Gender Earnings Gaps in STEM Fields: Exploring the Role of Job Tenure*

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ABSTRACT

Previous research has found a considerable earnings gap between males and females across occupational fields, including STEM (science, technology, engineering, and mathematics). Using data from the Current Population Survey for 2003-2017, we build upon this research by considering how job tenure shapes patterns of gender earnings inequality for college-educated STEM and non-STEM workers. Further, we decompose pay trends across those working in four STEM subfields, computer, engineering, science, and mathematics, and uncover very different returns to work experience across these different occupational domains. We find the gender gap in earnings decreased across the time period of our study for non-STEM workers but not for STEM workers (broadly defined) and increased by job tenure for non-STEM workers but decreased by job tenure for STEM workers. Our analysis of the four STEM subfields reveals important variations: women working in engineering and math fields experience extraordinary aggregating gender disadvantages across additional years of work experience (e.g., a greater than 300 percent increase in the expected gender gap in pay across 20 years of work experience in engineering), while those working in computer and science fields see more stable to slightly decreasing disadvantages in the gender gap in pay as they gain additional years of work experience.

Keywords: STEM, gender, earnings gap, occupational segregation, job tenure

Gender Earnings Gaps in STEM Fields: Exploring the Role of Job Tenure

In the United States, the gender gap in earnings narrowed considerably during the 1970s and 1980s but has changed more slowly since then (Blau and Kahn 2006; Blau and Kahn 2017). By 2017, women's median annual earnings were 80.5 percent of men's for full-time, year-round workers (Hegewisch 2018). Gender differences in human capital (e.g., education, experience, and skills) continue to be an important mechanism in explaining this earnings gap (Blau and Kahn 2017; Misra and Murray-Close 2014), but these gender differences have declined in recent years as the gap in men's and women's labor force experience has narrowed (Blau and Kahn 2017) and women's college enrollment and completion have overtaken men's (DiPrete and Buchmann 2013).

Despite the declining human capital differences between men and women, the gender gap in earnings has remained a persistent feature of the U.S. occupational structure. Some suggest that the residual gender differences in pay are due to between-occupational inequality (Mouw and Kalleberg 2010), with women selecting or being sorted[2] into lower-paying occupations, coupled with predominately female occupations being devalued as larger proportions of women entered the labor force (England, Allison, and Wu 2007; Levanon, England, and Allison 2009). One occupational domain where this type of gender segregation is pronounced and has received considerable attention and research is the science, technology, engineering, and mathematical occupational fields (hereafter, STEM). While over time, women's representation in STEM fields

[2] We use the term "sorted" to suggest an *institutional* sorting such that employers and families received expectations regarding gendered roles shape the choices of women while also shaping the decisions that others might make for them. This can operate through women selecting less upwardly mobile occupations that afford a range of non-monetary compensating differentials.

has increased, women still are less likely to work in STEM occupations than men (Sassler et al. 2017; Xie and Shauman 2003), despite the income advantages experienced by STEM workers.

Moreover, there are important differences in gender composition across the different disciplines of STEM occupations. Using data from the Current Population Survey (CPS), Figure 1 shows the proportion of females working in computers, engineering, science, and mathematical (math) fields from 2003 to 2017. The proportion of women in the engineering and science fields has increased by around 5 percent in the past 14 years (from around 10 to 15 percent for engineers and 31 to 36 percent for scientists). In the math fields, the representation of women has increased at an even greater rate of around 15 percent (23 to 38 percent). However, computer-based occupations have seen a decline in the proportion of women across this time period. In 2003, around 26 percent of computer worker were female, and by 2017 the ratio had declined to around 23 percent. These labor market trends, coupled with research that shows women experience difficult treatment in STEM fields (for a recent summary, see Hill, Corbett, and Rose 2010), make it important to further examine the occupational dynamics that shape income inequality for women employed in STEM fields.

[FIGURE 1 ABOUT HERE]

With the CPS data, we can observe how gender dynamics have changed within STEM fields over the past 14 years. We are not the first to explore some of these processes, and this study builds upon the research on female underrepresentation in STEM occupations (Michelmore and Sassler 2016; Sassler et al. 2017; Xie and Shauman 2003), along with theoretical and empirical work on human capital factors (e.g., Blau and Kahn 2017) and within- and between-occupational factors related to gender income inequality (Blau and Kahn 2006; Mouw and Kalleberg 2010). We offer several contributions to these areas of study: first, the CPS data allow us to examine how gendered compensation processes among STEM and non-STEM workers have changed over a 14-year period of time (2003-2017). Second, using additional data from the CPS Job Tenure Supplement (CPS-JTS), we can examine how the gender gap in earnings varies by job tenure (i.e., the number of years in current job) between STEM and non-STEM fields. Third, given the large sample of STEM workers in the CPS, we can formally model differences in the gender gap in pay overtime across different categories (subfields) of STEM occupations. Finally, we can examine how the gender gap in earnings varies by job tenure for these different categories of STEM occupations.

We find that the gender gap in pay for college-educated STEM workers in the United States is smaller than the gap for college-educated non-STEM workers when averaged over the 14 year period of our study, which parallels the broad trends of a 'STEM premium' in the earnings of STEM versus non-STEM workers that has been found (Noonan 2017). However, while the gender gap in pay for college-educated non-STEM workers has declined slightly over time, we find that the gender gap in pay for college-educated STEM workers has not declined over the same time period. Our analyses also uncover effects of job tenure on non-STEM workers that greatly increase the gender inequality in pay, while the effects of job tenure for STEM workers, broadly defined, appear to decrease gender inequality (i.e., the gender gap in pay) within this occupational domain. Across our different categories (subfields) of STEM occupations, those in engineering show the lowest average gender gap in income (at around a 10 percent disadvantage for women) while those working in the sciences show the largest gender gap in pay (at around a 16 percent gender gap in income). Despite this, those in engineering, the sciences, and math fields all show a declining gender gap in pay over time. Only those working in the computer fields show meaningful growth over time in the gender gap in pay. Moreover, those working in engineering and the sciences see a large growth in income inequality with additional years of work experience, while those in the computer and math fields show stable or decreasing levels of income inequality across additional years of work experience.

GENDER, TENURE, EARNINGS, AND STEM

The gender income gap remains one of the most tenacious characteristics of the U.S. occupational structure over the past century (Blau and Kahn 2006; Blau and Kahn 2007; England 2005; Mouw and Kalleberg 2010). In the 1950s, there was a steady increase in women who entered the paid labor force in what Goldin claimed was "the most significant change in the labor market during the past century" (Goldin 2006:1). Despite this "quiet revolution," studies have consistently found that women are underpaid relative to men in similar jobs (within-occupation inequality) and that women are disproportionally sorted into lower-paying jobs (between-occupational inequality) (Cohen and Huffman 2003; England 2005; Petersen and Morgan 1995). Some of the occupations that saw the largest influx of female employees came to be culturally defined as feminized, and the work within those domains became increasingly devalued (England et al. 2007; Levanon et al. 2009). Within-occupational mobility for female workers was often systematically constrained, as the metaphorical "glass ceiling" prevented women from receiving the same opportunities as their male counterparts (Caceres-Rodriguez 2013; Cotter et al. 2001; Fernandez 1998; Naff and Thomas 1994; Scholarios and Taylor 2011).

