Exploring Gender Inequality in Entry STEM Careers

A study on recent trends of STEM employment with evidence from Millenial Birth Cohorts

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The field of science, technology, engineering, and mathematics (STEM) has predominantely been occupied by men up until the late nineteenth century where enrollment in U.S. higher educated has seen an increase of women. Many individuals would argue that the lack of women representation in STEM careers may suggest less gender inequality. Although progressive efforts have shown that the wage gap between males and females are becoming less significant, data from recent cohorts in the American Community Survey between 2009 and 2018 that track the evolution of gender inequalities in STEM employment showed that women with STEM degrees face employment prospects that Wage Gap, STEM, feminism, patriarchy resemble those of men without STEM degrees.

Gender Inquality,

## Introduction

In this paper, we will be discussing about the gender inequalities in STEM careers. The feminist revolution in the United States began in the 1960’s and ’70s where women fought for gender equality such as rights, opportunities and greater personal freedom. Many feminists such as Micky Lee (2011) suggest that scarcity in feminist political-economic studies is due to a lack of female representation, which is what many would argue is applicable to the disparity of women in STEM ([Lee 2011](#ref-Lee2011)). Therefore, it is important to acknowledge the history of feminism and how it connects to gender inequality within STEM as the feminist revolution resulted in ending the systemic patriarchal society in the U.S. After the revolution, women were granted equal opportunities that lead to independence as it shifted the paradigm of no longer needing to rely on men for their social economic status.

Referring back to Lee’s argument on the scarcity of female representation in political-economic studies, STEM, most notably, computer science, is another discipline that many can argue lacks female representation. Prior to contrary belief, the field of computer science was originally dominated by women during World War II, during that time, men viewed computer science as “secretarial” but later chose to pursue the discipline upon returning from the war front. This shifted women back to pursuing careers that were deemed as “nurturing” (e.g. nurse, teacher, homemaker), which is what many psychologists such as Freud (1989) may argue. Lee (2011) quotes Freud’s psychoanalytic theory of maximizing pleasure in which, she suggests that women are motivated to choose a career that brings pleasure.

It is important to note that Freud (1989) is often critiqued for being sexist in the study of psychology. Respectively, his theories overemphasized gender as being a major factor for motivation and are often used as an argument for women pursuing careers that are cognitively laborious (e.g. teacher, psychologist, nurse, etc). To counteract this juxtaposition, I propose feminist psychologist, Karen Horney’s critiques against Freud with her argument that male realities cannot describe female psychology or define their genders due to the inability to experience reality from a female perspective.

With this in mind, it is important to acknowledge that feminist perspectives are essential to the development in STEM as women have the ability to provide a more holistic perspective to solving problems that will result in technology being more fair and equitable. For instance, AI bias or Artificial Intelligence Bias is the output of machine learning algorithms that are created from prejudiced assumptions made during the algorithm development process or prejudices in the training data ([“Bias in AI: What It Is, Types, Examples & 6 Ways to Fix It in 2022”](#ref-Dilmegani2020)). AI bias is prominent in technology industries that fail to train data and produce the algorithms that are efficient in achieving an objective for an individual. A study in a systematic review of decision-making algorithms in human resources recruitment and development found that there was a possible threat of discrimination and unfairness for women [[Köchling and Wehner](#ref-Kochling2020) ([2020](#ref-Kochling2020))).One prominent example is Amazon’s CV screening tool which is trained on biased historical data the led to a preference for male candidates. Historically, Amazon has hired more male software engineers and the algorithms for CV screenings that were trained with this historical data led to gender discrimination ([Martin 2022](#ref-Martin2022)).

Recruitment is not the only inequality women face within STEM. It was found that women who hold bachelor’s degrees in STEM related fields still made less than their male counterparts. ([VanHeuvelen and Quadlin 2021](#ref-VanHeuvelen2021)) used data from the American Communitiy Survey (ACS) between 2009 and 2018 to assess how gender disparities in STEM education translate into subsequent employment and earnings inequality within the industry. They argue from a theory of gender inequality that view men as “ideal workers” within organizations which eventually result in women exiting the industry, despite the investment in their STEM related degree ([Benard and Correll 2010](#ref-Benard2010)). Their analyses show despite the progressive efforts of minimizing the gender gap in STEM education in recent cohorts, women still face a challenge working in STEM occupations and the industries where STEM degree holders tend to be concentrated. The probabilities showed that STEM-trained women who are employed either in STEM occupations or high-tech industries were closer to their male counterpoints without STEM degrees, making them farther from men who hold STEM degrees. It was found that there was still a large earnings gap between men and women with STEM training in their early careers as the accumulation of gender penalties over a 10-year sample are approximate to one year’s salary of STEM work. Although obtaining STEM education may provide greater opportunities for women, the results show that there is still a disparity of closing the gender wage gap and achieving greater gender parity.

