitude to those observed in computer science but never attain statistical significance at conventional levels. These results further extend the findings of Anastasia Prokos and Irene Padavic (2005) and are consistent with the theory that the gender wage gap in STEM is due to a larger gap among older cohorts of college graduates and that we should expect a narrowing of this gap as older cohorts retire from the labor force.

DISCUSSION

Women have made great strides in closing the gender wage gap over the last several decades but continue to earn less than men. Numerous studies have examined the source of this gap, noting differences in occupation choice, working patterns, and discrimination. Analyzing the gap in STEM occupations alone eliminates some potential factors, such as human capital differences and differences in occupation choice, that contribute to wage disparities. It also enables us to ask whether the STEM labor force exhibits gender wage gaps similar to those in the overall labor force. Increasing the representation of women in STEM has been promoted as one means of reducing the overall earnings disparities between women and men. We use SESTAT data and assess how women's representation in STEM and in particular STEM occupations is associated with wages, whether the gender pay gap narrows among more recent cohorts, and whether an increase in the proportion of women working in fields that remain largely male is associated with higher wages in those fields.

We find sizable and significant gender wage gaps among women working in STEM occupations, though these are smaller than those in the broader labor force. White women in the STEM workforce earn about 84 cents for every dollar their male counterparts earn, which is higher than the 77 cents in the overall labor force. Increasing women's representation in STEM occupations could therefore reduce the overall gender wage gap. Even when women work in STEM occupations, however, they concentrate in lower paid fields, such as the life sciences and physical sciences. These areas also employ smaller shares of the STEM workforce than computer science and engineering do. Although increasing women's representation in STEM occupations can reduce the gender wage gap, narrowing it further would require that women change their concentrations within STEM.

Differences in human capital accumulation accounted for the largest portion of the gender wage gap in many STEM occupations. Women who work in STEM have less potential work experience than the men, because the men who work in STEM tend to be older than their female counterparts. But among more recent cohorts reductions in the gap have been sizable, at least among women in particular fields. Whereas there was never any observed gender wage gap among various cohorts of physical scientists after controlling for observable characteristics, more recent cohorts of women employed as engineers and life scientists have experienced wage increases, and on average women actually outearn men in those fields. Little evidence of a cohort change in the gap, however, is observed among computer scientists, suggesting that women do not experience the same returns to work experience as their male counterparts.

That particular fields of growing importance to the American and global economy continue to manifest gender pay discrepancies requires additional study, and with different types of data than what we use here. Our results document persistent gaps in the wages of men and women in computer science, and these differentials cannot be explained by demographic characteristics alone, or human capital measures such as experience. Many have called attention to the declining proportion of women obtaining college degrees in computer science, and the dearth of women (and minorities) in various high technology corporations. Our results provide some purchase on why women may find computer science an unwelcoming field and highlight the challenges to increasing women's representation there. Not only do they continue to earn less than men, but growing their presence in the field also does not appear to be beneficial. In fact, increasing the share of women working in computer science was associated with lower wages, though in general those working in the field were among the most highly remunerated. Computer science, then, seems most resistant to the increasing presence of women, even though the representation of women is even smaller in engineering. Additional research is required to ascertain how climate factors contribute to the retention of women in some fields and the attrition of women in others.

Our study is not without limitations. We cannot determine, for example, whether the frustration and dissatisfaction women have with the STEM labor force potentially pushes them into other occupations with the current data, or whether this process occurs to any greater extent for women than for men. Despite the increasing presence of women in STEM fields of study, recent research has suggested that these women become dissatisfied with working conditions in STEM; they are significantly less likely to be retained in the STEM labor force than other women with professional degrees, instead exiting the STEM labor force in early or midcareer for non-STEM jobs (Glass et al. 2013). Although we find no evidence of a widening gender wage gap as a function of time since graduation, further research is needed to explore which of these factors is likely driving these differences in potential work experience.

Over the past four decades, progress in closing the gender wage gap has been notable. Our results indicate that disparities in the wages of male and female STEM professionals are smaller than for the overall labor force, and among some fields recent cohorts of women are earning as much as or more than comparable men. Nonetheless, challenges remain. Women remain concentrated in the lower-paying STEM occupations. When they do work in the best-remunerated fields of computer science and engineering, they continue to earn less than comparable men. Additional study into the particular climate welcoming (or repelling) women STEM professionals is needed if we are to better understand the factors that serve to perpetuate the gender wage gap.