Another often-explored mechanism that may contribute to the gender income gap is cultural expectations concerning marriage (Cheng 2016; Dougherty 2006; Killewald and Gough 2013) and motherhood (Budig and England 2001; Budig and Hodges 2010; Korenman and Neumark 1992). There exist cultural expectations that, in opposite-sex marriages, women will shoulder a greater amount of the household labor than men and thereby spend less of their time and energy on paid labor (Hersch and Stratton 2000). Consequently, married heterosexual women may not be viewed by employers as the primary source of income for the household, and they are believed to have lower levels of motivation at work (Rodgers and Stratton 2010), as well as to have invested less in their human capital (Becker 1985). Similar cultural expectations may be present for mothers, with women who take time off to give birth and raise their children accumulating less job experience than men (Klerman and Neumark 1999). Employers may assume that mothers will be less productive at work because of the expectations concerning their role in child care (Becker 1981), and some women with children may seek out jobs that provide more flexibility, even if they pay less, because this flexibility represents an important compensating differential (Budig and England 2001). Finally, it is possible that employers are engaging in discrimination of married women and mothers over and above any sex discrimination. In this situation, women are paid less than men on average (sex discrimination), and among these women, those who are married or who have children are paid even less than unmarried women or women without children (marriage and motherhood discrimination) (Budig and England 2001).

While the moments of sex discrimination (as well as the marriage and motherhood penalties) still disadvantage women in terms of pay, gender differences in human capital continue to be an important source of the gender gap in earnings. Gender gaps in human capital have declined in recent years, however, as the proportion of women workers employed full-time and year-round has increased. This is in large part because women spend less time out of the labor force due to childbearing and childrearing than in the past. Blau and Kahn (2017) report that men had almost seven more years of full-time labor market experience on average than women in 1981 but only 1.4 more years in 2011. There also have been important changes in the nature of the educational gap between men and women, as women's college enrollment and completion have surpassed men's, resulting in a 'new' or 'reverse' gender gap in education (DiPrete and Buchmann 2013). The positive effect of this educational shift, in particular, can be seen in the relative narrowing of the gender earnings gap among younger workers (ages 25-34) to 93 percent, according to a Pew Research Center (2013) study.[3] Despite these positive trends towards income parity, men appear to receive a greater return on their educational investment relative to similarly educated women (Blau and Kahn 2006; Blau and Kahn 2017; Bobbitt-Zeher 2007; Cotter, Hermsen, and Vanneman 2004).

Within the literature on human capital and the gender gap in earnings, less attention has been paid to job tenure. Part of the reason for this is the lack of nationally representative data with information on job tenure and large enough samples to capture within- and between-occupational differences. A longer length of time in the same job or with the same employer can be a form of human capital, as a worker gains experience and possibly on-the-job training (Xu 2015), although receipt of on-the-job training may vary gender (Munasinghe, Reif, and Henriques 2008). There is some evidence that women have lower earnings returns to tenure with an employer than men, although this research has tended to focus on the early years (e.g., the first 10-15 years) of careers (e.g., Munasinghe et al. 2008). Because employment instability (e.g., changes in employers and occupations) has increased for both women and men (Hollister 2012; Hollister and Smith 2014), more research on possible gender differences in earnings returns to tenure is needed.

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[3] The gender earnings gap widens with age, however, because women still are more likely than men to take some time out of the work force or to reduce work hours for childrearing and other family-related reasons (Bertrand, Goldin, and Katz 2009; Budig and England 2001; Goldin 2014).

Declines over time in occupational segregation have been another important reason for the narrowing of the gender earnings gap. After large declines in occupational segregation by gender during the 1970s and 1980s, the index of occupational dissimilarity has remained around 50 for most years since 1996, that is, 50 percent of women would have to move from occupations in which women are overrepresented to occupations in which women are underrepresented for there to be equality in the occupations held by men and women (Hegewisch and Hartmann 2014; Weeden et al. 2018). It should be kept in mind that occupational segregation by gender may result from discriminatory processes in education and the workplace, such as encouraging women and men to pursue different majors in college and hiring and training women for different jobs than for men (e.g., Misra and Murray-Close 2014).

Gender segregation in STEM fields has been pronounced and the subject of considerable attention and research. Over time, women's representation in STEM fields has increased, although, as we showed in Figure 1 (described earlier), women still are less likely to work in STEM occupations than men. Relevant to our research, Michelmore and Sassler (2016) examined whether the gender gap in earnings among college graduates varies by STEM subfield and whether relationships between the gender gap in earnings and STEM subfield vary over time. To carry out their research, Michelmore and Sassler analyzed data from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System for individuals who received a bachelor's degree in STEM between 1970 and 2004 and were working in a STEM occupation at the time of data collection. Michelmore and Sassler found larger gender earnings gaps in computer science and engineering than in life and physical sciences (subfields with higher proportions of women workers) with other factors controlled (years since college degree, college cohort, any advanced degrees, marriage, and children). They also found evidence that the gender earnings gap may be decreasing for more recent cohorts of college graduates working in life science and engineering fields, but no clear patterns of change emerged in the gender earnings gap for their counterparts working in computer science and physical science fields. Overall, Michelmore and Sassler's research demonstrates the importance of examining the gender pay gap by STEM subfield and jointly by STEM subfield and time.

In considering possible gendered process across occupational fields, some researchers have suggested that there are few differences in the career processes of women in STEM occupations compared to other occupations and that the problems of women in STEM simply are more visible because of the small pool of women in this occupational domain (e.g., Hunt 2010). Contrary to this position, others argue that there are specific processes within STEM jobs that affect women's experiences differently from women's experiences in other jobs (Glass et al. 2013). Central to this latter position are arguments that the culture and organization of STEM work create a "chilly climate" for women. Peers and supervisors in STEM may hold more traditional gender ideologies and may perceive women as less capable and competent than men (Glass et al. 2013). Moreover, peers and supervisors in STEM also may be less positive towards and supportive of women workers (which could make combining work and family more difficult) and may discriminate against them in a number of ways (Hill et al. 2010; Simon, Wagner, and Killion 2017). The results of an experimental study conducted by Moss-Racusin et al. (2012) illustrate some of the biases women in STEM may face. Using applications for an undergraduate laboratory management position that were randomly given either a female or a male first name, Moss-Racusin et al. found both male and female university faculty in biology, chemistry, and physics rated a male applicant as more competent, hirable, and deserving of mentoring compared to a female applicant. Perhaps most in line with our concerns here, these faculty members consistently offered a higher salary to a male applicant.

Building upon the thesis of a chilly (or a chillier) climate faced by women within STEM occupations, Glass et al. (2013) compared women college graduates in STEM-related occupations to women college graduates in other professional/managerial occupations. Women originally in STEM occupations were more likely to leave their occupation than women originally in professional/managerial occupations. After 12 years, 50 percent of women originally in STEM occupations but only 20 percent of women originally in professional/managerial occupations had left for another field of work. Surprisingly, having an advanced degree in a STEM field and a high level of job satisfaction were not associated with remaining in a STEM occupation if a woman started there. Glass et al. argue that the biased attitudes of coworkers and supervisors and the organization of STEM work may contribute to women's exits from STEM in spite of advanced training or satisfaction with one's job.