## Data

### Methodology

The original research was conducted by Tom VanHeuvelen from the University of Minnesota, Minneapolis and Natasha Quadlin from the University of California, Los Angeles.The data was used from ACS from 2009 to 2018 which is considered ideal for the purposes of providing highly detailed and nationally representative data on earnings, field of study, industry, occupation, and sociodemographics. Data was analyzed in 2009, the first year ACS collected information on respondent’s fields of study making it feasible to track a decade’s worth of gender inequality. Samples were restricted to those with only bachelor’s degrees who were born between 1986 and 1988, or those who would enter the labour market with bachelor’s degrees in the first wave of the sample year 2009. Data from this cohort who are employed and have yet transitioned into a parenthood role by 2018.

### Dependent and Indepdendent Variables

There are five primary variables focused on in this which are a respondent’s (1) logged weekly earnings, measured by dividing the annual pretax income with the number of working weeks in a year. Whether the respondent is (2) female, (3) has a STEM degree, (4) works in a STEM occupation, and (5) works in a high-tech industry. STEM majors include but are not limited to the following: agriculture, environmental, and natural resources, computer sciences, engineering, engineering technologies, biology and life sciences, math and statistics.

In an attempt to attend trends of gender inequality, the sample is restricted to two-thirds of the sample whom did not have children by ages 30-32.For those who did not have children by 2018,the sample is restricted in each year to those without children. Then, a re-weighting technique developed by labour economists was used to construct a comparable sample of respondents based on a chosen set of observed characteristics ([DiNardo, Fortin, and Lemieux 1996](#ref-DiNardo1996)). All time in-varient characteristics are collected and avaiable in the ACS: sex, quarter of birth, year of birth, state/non/US location of birth, race/ethnicity, Hispanic identity and whether the respondent was born in the US. Then, the logistic regression models were estimated with these characteristics as independent variables separately for each wave from 2009 through 2017 which helped to predict whether an individual case was in that wave or the 2018 wave.The resulting predicted probabilities were used to calculate weights that were incorporated into the survey weights provided by the ACS. The following formula was used to calculate the new weights:

$$Reweigt\_{yi} = \pi\_{yi} \times \left( \frac{p\_{yi}}{(1-p\_{yi})} \middle/ \frac{\mu\_{y}}{(1-\mu\_{y})} \right)$$

#import .csv file to global environment  
descriptive\_statistics <- read.csv(file = "reweighted.csv")  
  
#formatting table  
knitr::kable(descriptive\_statistics, "pipe")

| X | Total | Men | Women | Gender.Difference |
| --- | --- | --- | --- | --- |
| Logged weekly wages | 6.574 | 6.649 | 6.499 | −.150 |
| STEM degree | 0.236 | 0.322 | 0.150 | −.172 |
| STEM occupation | 0.158 | 0.234 | 0.081 | −.153 |
| High-tech industry | 0.139 | 0.188 | 0.091 | −.097 |
| STEM degree in STEM occupation | 0.661 | 0.701 | 0.544 | −.157 |
| STEM degree in other occupation | 0.156 | 0.205 | 0.115 | −.090 |
| STEM degree in high-tech industry | 0.512 | 0.593 | 0.342 | −.251 |
| STEM degree in other industry | 0.192 | 0.259 | 0.131 | −.128 |
| STEM occupation in high-tech industry | 0.553 | 0.631 | 0.388 | −.243 |
| STEM occupation in other industry | 0.094 | 0.143 | 0.051 | −.092 |

* Table: Descriptive Statistics
* Gender Wage Gaps across STEM work between ages 25 to 64
* Note the critical comparison across recent cohort and total sample of ACS
* Mention two critical points from the data

## Results

* Implications and observations
* Graph: Probability of STEM employment over time, by gender and degree type
* Trends in Gender Earnings Gaps

## Discussion

* Research has made clear of the challenges women face in science and technology, both in education and in work
* Women in STEM often feel they are less competent and less committed than men
* Analyze 10 years of data from the ACS to groups early in their careers prior to parenthood
* Despite womens’ gains in STEM majors over the past half century, there are still substantial inequalities when it comes to employment and earnings
* Include gender earnings gaps over time by STEM degree and STEM work
* Concluding that equalization in STEM education does not guarantee access to, and equality within, STEM work

cons and implications: self reported data is imposes bias

## References

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