APPENDIX

Table A1. Specific Occupations in STEM Fields

Computer science	Computer scientists	**Physical science**	Chemists
	Mathematicians		Earth scientists
	Postsecondary math or computer science teachers		Physicists
Life sciences	Agriculture and food scientists		Other physical scientists
	Biological scientists		Postsecondary physical scientists
	Environmental scientists	**Engineering**	Aerospace engineers
	Postsecondary life science teachers		Chemical engineers
			Civil engineers
			Electrical engineers
			Industrial engineers
			Mechanical engineers
			Other engineers
			Postsecondary engineering teachers

Source: Authors' compilation.

Table A2. Descriptive Statistics for STEM

	Men		Women		All	
	Mean	Std Err	Mean	Std Err	Mean	Std Err
Hourly wage (2014 dollars)	41.57*	0.19	34.78*	0.65	30.22	0.21
Female					0.20	0.00
Race-ethnicity						
White	0.75*	0.00	0.65*	0.00	0.73	0.00
Black	0.03*	0.00	0.07*	0.00	0.04	0.00
Hispanic	0.05	0.01	0.06	0.00	0.05	0.00
Asian	0.17*	0.00	0.22*	0.00	0.18	0.00
Foreign born	0.23*	0.00	0.27*	0.00	0.24	0.00
Years since graduation	14.34*	0.04	12.00*	0.07	13.88	0.03
College cohort						
BA 1970–1974	0.09*	0.00	0.04*	0.00	0.08	0.00
BA 1975–1979	0.11*	0.00	0.08*	0.00	0.10	0.00
BA 1980–1984	0.16*	0.00	0.13*	0.00	0.15	0.00
BA 1985–1989	0.18*	0.00	0.16*	0.00	0.17	0.00
BA 1990–1994	0.19*	0.00	0.20*	0.00	0.19	0.00
BA 1995–1999	0.17*	0.00	0.23*	0.00	0.18	0.00
BA 2000–2004	0.11*	0.00	0.16*	0.00	0.12	0.00
STEM occupation						
Computer and mathematical sciences	0.36*	0.00	0.39*	0.00	0.37	0.00
Life sciences	0.08*	0.00	0.22*	0.00	0.11	0.00
Physical sciences	0.08*	0.00	0.12*	0.00	0.09	0.00
Engineering	0.49*	0.00	0.26*	0.00	0.45	0.00
Undergraduate major						
Computer and mathematical sciences	0.21*	0.00	0.29*	0.00	0.23	0.00
Life sciences	0.10*	0.00	0.27*	0.00	0.14	0.00
Physical sciences	0.12*	0.00	0.15*	0.00	0.12	0.00
Engineering	0.57*	0.00	0.30*	0.00	0.52	0.00
Graduate degrees						
Has master's degree in STEM	0.29	0.00	0.29	0.00	0.29	0.00
Has PhD in STEM	0.08*	0.00	0.09*	0.00	0.08	0.00
Has advanced degree in non-STEM	0.07	0.00	0.07	0.00	0.07	0.00
Family characteristics						
Married	0.71*	0.00	0.59*	0.00	0.69	0.00
Cohabiting	0.02*	0.00	0.03*	0.00	0.02	0.00
Has children < six	0.26*	0.00	0.20*	0.00	0.25	0.00
Has children > six	0.33*	0.00	0.24*	0.00	0.31	0.00
Lagged share of women in STEM occupation	19.80*	0.06	25.69*	0.09	20.99	0.08
Number of observations	46,366		15,051		61,417	

Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.

Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. Women with children are defined as those who have at least one child under the age of eighteen living in the household. Marriage and cohabitation evaluated at the time of the survey. All wages reported in 2014 dollars.

* Indicates significant difference between men and women at $p < 0.05$ level.