Our research examines the relationship between job tenure, in terms of length of time in the current job, and the gender gap in earnings for college graduates working in STEM and non-STEM fields. Previous research on the gender gap in earnings in STEM or in both STEM and non-STEM fields either has not examined tenure or related measures in any way (e.g., Buchmann and McDaniel 2016) or has examined potential work experience or career duration instead. For example, Michelmore and Sassler (2016) used years since receipt of a bachelor's degree as a measure of potential work experience, while Xu (2015) used the number of jobs held since college graduation as a measure of work experience and any change in occupation since college graduation and number of years in the same career in an industry as measures of career duration. Michelmore and Sassler found years since degree had a positive effect on earnings, and along with other factors (college cohort, any advanced degrees, STEM occupational subfield, marriage and children), reduced gender earnings gaps.

Xu found positive relationships between career duration (in terms of number of years pursing the same career in one's industry) and earnings that were much stronger for men who graduated from college in non-STEM fields and women who graduated in STEM and non-STEM fields than for men who graduated in STEM fields. Xu also found job status (working full-time instead of part-time) was more important to the earnings of women from STEM and non-STEM fields than to men in STEM fields. Xu argues her findings support Blau and Kahn's (2007) observation that "work experience is valued more for women than for men in the determination of earnings" (p. 513). Overall, Xu found similar patterns of findings for women from STEM and non-STEM fields with one noteworthy exception: prior pay level did not have a significant effect on current pay of women from STEM fields but did have a significant effect for women from non-STEM fields (and men from both fields), which Xu posits is an indication of differential treatment of STEM women in the workplace (p. 515).

SUMMARY

In summary, although gender differences in human capital (e.g., education, experience, and skills), have declined over time, human capital remains an important source of the gender gap in pay (Misra and Murray-Close 2014). Occupational segregation by gender is another important source of the earnings gap: women tend to be overrepresented in lower-paying occupations and men tend to be overrepresented in higher-paying ones. Women's representation in STEM fields is especially important to the study of occupational gender inequality, as STEM occupations tend to be rewarded more than non-STEM occupations (i.e., a 'STEM premium' in earnings; Noonan 2017) and because STEM workplaces may have chilly climates for women

(Hill et al. 2010). Our study examines the size of the gender earnings gap in STEM and non-STEM fields and whether the size of the gender earnings gap varies over time. In doing so, we focus on whether job tenure (length of time in the current job), a potentially important but understudied form of intra-firm human capital, is a factor in the relationship between the gender gap in pay in STEM and non-STEM fields of work. Given evidence that women in STEM face a chilly climate, and are subject to unsupportive and biased treatment by peers and supervisors, we might expect a wider gender gap in earnings with length of job tenure in STEM fields compared to non-STEM fields. Finally, because gendered processes may vary across areas of STEM (as suggested by differences in the representation of women across STEM subfields), we also investigate differences in the gender gap in earnings by STEM subfield and by both STEM subfield and job tenure.

METHODS

Data

We use data from the Annual Social and Economic Supplement (ASES) of the Current Population Survey (CPS) from 2003 to 2017.[4] The CPS is sponsored by the Bureau of Labor Statistics and provides nationally representative information on occupations, earnings, and other demographic characteristics. These data have been used to study between- and within-occupational income inequality (Burkhauser, Feng and Jenkins 2009; Mouw and Kalleberg 2010; Schwartz 2010). Following previous research (e.g., Schwartz 2010), we further limit our sample to individuals ages 18 to 65, who are currently employed, and who worked at least 50 weeks in the previous year. Because we are interested in individuals in the STEM fields, we also focus our sample on those who have completed a Bachelor's degree or greater. Having made these

[4] These CPS data extracts are downloaded from the IPUMS-CPS database at the University of Minnesota (Flood et al. 2017).

changes, we create two specific analytical sample for our statistical analyses. The first makes use of these CPS data to isolate individuals working in the STEM fields in comparison to their educational peers. The CPS asks respondents about their primary occupation, and with this information we can isolate 44,018 individuals who work in the STEM fields, or about 2,500 STEM workers, on average, for each survey year. Included among these individuals are 10,233 females working in the STEM fields across the 14 years captured in these data.

While the Annual Social and Economic Supplement (ASES) is an excellent dataset for studying earnings inequality, it does not collect information about how long respondents have worked in their current jobs. In order to capture the theoretically and empirically interesting patterns of job tenure across the gender earnings gap, we merge information from the CPS-Job Tenure Supplement (CPS-JTS) to control for work experience in our models. The JTS was collected in January or Febuary every two years since 1996. Some of these respondents also provided information for CPS-ASEC, and this allows us to merge the job tenure information into our analytical CPS dataset for analysis.[5] Our second analytical sample will focus on those individuals who provide information to both the CPS-ASES as well as the CPS-JTS. This second sample is much smaller in size but provides additional information of theoretical interest. In this Job Tenure sample, we capture 5,955 individuals who work in the STEM field. Included among these individuals are 1,439 who are female. While the sample size shrinks significantly, the proportion of STEM worker remains very similar ($ASES = 13.5\ percent; JTS =$

[5] We merged this information using the matching algorithm proposed by Madrian and Lefgren (1999, 2000). This approach matches individuals across household ID, race, gender, age, marital status, and relationship to head of household to ensure matching individuals correctly. The code for implementing this algorithm is available at: http://www.nber.org/data/cps_match.htm.

$13.4\ percent$) and the proportion of female STEM workers is also very similar across samples ($ASES\ =\ 24.2\ percent; JTS\ =\ 23.3\ percent$).

Key Independent Variables: STEM Occupations, Gender, Job Tenure, and Time. Because the CPS is a labor force dataset, it collects information about respondents' occupation. This allows us to isolate individuals in particular occupations for comparison. The CPS asks respondents, "What kind of work do you do, that is, what is your occupation?"[6] The responses to this question are open-ended and then categorized into the Census occupational coding schemes. The CPS has changed occupational coding systems multiple times and twice across our time series. For example, in 2003 the CPS implemented the 2000 occupation codes and in 2010 they began using the 2010 occupational coding. Across these two coding systems, the CPS has more than 529 different occupational categories. To model inequality in the STEM fields, we take individuals who report their primary occupation in a STEM field (coded 1) to create an indicator for those working in these fields compared to those working in other occupational domains (coded 0). For example, someone who reports working as a 'biological scientist' would be included in our STEM indicator while someone working as an 'accountant' would not. Overall, around 13.5 percent of individuals in our analytical sample report working in a STEM occupation. For comparison, around 7 percent of the females in our ASES sample work in a STEM job compared to around 20 percent of males.

[TABLE 1 ABOUT HERE]

We also take advantage of our large sample of those working in the STEM field to further decompose this measure by type (subfield) of STEM occupation. Here, we will focus on those working in the Science Fields, Computer Fields, Engineering Fields, and Math/Statistics/Other

[6] For more information about the occupational questions in the CPS, see: http://www2.census.gov/programs-surveys/cps/techdocs/questionnaires/Labor%20Force.pdf .

Technical Fields (here after, Math Fields). Table 1 presents detailed information on our coding strategy for these categories of STEM Occupations. Overall, in our ASES sample, around 48 percent of individuals who work in the STEM fields have a computer job, 29 percent work as an engineer, 15 percent in the Sciences, and 8 percent in the Math fields. In terms of gender composition of STEM fields, 25 percent of the computer workers are female, 12 percent of engineers, 35 percent of scientists, and 31 percent of those in the Math Fields.[7] Table 1 presents our formal coding strategy for creating these STEM occupational categories. Here, we follow previous work (e.g., Glass et al. 2013; Michelmore and Sassler 2016) in the occupations we treat as STEM occupations, although our four STEM categories differ somewhat from those used by others (e.g., Glass et al. 2013; Michelmore and Sassler 2016). In pooled analyses of STEM areas, we examine the effects of working in the Science Fields, Engineering Fields, and Math Fields relative to the Computer Fields.

The CPS collects information about respondents' gender, and we use this information to create a binary indicator of those who are *female* (coded 1) to compare to those who are male (coded 0). We will use this indicator variable in several different regression interactions to decompose average gender differences in income as well as different income trends across time and job tenure in our statistical analyses. The CPS job tenure information asked how long respondents have worked in their current job, and we code this information into a continous variable (J*ob Tenure*) that runs from "less than one year" (coded 0) to "32 years or more" (coded 32).[8] We also include a *tenure*^{2} measure to account for any curvilinear relationship between

[7] Percentages do not add to 100 due to rounding.

[8] In 2012, the CPS-JTS began topcoding this variable. It is unclear from the documentation whether this topcode was at "32 year or more" or "35 years or more." For consistency across all years, we recode all information with a topcode for those working "32 years or more".

tenure and income. The Job Tenure information is only available in the JTS sample, and will not be included in any model on the ASES sample. Finally, to capture change over time, we include a continuous *year* of survey variable, coded in 2003 to 14 for the most recent year 2017.[9] Since the JTS information was only captured every other year, the year of survey variable here is coded 0 in 2004 and proceeds in two-year increments to 12 in 2016.

Dependent Variable: *Natural Log of Yearly Income.* The outcome variable for our analyses is the respondents' reported pretax yearly wage and salary income. We standardize this information into 2017 dollars to allow for over time comparison and we take the natural logarithm of the variable to account skew in the distribution. To protect respondent anonymity, the CPS has top-coded the upper end of the distribution of their income information. To adjust for this, we replace the top-coded income with 1.4 times that value. (This is call the "Rule of Thumb" adjustment; see Burkhauser, Feng and Jenkins 2009.) Across the time captured here, the CPS used a set of group income models to generate different topcode values based on different demographic characteristics. For consistency, we transform these topcoded amounts to a single value to implement our adjustment across our analytical samples. The CPS uses a "hot-deck" imputation strategy to adjust for missing information on income, and Mouw and Kalleberg (2010) have shown that this adjustment can affect wage estimates. Following their suggestion, we exclude all individuals with imputed wage values to avoid this issue.

Control Variables. The CPS provides additional information on the respondents' work, education, and demographic characteristics that allows us to control for several factors related to individual income and, in particular, gender differences in earnings (e.g., Blau and Kahn 2017; Misra and Murray-Close 2014). In terms of work, the CPS asks respondents how many hours

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[9] In additional models, we tested for a curvilinear effect of time on the gender gap in pay for our sample and found an insignificant effect of *year* ^{2} across our models.

they work in a typical week (from 1 to 99, a topcode) and we include this as a continuous control for *hours worked/week*. In addition, because we expect diminishing returns of working more hours, we also include an hour-squared (*hour*^{2}) term to capture any curvilinear effects. While we limit our samples to those who have completed a bachelor's degree or higher, we further control for educational difference by including an indicator for those who have completed an *advanced degree*, compared to those with a bachelor's degree only. To control for racial differences, we include two racial indicator variables for *black* and *other race* individuals, with white as the reference group. We also include a continuous *age* variable (18-65 years old) as well as an age^2 term to capture age differences in income. We include controls for respondents who are currently *married* or have (a) *child(ren) in the home* to account for the effects of family structure on income. Finally, we include an indicator for *living in a city* as well as a series of indicators for those working in the American *Midwest*, *South*, and *West*, compared to those living in the Northeast to account for regional variation in income.

[TABLE 2 ABOUT HERE]

Analytical Strategy

To map out gender differences in income among STEM workers, we use a series of linear regression models that take the following basic form:

$$y = \beta_0 + \beta_1(STEM) + \beta_2(Female) + \beta_3(Year) + \boldsymbol{\beta_4}(\boldsymbol{interactions}) + \boldsymbol{\beta_5}(\boldsymbol{Cont.}) + \mathcal{E}$$

where y is the natural log of yearly income in 2017 dollars, $STEM$ contains our indicator for those working in the STEM occupational fields with the β_1 coefficient capturing difference in STEM wages compared to the college educated in the general population. $Female$ contains our indicator for female workers and β_2 captures the gender differences in expected income. *Year* is a continuous measure of time and the β_3 vector allows to track any income trends. Some of our models include interactions which are represented by the $\boldsymbol{interactions}$ vector with corresponding $\boldsymbol{\beta_4}$ vector of coefficients. Finally, the vector $\boldsymbol{Cont.}$ Includes all of our main control variables with the accompanying $\boldsymbol{\beta_5}$ vector of coefficients. Ɛ captures any residual model error.

There is not much missing data for our analyses,[10] and the regression models presented in this paper utilize a listwise deletion approach to adjust for missing information. In additional models (not shown here), we run our regressions using maximum likelihood with missing values estimators to account for missing data (Allison 2002; Allison 2003), and our results are qualitatively unchanged with this adjustment. We present unadjusted results in this paper.

RESULTS

Table 3 presents a series of linear regression models on the natural log of yearly income across our ASES and JTS samples of college-educated, employed individuals within the general population. Models 1 shows general income pattern for STEM workers and females as well as the general time trend within this sample. This model also shows that, averaged over these fourteen years, STEM workers earn significantly more per year than non-STEM workers holding additional factors constant. To make this more concrete, STEM workers earn around 26 percent more per year relative to college educated non-STEM workers.[11] Females, however, experience a meaningful income disadvantage according to this model. Females earn around 21 percent less yearly income relative to males, while controlling for several additional covariates. This model also detects no meaningful change in expected income over time across these 14 years ($Year\ of\ Survey, Coef. = 0.0005; p\ value = 0.08$). As we will see, once we decompose this

[10] The measure with the largest proportion missing in these data is our measure of income, which has around 7 percent missing after making all of the adjustments described above.

[11] $Simple\ percentage\ difference = (\exp(coefficient) - 1)100$

time trend across additional covariates, we will uncover some meaningful income trends for some of our groups of interest.

[TABLE 3 ABOUT HERE]

Model 2 explores whether the positive effect of working in the STEM fields is similar for male and female STEM workers. According to this model, male STEM workers earn around 23 percent more than male non-STEM workers. The female STEM worker advantage is even greater at around 33 percent compared to the female non-STEM workers. This pattern, however, is driven primarily by the relatively low earnings among female non-STEM workers. To make this distinction clear, we plot the predicted income across these four groups in Figure 2. The top row shows the gender income difference for STEM and non-STEM workers. This plot shows that female non-STEM workers earn around $15,433 less yearly income compared to male non-STEM workers. For the STEM workers, the gender disadvantage is slightly smaller at around $13,095 less average income relative to male STEM workers.