Table A3. Trends in Motherhood Wage Gap

	Computer Science	Life Sciences	Physical Sciences	Engineering
Trends over time for mothers				
Mother	0.09	0.00	0.06	0.08
Mother*1970–1974				
Mother*1975–1979	−0.24***	−0.04	−0.01	0.02
Mother*1980–1984	−0.08	0.00	0.08	−0.06
Mother*1985–1989	−0.11	0.03	0.05	0.04
Mother*1990–1994	−0.12	0.20*	−0.02	−0.06
Mother*1995–1999	−0.18*	0.13	0.03	0.03
Mother*2000–2004	−0.15	0.09	0.1	0.03

Source: Authors' calculations based on data from the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008.
Notes: All men and women graduating with a STEM bachelor's degree between 1970 and 2004, working at least thirty-five hours a week in a STEM occupation. All regressions include controls from model (5) in table 1, weighted by person weights. Each column represents a separate regression—regressions run separately for each of the four main STEM fields. Regressions of logged wages on interaction of indicator for being a mother and college cohort, along with full set of controls. Wages are calculated by dividing annual salary by number of weeks worked per year and average number of hours worked per week. All wages reported in 2014 dollars.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

REFERENCES

Beede, David N., Tiffany Julian, David Langdon, George McKittrick, Beethika Khan, and Mark Doms. 2011. "Women in STEM: A Gender Gap to Innovation." ESA Issue Brief no. 04-11. Washington: U.S. Department of Commerce, Economics and Statistics Administration.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2009. "Dynamics of the Gender Gap for Young Professionals in the Corporate and Financial Sectors." *NBER* working paper no. 14681. Cambridge, Mass.: National Bureau of Economic Research.

Blau, Francine D., and Lawrence M. Kahn. 1994. "Rising Wage Inequality and the U.S. Gender Gap." *American Economic Review* 84(2): 23–28.

———. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics* 15(1): 1–42.

———. 2006. "The U.S. Gender Pay Gap in the 1990s: Slowing Convergence." *Industrial and Labor Relations Review* 60(1): 45–66.

Buchmann, Claudia, and Anne McDaniel. 2016. "Motherhood and the Wages of Women in Professional Occupations." *RSF: The Russell Sage Journal of the Social Sciences* 2(4). doi: 10.7758/RSF.2016.2.4.05.

Budig, Michelle J., and Paula England. 2001. "The Wage Penalty for Motherhood." *American Sociological Review* 66(2): 204–25.

Byker, Tanya. 2016. "The Opt-Out Continuation: Education, Work, and Motherhood from 1984 to 2008." *RSF: The Russell Sage Journal of the Social Sciences* 2(4). doi: 10.7758/RSF.2016.2.4.02.

Cohen, Philip N., and Matt L. Huffman. 2003. "Individuals, Jobs, and Labor Markets: The Devaluation of Women's Work." *American Sociological Review* 68(3): 443–63.

———. 2007. "Working for the Woman? Female Managers and the Gender Wage Gap." *American Sociological Review* 72(5): 681–704.

Committee on Maximizing the Potential of Women in Academic Science and Engineering and Committee on Science Engineering and Public Policy (Committee on Maximizing the Potential of Women). 2006. *Beyond Bias and Barrier: Fulfilling the Potential of Women in Academic Science and Engineering.* Washington, D.C.: National Academies Press.

Cotter, David A., JoAnn DeFiore, Joan M. Hermsen, Brenda Marsteller Kowalewski, and Reeve Vanneman. 1997. "All Women Benefit: The Macro-Level Effect of Occupational Integration on Gender Earnings Equality." *American Sociological Review* 62(5): 714–34.

DiPrete, Thomas A., and Claudia Buchmann. 2013. *The Rise of Women: The Growing Gender Gap in Education and What It Means for American Schools*. New York: Russell Sage Foundation.

Ginther, Donna K. 2003. "Is MIT an Exception? Gender Pay Differences in Academic Science." *Bulletin of Science, Technology, and Society* 23(1): 21–26.

Glass, Jennifer L., Sharon Sassler, Yael Levitte, and Katherine M. Michelmore. 2013. "What's So Special About STEM? A Comparison of Women's Retention in STEM and Professional Occupations." *Social Forces* 92(2): 723–56.

Goldin, Claudia. 2002. "A Pollution Theory of Discrimination: Male and Female Differences in Occupations and Earnings." *NBER* working paper no. 8985. Cambridge, Mass.: National Bureau of Economic Research.

———. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104(4): 1091–119.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the Gender Gap in College." *Journal of Economic Perspectives* 20(4): 133–56.

Hakim, Catherine. 2000. *Work-Lifestyle Choices in the 21st Century: Preference Theory*. Oxford: Oxford University Press.

Halrynjo, Sigtona, and Selma Therese Lyng. 2009. "Preferences, Constraints or Schemas of Devotion? Exploring Norwegian Mothers' Withdrawals from High Commitment Careers." *British Journal of Sociology* 60(2): 321–43.