[FIGURE 2 ABOUT HERE]

Model 3 decomposes the time trend across males and females among both STEM and non-STEM workers. Triple interactions can be difficult to interpret,[12] so we plot the gender difference in predicted income for these groups to determine whether there has been any meaningful decrease in the gender gap in pay for STEM and non-STEM workers. The results are

[12] Under the conditions here, the STEM Worker coefficient captured the difference between male STEM workers and non-STEM worker in 2003, the Female coefficient is the intercept different between female non-STEM workers and male non-STEM workers, and the STEM*Female coefficient is the difference between female STEM workers and male non-STEM workers. Here, the Year of Survey coefficient captured the expected change in income for male non-STEM workers, the STEM*Year the expected change for male STEM workers, the Female*Year the change for female non-STEM workers, and finally, the STEM*Female*Year the expected change for female STEM workers.

captured in the second row of Figure 2. Here, a positive slope indicates a decreasing gender gap in income while a negative slope shows that the gender gap is increasing. For the non-STEM workers, we see that the gender gap in income has been decreasing across these fourteen years. In 2003, the gender gap in pay was around $15,949 and by 2017 this amount has decreased to $14,937, a 6 percentage point decrease across these 14 years holding additional factors constant. Those in the STEM occupations, however, show little to no meaningful decrease in the gender gap in pay over these 14 years. In 2003, the gender gap in pay was around $12,708 and by 2017 this amount has increased to $13,453. This captures a 6 percentage point increase in the gender gap in pay among these STEM workers across these 14 years.

Models 4 and 5 come from analyses of our CPS-JTS data. Model 4 replicates the procedure from Model 2 on this additional sample, while controlling for the effect of job tenure. Across our coefficients of interest, we see a similar pattern to the one seen in the ASES sample. Female non-STEM workers earn the smallest income when averaged over these 12 years and male STEM workers earn the largest amount. We also capture similar gaps in pay across these two groups. The model also captures the general positive trends of years in the same job, but the returns to experience diminish as the length of tenure increase. Model 5 decomposed the effects of job tenure for our groups of interest, and the predicted income plots across tenure are presented in the bottom row of Figure 2. Here, we can see the gender gap in pay increases across years worked in a job for the non-STEM worker. The gender gap in pay for those with less than one year of work experience is around $11,244, and by the time they have 20 years of experience, the gap has grown to around $20,648, an 84-percentage point increase in gender gap across these years of work experience. In comparison, those working in a STEM occupation see meaningful declines in the gender gap in pay across years of work experience. The gender gap in pay for these individuals who have less than one year of work experience is around $14,407, and by the time they have 20 years of experience the gap has narrowed to around $12,852, an 11-percentage point decrease in gender gap across these years of work experience.

[TABLE 4 ABOUT HERE]

While our above analyses have uncovered some meaningful between-occupation gender differences for STEM and non-STEM workers, we also expect to uncover some meaningful within-occupation gender differences across our categories (subfields) of STEM jobs. Table 4 presents a series of linear regressions on our sample of STEM workers. While the logic behind these models is like the strategy pursued above, we do not test the curvilinear effect of job tenure here.[13] As with our full analyses, we plot the predicted income for our groups of interest from our interactive models in Table 4 to visualize the differences captured by our regression strategy. Figure 3 presents our results.

[FIGURE 3 ABOUT HERE]

The top row of Figure 3 shows the average expected income differences across STEM job categories for males and female in this sample.[14] For both men and women who work in STEM occupations, engineers and computer workers earn significantly more than science and math workers according to our models. In terms of the gender gap across these STEM categories, those in the engineering fields show the lowest average gender gap in income (at around a 10 percent disadvantage for women) while those working in the sciences show the largest gender gap in pay (at around 16 percent gender gap in income). The gender gap in pay for those in the

[13] Formal tests show that the effects of job tenure for these individuals is well captured with a linear effect and, as we can see from Figure 2, the inclusion of the curvilinear variable still produces a linear result.

[14] The predicted incomes for this part of the figure are calculated from the income regression presented in Model 2 of Table 4.

math and computer fields is quite similar at around 13.5 percent of expected yearly income. Model 3 from Table 4 decomposes our time trend across gender and STEM categories and the trends in the gender difference in income over time are plotted in the second row of Figure 3. Here, we can see that the gender gap in income among computer workers has increased across these 14 years. In 2003, the gender income among these workers was around 11 thousand dollar per year and by 2017 this among has increased to around 15 thousand dollar in expected income, a 36 percent increase in the income gap for those in computer based occupations. For all other STEM categories, we observe a decline in the gender gap in pay. Engineers experience a 38 decrease in their expected gender income gap and Science workers a 25 percent decrease in the gender gap for these individuals. Math workers experience the largest percentage decrease in the gender gap in income among the categories explored here, a 44 percent decrease ($13,106 in 2003 which drops to $7,397 in 2017).

Our final set of analyses focuses on the different effects of job tenure on the gender gap in pay across these STEM occupational categories. Model 5 from Table 4 presents our regression results and the bottom row of Figure 3 plots the expected differences in income across job tenure. Again, we uncover an interesting pattern across these groups. For those working in the engineering and science areas, we see an aggregated disadvantage in terms of income for women working in these areas. Female engineers with one year of work experience are expected to earn, on average, $3,791 less than similar men. This is an insignificant difference in our models. However, by the time female engineers have accumulated 20 years of work experience they are expected to earn $16,363 less per year than similar men, a greater than 300 percent increase in the expected gender gap in pay across these years of work experience. Similarly, those in the math fields experienced a 450 percent increase in the gender gap across the same increase in work experience ($4,875 at one year of tenure and $27,488 at 20 years of experience).

In comparison, women working in the computer fields see a declining gender gap with job tenure. For those with one year of work experience, the gender income gap is $16,131, and by the time women in this area have accumulated 20 years of work experience, the gender gap has shrunk to $13,720, a 15 percent improvement in the gender gap across these years of job tenure. Finally, women working in a science occupation experience an even greater decrease in the gender gap across job tenure at around 18 percent across the same years of experience.

DISCUSSION AND CONCLUSION

Using data from the Current Population Survey (CPS) for the years 2003 to 2017, we examined how gender gaps in earnings by time and by job tenure vary between college-educated workers in STEM, broadly defined, and college-educated workers not in STEM. We also examined how gender pay gaps by time and by job tenure vary within four STEM subfields (categories): computer science, engineering, science, and math. Our results indicate the gender gap in earnings differs between college-educated STEM and non-STEM workers in a number of ways. Consistent with overall patterns in the U.S. labor force, we found among our college-educated sample that men and women in STEM earn more than their counterparts not in STEM, a so-called STEM premium, as well as a smaller gender gap in earnings for STEM workers than for non-STEM workers. Examining trends in the gender gap in earnings over time (2003 to 2017) for our college-educated sample, we found a decrease in the gender gap in earnings among non-STEM workers but not among STEM workers, which also parallels the overall trends for the gender gap in earnings in the United States (Noonan 2017).

Human capital (education, experience, and skills) is an important factor for earnings and for the size of the gender earnings gap (Blau and Kahn 2017; Misra and Murray-Close 2014). Among human capital variables, relatively less attention has been paid to job tenure, a form of intra-firm human capital, and the effect it may have on the size of the gender pay gap in STEM versus non-STEM fields. A strength of our data is the ability to examine number of years in a current job, as opposed to the more general measures of work experience and career duration that have been used . Compared to men, women still tend to accumulate less work experience due to childbearing and other family-related reasons (Budig and England 2001), and they may receive less on-the-job training as well (Munasinghe et al. 2008). Therefore, we might expect the gender gap in earnings to widen with length of job tenure. Given evidence that women in STEM face a chilly climate, and are subject to unsupportive and biased treatment by peers and supervisors (Hill et al. 2010), we might expect a wider gender gap in earnings with length of job tenure in STEM fields compared to non-STEM fields. In contrast to this explanation, we found the gender gap in earnings generally increases with job tenure for non-STEM workers but decreases with job tenure for STEM workers in general.

Our analysis of the gender gap in earnings by time and by job tenure for the four STEM subfields reveals important variations. We found the gender gap in pay increased between 2013 and 2017 for workers in computer science but decreased for workers in the other three subfields. Our findings for the gender earnings gap by job tenure for the four STEM categories revealed striking differences: women working in engineering and math fields experience extraordinary aggregating gender disadvantages across additional years of work experience, while those working in computer and science fields see more stable to slightly decreasing disadvantages in the gender gap in pay as they gain additional years of work experience. Thus, the overall trend of a decreasing gender earnings gap by job tenure for STEM workers in general (shown in Figure 2) is driven by those in the computer and science occupations. It should be noted that our finding of a small decline in the gender pay gap by job tenure in computer science contrasts with the bleak news that women's representation in computer science has been declining (Figure 3; see also Michelmore and Sassler 2016).

There are two particularly key implications of our research. One is the importance of examining job tenure. Given the large exits of college-educated women from STEM fields in the early years of their careers, which is likely due in part to the chilly (chillier) climate women face in STEM compared to other fields (Glass et al. 2013), there may be something different about women who are able to remain in a STEM job for a longer period of time. Possible factors that may explain this finding include variation in women's ability to cope with a discriminatory STEM work environment and variation in how discriminatory particular STEM work environments are.

A second implication of our study is the importance of examining variation in gendered processes by STEM occupational areas (subfields). This was illustrated well by our findings of STEM subfield variation in the size of the gender earnings gap by job tenure. We will add to these findings in the near future by considering the roles of marital and parent statuses and race-ethnicity in gender earnings equality by STEM subfield more closely than we have thus far. Beyond our planned analyses, research that examines how the culture and organization of workplaces varies by STEM subfield will enhance our understanding of the processes shaping gender occupational inequality in the contemporary United States.

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TABLES

Table 1: STEM Occupation Categorization

Job Categories	Types of Jobs
Computer Occupations	Computer and Information Systems Managers; Computer Scientists and Systems Analysts; Computer and Information Research Scientists[2]; Computer Systems Analysts[2]; Information Security Analysts[2]; Computer Programmers; Computer Software Engineers[1]; Software Developers, Applications and Systems Software[2]; Web developers[2]; Computer Support Specialists[3]; Database Administrators[1]; Network and Computer Systems Administrators; Computer Network Architects[2]; Computer Occupations, All Other[2]; Network Systems and Data analysts[1]; Computer Operators; and Computer Control Programmers and Operators
Engineering Occupations	Engineering Managers; Aerospace Engineers; Agricultural Engineers; Biomedical Engineers; Chemical Engineers; Civil Engineers; Computer Hardware Engineers; Electrical and Electronics Engineers; Environmental Engineers; Industrial Engineers, Health and Safety; Marine Engineers and Naval Architects; Materials Engineers; Mechanical Engineers; Mining and Geological Engineers, etc; Nuclear Engineers; Petroleum Engineers; Engineers, All Other; and Engineering Technicians, Not Drafters
Science Occupations	Natural Sciences Managers; Agricultural and Food Scientists; Biological Scientists; Conservation Scientists and Foresters; Medical Scientists; Life Scientists, All Other[2]; Astronomers and Physicists; Atmospheric and Space Scientists; Chemists and Materials Scientists; Environmental Scientists and Geoscientists; Physical Scientists, All Other; Agricultural and Food Science Technicians; Biological Technicians; Chemical Technicians; Geological and Petroleum Technicians; Nuclear Technicians; and Other Life, Physical, and Social Science Technicians
Math, Statistics, Other Technical Occupations	Actuaries; Mathematicians; Operations Research Analysts; Statisticians; Miscellaneous Mathematical Science Occupations; Architects, except Naval; Surveyors, Cartographers, etc.; Drafters; Surveying and Mapping Technicians; Sales Engineers; and Statistical Assistants

[1] This category only available in the 2000 census occupational coding system.
[2] This category only available in the 2010 census occupational coding system.
[3] This category is available in the 2000 and 2010 census occupational coding system, but numerical value changed across coding systems.

Table 2: Summary Statistics

	Non-STEM Jobs (ASES)		STEM Jobs (ASES)		STEM Jobs (JTS)	
	Male	Female	Male	Female	Male	Female
Mean Income (2017$)	$98,361	$62,318	$99,986	$78,794	$99,330	$78,506
Median	$74,941	$52,073	$91,238	$72,191	$91,224	$72,559
Job Tenure (Years)					9 years	8 years
STEM Categories						
Computer Jobs			47%	52%	46%	53%
Engineering Jobs			33%	15%	34%	15%
Science Jobs			13%	23%	13%	23%
Math Jobs			07%	10%	07%	09%
Controls						
Hours Worked/Week	45 hours	40 hours	44 hours	41 hours	43 hours	41 hours
Bachelor's Deg.	64%	66%	64%	61%	65%	62%
Advanced Deg.	36%	34%	36%	39%	35%	38%
Age	44 years	42 years	42 years	40 years	43 years	41 years
White	84%	80%	76%	70%	82%	76%
Black	07%	10%	05%	08%	03%	07%
Other Race	09%	10%	19%	22%	15%	17%
Married	77%	66%	78%	65%	75%	63%
Child in Home	61%	57%	61%	53%	54%	47%
Lives in City	87%	85%	92%	92%	90%	91%
Northeast	22%	22%	23%	23%	24%	24%
Midwest	23%	23%	21%	20%	22%	23%
South	31%	32%	30%	33%	28%	29%
West	24%	23%	26%	24%	26%	25%
Observations	135,629	146,241	33,785	10,233	4,516	1,439

Table 3: Linear Regression Models on the Natural Log of Income across STEM and Non-STEM Workers, 2003-2017