Hill, Catherine, Christianne Corbett, and Andresse St. Rose. 2010. *Why So Few? Women in Science, Technology, Engineering, and Mathematics*. Washington, D.C.: American Association of University Women. Accessed April 6, 2016. https://www.aauw.org/files/2013/02/Why-So-Few-Women-in-Science-Technology-Engineering-and-Mathematics.pdf.

Huffman, Matt L., and Steven C. Velasco. 1997. "When More Is Less: Sex Composition, Organizations, and Earnings in U.S. Firms." *Work and Occupations* 24(2): 214–44.

Jacobsen, Joyce P. 2007. "Occupational Segregation and the Tipping Phenomenon: The Contrary Case of Court Reporting in the USA." *Gender, Work, and Organization* 14(2): 130–61.

Kogan, Irena, and Frank Kalter. 2006. "The Effects of Relative Group Size on Occupational Outcomes: Turks and Ex-Yugoslavs in Austria." *European Sociological Review* 22(1): 35–48.

Levanon, Asaf, Paula England, and Paul Allison. 2009. "Occupational Feminization and Pay: Assessing Causal Dynamics Using 1950–2000 U.S. Census Data." *Social Forces* 88(2): 865–92.

Ma, Yingyi, and Gokhan Savas. 2014. "Which Is More Consequential: Field of Study or Institutional Selectivity?" *Review of Higher Education* 37(2): 221–47.

Mandel, Hadas. 2013. "Up the Down Staircase: Women's Upward Mobility and the Wage Penalty for Occupational Feminization, 1970–2007." *Social Forces* 91(4): 1183–207.

Mandel, Hadas, and Moshe Semyonov. 2014. "Gender Pay Gap and Employment Sector: Sources of Earnings Disparities in the United States, 1970–2010." *Demography* 51(5): 1597–618.

Mann, Allison, and Thomas A. DiPrete. 2013. "Trends in Gender Segregation in the Choice of Science and Engineering Majors." *Social Science Research* 42(6): 1519–41.

Morgan, Laurie A. 1998. "Glass-Ceiling Effect or Cohort Effect? A Longitudinal Study of the Gender Earnings Gap for Engineers, 1982 to 1989." *American Sociological Review* 63(4): 479–93.

Pal, Ipshita, and Jane Waldfogel. 2015. "The Family Gap in Pay: New Evidence for 1967 to 2013." *RSF: The Russell Sage Journal of the Social Sciences* 2(4). doi: 10.7758/RSF.2016.2.4.04.

Pew Research Center. 2013. "On Pay Gap, Millennial Women Near Parity—For Now." Washington, D.C.: Social & Demographic Trends Project. Accessed April 6, 2016. http://www.pewsocialtrends.org/2013/12/11/on-pay-gap-millennial-women-near-parity-for-now/.

Prokos, Anastasia, and Irene Padavic. 2005. "An Examination of Competing Explanations for the Pay Gap Among Scientists and Engineers." *Gender and Society* 19(4): 523–43.

Roos, Patricia A., and Barbara F. Reskin. 1992. "Occupational Desegregation in the 1970s: Integration and Economic Equity?" *Sociological Perspectives* 35(1): 69–91.

Sana, Mariano. 2010. "Immigrants and Natives in U.S. Science and Engineering Occupations, 1994–2006." *Demography* 47(3): 801–20.

Sassler, Sharon, Jennifer L. Glass, Yael Levitte, and Katherine M. Michelmore. 2011. "The Missing Women in STEM? Accounting for Gender Differences in Entrance into Science, Technology, Engineering, and Math Occupations." Presented at the 2012 Population Association of America annual meeting, Washington, D.C. (September 19, 2011).

Stähli, Michèle Ernst, Jean-Marie Le Goff, René Levy, and Eric Widmer. 2009. "Wishes or Constraints? Mothers Labour Force Participation and Its Motivation in Switzerland." *European Sociological Review* 25(3): 333–48.

Weeden, Kim A., Youngjoo Cha, and Mauricio Bucca. 2016. "Long Work Hours, Part-Time Work, and Trends in the Gender Gap in Pay, the Motherhood Wage Penalty, and the Fatherhood Wage Premium." *RSF: The Russell Sage Journal of the Social Sciences* 2(4). doi: 10.7758/RSF.2016.2.4.03.

Xie, Yu, and Kimberlee A. Shauman. 2003. *Women in Science: Career Processes and Outcomes*. Cambridge, Mass.: Harvard University Press.