	Annual Social and Economic Supplement Sample						Job Tenure Supplement Sample[a]			
	Model 1		Model 2		Model 3		Model 4		Model 5	
Main Effects	β	(SE)	β	(SE)	β	(SE)	β	(SE)	β	(SE)
STEM Worker	0.227***	(.003)	0.206***	(.004)	0.180***	(.008)	0.210***	(.010)	0.281***	(.020)
Female	-0.229***	(.002)	-0.237***	(.003)	-0.245***	(.005)	-0.232***	(.007)	-0.192***	(.012)
Year of Survey	0.000	(.000)	0.000	(.000)	-0.001	(.000)	0.002*	(.001)	0.002*	(.001)
Job Tenure $_{\text{Years}}$							0.018***	(.001)	0.023***	(.002)
Tenure^2							-0.000***	(.000)	-0.000***	(.000)
Interactions										
STEM*Female			0.080***	(.008)	0.089***	(.015)	0.063**	(.020)	0.008	(.037)
STEM*Year					0.004***	(.001)				
Female*Year					0.001*	(.001)				
STEM*Female*Year					-0.001	(.002)				
STEM*Tenure									-0.014***	(.004)
STEM*Tenure^2									0.000**	(.000)
Female*Tenure									-0.008***	(.002)
Female*Tenure^2									0.000**	(.000)
STEM*Female*Tenure									0.010	(.007)
STEM*Female*Tenure^2									-0.000	(.000)
Controls										
Hours Worked/Week	0.026***	(.000)	0.026***	(.000)	0.026***	(.000)	0.026***	(.000)	0.026***	(.000)
Advanced Deg.	0.229***	(.002)	0.229***	(.002)	0.229***	(.002)	0.216***	(.006)	0.216***	(.006)
Age	0.068***	(.001)	0.068***	(.001)	0.068***	(.001)	0.059***	(.002)	0.059***	(.002)
Age^2	-0.001***	(.000)	-0.001***	(.000)	-0.001***	(.000)	-0.001***	(.000)	-0.001***	(.000)
Black	-0.084***	(.004)	-0.084***	(.004)	-0.084***	(.004)	-0.107***	(.013)	-0.107***	(.013)
Other Race	-0.028***	(.004)	-0.028***	(.004)	-0.029***	(.004)	-0.003	(.011)	-0.004	(.011)
Currently Married	0.090***	(.003)	0.090***	(.003)	0.090***	(.003)	0.083***	(.007)	0.082***	(.007)
Child in Home	0.043***	(.003)	0.043***	(.003)	0.043***	(.003)	0.045***	(.007)	0.045***	(.007)
Lives in City	0.243***	(.003)	0.242***	(.003)	0.242***	(.003)	0.236***	(.009)	0.237***	(.009)
Midwest	-0.099***	(.003)	-0.099***	(.003)	-0.099***	(.003)	-0.100***	(.009)	-0.100***	(.009)
South	-0.053***	(.003)	-0.053***	(.003)	-0.053***	(.003)	-0.042***	(.008)	-0.042***	(.008)
West	-0.038***	(.003)	-0.038***	(.003)	-0.038***	(.003)	-0.031***	(.009)	-0.031***	(.009)
N			325,888					44,592		
R^2	0.29		0.29		0.29		0.31		0.31	
adj. R^2	0.29		0.29		0.29		0.31		0.31	

Source: Current Population Survey. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$;

[a]The Job Tenure Sample is collected every two years from 2004-2016

Table 4: Linear Regression Models on Income across Different Categories of STEM Workers, 2003-2017

	Annual Social and Economic Supplement Sample						Job Tenure Supplement Sample[a]			
	Model 1		Model 2		Model 3		Model 4		Model 5	
Main Effects	β	(SE)	β	(SE)	β	(SE)	β	(SE)	β	(SE)
Engineering Fields	0.017**	(.01)	0.010	(.01)	0.010	(.01)	0.005	(.02)	0.014	(.02)
Science Fields	-0.149***	(.01)	-0.140***	(.01)	-0.161***	(.02)	-0.158***	(.02)	-0.224***	(.03)
Math Fields	-0.108***	(.01)	-0.113***	(.01)	-0.104***	(.02)	-0.126***	(.03)	-0.152***	(.04)
Females	-0.149***	(.01)	-0.155***	(.01)	-0.130***	(.02)	-0.183***	(.02)	-0.202***	(.03)
Year of Survey	0.002***	(.00)	0.002***	(.00)	0.002	(.00)	0.005**	(.00)	0.005**	(.00)
Job Tenure $_{\text{Years}}$							0.005***	(.00)	0.004**	(.00)
Interactions										
Engnr.*Female			0.048**	(.02)	-0.009	(.03)	0.092*	(.04)	0.159**	(.06)
Sci.*Female			-0.023	(.01)	-0.084**	(.03)	0.014	(.04)	0.023	(.06)
Math.*Female			0.016	(.02)	-0.059	(.04)	0.005	(.05)	0.136	(.08)
Engnr.*Year					-0.000	(.00)				
Sci.*Year					0.003	(.00)				
Math.*Year					-0.001	(.00)				
Engnr.*Female*Year					0.008*	(.00)				
Sci.*Female*Year					0.008*	(.00)				
Math.*Female*Year					0.010*	(.00)				
Engnr.*Tenure									-0.000	(.00)
Sci.*Tenure									0.007**	(.00)
Math*Tenure									0.003	(.00)
Engnr.*Female*Tenure									-0.010	(.01)
Sci.*Female*Tenure									0.001	(.01)
Math.*Female*Tenure									-0.018*	(.01)
Controls										
Hours Worked/Week	0.019***	(.00)	0.019***	(.00)	0.019***	(.00)	0.019***	(.00)	0.019***	(.00)
Advanced Deg.	0.140***	(.01)	0.139***	(.01)	0.139***	(.01)	0.165***	(.01)	0.166***	(.01)
Age	0.065***	(.00)	0.065***	(.00)	0.065***	(.00)	0.057***	(.01)	0.057***	(.01)
Age^2	-0.001***	(.00)	-0.001***	(.00)	-0.001***	(.00)	-0.001***	(.00)	-0.001***	(.00)
Black	-0.089***	(.01)	-0.089***	(.01)	-0.089***	(.01)	-0.093**	(.03)	-0.096**	(.03)

Table 4 (cont.)

	Annual Social and Economic Supplement Sample						Job Tenure Supplement Sample[a]			
	Model 1		Model 2		Model 3		Model 4		Model 5	
Controls (cont.)	β	(SE)	β	(SE)	β	(SE)	β	(SE)	β	(SE)
Other Race	0.004	(.01)	0.004	(.01)	0.004	(.01)	0.032	(.02)	0.033	(.02)
Currently Married	0.082***	(.01)	0.082***	(.01)	0.082***	(.01)	0.058***	(.02)	0.058***	(.02)
Child in Home	0.039***	(.01)	0.039***	(.01)	0.039***	(.01)	0.053***	(.02)	0.053***	(.02)
Lives in City	0.198***	(.01)	0.199***	(.01)	0.198***	(.01)	0.202***	(.02)	0.202***	(.02)
Midwest	-0.084***	(.01)	-0.084***	(.01)	-0.084***	(.01)	-0.086***	(.02)	-0.087***	(.02)
South	-0.028***	(.01)	-0.029***	(.01)	-0.029***	(.01)	0.004	(.02)	0.003	(.02)
West	0.008	(.01)	0.007	(.01)	0.007	(.01)	0.005	(.02)	0.003	(.02)
N	44,018		44,018		44,018		5,955		5,955	
R^2	0.23		0.23		0.23		0.25		0.25	
Adj. R^2	0.23		0.23		0.23		0.25		0.25	

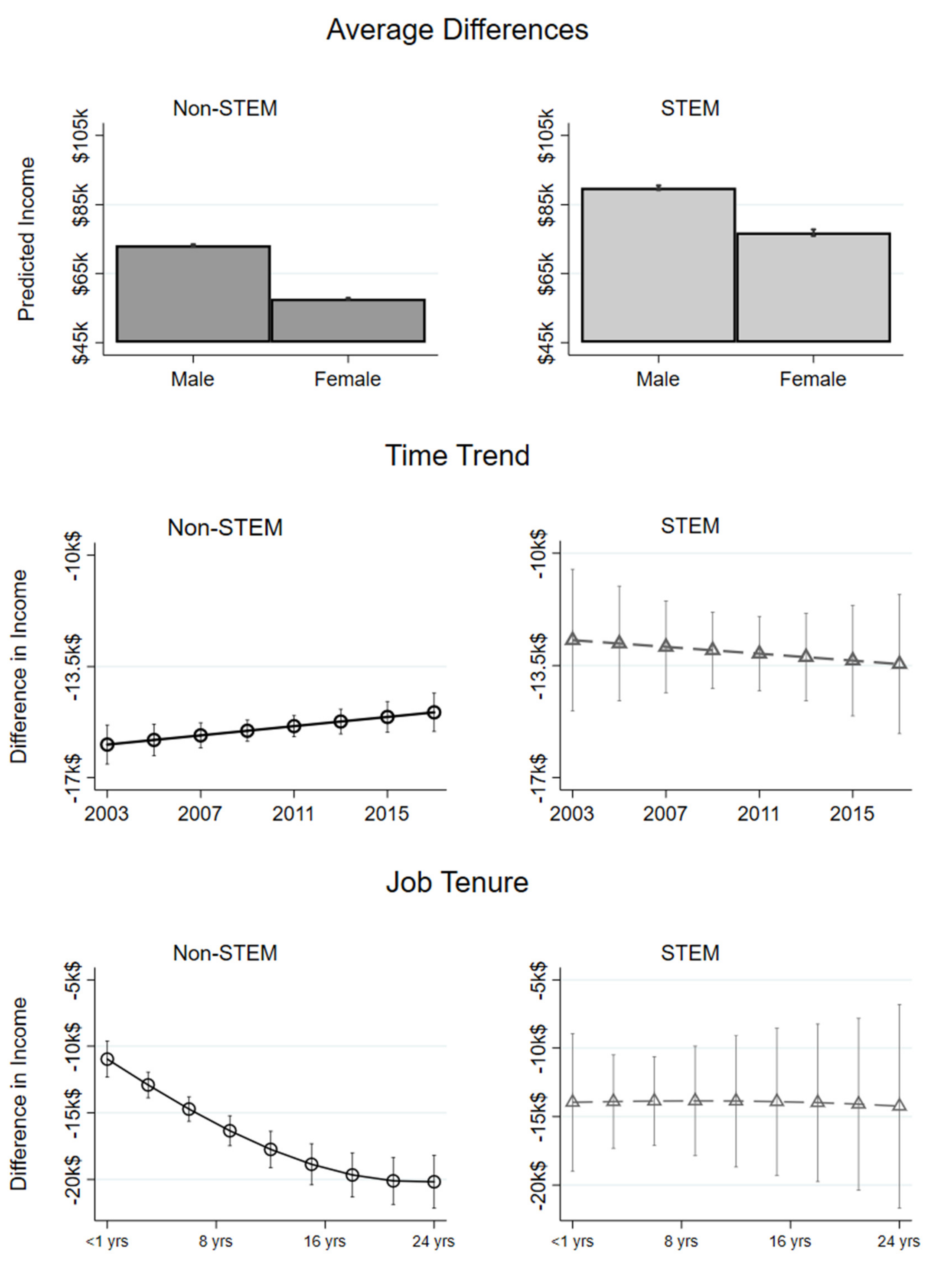
Source: Current Population Survey. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;
[a]The Job Tenure Sample is collected every two years from 2004-2016

FIGURES

Figure 1. Trends in the Proportion of Women in STEMs Categories

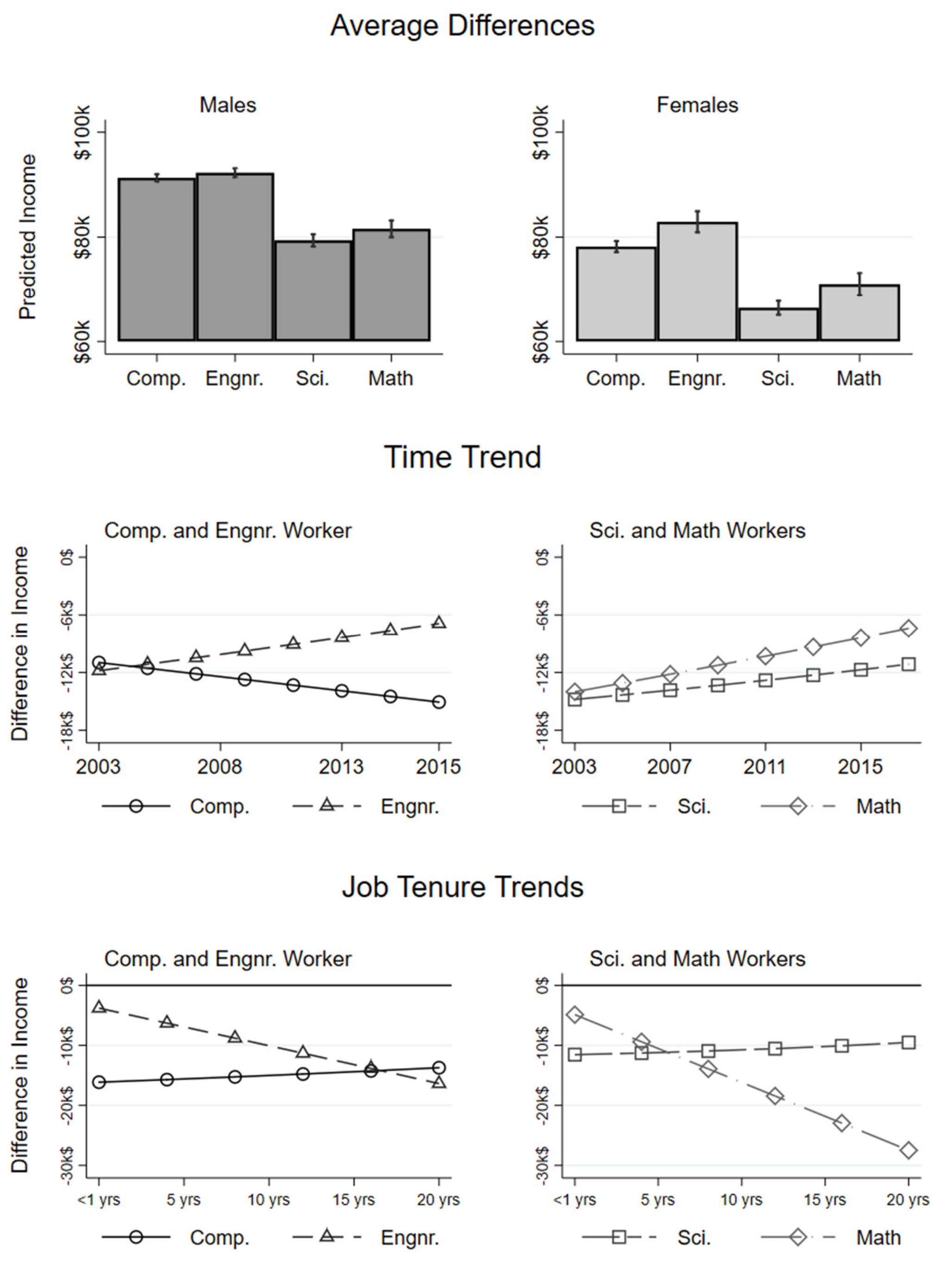
Source: Annual Social and Economic Supplement of the Current Population Survey, 2003-2017. Scale on Y axis varies across categories.

Figure 2. Predicted Income Plots across Time and Job Tenure



Source: Current Population Survey. Models for predictions come from Table 3.

Figure 3. Predicted Income Plots across STEM Categories by Gender



Source: Current Population Survey. Models for predictions come from Table 4.