State of Washington

Earnings Premium Estimates by Gender and Race Category for STEM Bachelor's Degrees in Washington State

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Abstract

This paper uses data from the Education Research and Data Center (ERDC) to estimate the earnings premium by gender and race category associated with bachelor's degrees in science, technology, engineering and mathematics (STEM) majors compared to degrees in non-STEM fields in the state of Washington, adjusting for selection bias. We use propensity score matching to control for selection bias. This paper is one of the first to explicitly adjust for selection bias while estimating the STEM earnings premium.

We find the STEM earnings premium (STEM median earnings – non-STEM median earnings) for males is $18,300 for the eighth year after high school graduation. In stark contrast, the female STEM earnings premium remains quite low through the first seven years after high school and rises to $2,800 in the eighth year. Females gained a much smaller earnings premium than males from earning a STEM degree in terms of median real annual earnings. Across race categories, the female STEM earnings premium ranges from -$5,200 to +$7,400 while the male STEM earnings premium ranges from +$16,300 to +$21,900 in the eighth year after high school graduation.

Overall, it is clear that STEM degrees have a much higher payoff for males than for females. Median real annual earnings are substantially higher for males with STEM degrees.

JEL Classification: C23, H40, I21, J24, J31

Keywords: propensity score matching, selection bias, gender, race returns to education, STEM, science, technology, engineering and mathematics.

Contents

1. Introduction

As the United States develops workforce strategies at the national, state and local levels, many policy advocates are calling for an expansion of postsecondary programs in science, technology, engineering and mathematics (STEM) fields. STEM majors are identified by referencing the Office of Financial Management (OFM) list of STEM Classification of Instructional Programs (CIP)[1]. The emphasis on STEM degrees is intended to increase international competitiveness in STEM fields and lead to higher earnings for STEM degree graduates. This paper estimates the earnings premium by gender and race category associated with bachelor's degrees in STEM majors compared to degrees in non-STEM fields in the state of Washington, adjusting for selection bias.

This study is the third in a series that provides information on the economic returns to postsecondary education in Washington state using data from the Education Research and Data Center (ERDC) in the Office of Financial Management. The U.S. Department of Labor has funded state Workforce Data Quality Improvement (WDQI) grants to promote the inclusion of unemployment insurance (UI) earnings and employment data. This educational study is funded by the Washington state WDQI grant. The study demonstrates the value of connecting micro-level education data with micro-level workforce data.

This assessment is challenging because the determinants of earnings include more than educational attainment. Many factors influence both the decision to pursue a STEM degree and subsequent earnings, which will confound the findings unless taken into account. These factors include academic ability, work effort and persistence, future versus present orientation, parents' income and education and the students' choice about major fields of study, among others. These factors are often collectively summarized as selection bias. Simply measuring the post-graduation earnings of graduates with STEM degrees and comparing them to the earnings of graduates with non-STEM degrees will overstate the returns to STEM degrees because the STEM graduates may have higher earnings had they pursued non-STEM degrees, given the effects of the background characteristics.

Throughout the literature covering the STEM earnings premium, outcomes are commonly overstated due to uncontrolled selection bias. Caponi and Plesca (2007) mention the sparseness of postsecondary returns research and the persistent problem of ignored selection bias:

> "However, the literature does not account for the possibility that the estimated returns to education suffer from the selection bias that arises when the choice of education is related to unobserved characteristics, for example innate ability, which also affect earnings ... ." (Caponi and Plesca, 2007, p. 1).

Selection bias is not a factor in random, assignment-based experimental studies, such as clinical trials, because the treatment and comparison groups are statistically identical. Unfortunately,

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[1] STEM majors were identified using the OFM CIP list, a combination of STEM definitions from the National Science Foundation, the Consortium Student Retention Data Exchange and the Science, Mathematics and Research for Transformation lists. For a complete list see: http://www.ofm.wa.gov/hied/dashboard/stem_and_high_demand_CIP_codes.xlsx (note this list includes high demand as well as STEM majors,, those CIP with STEM=Y are those used in this study)

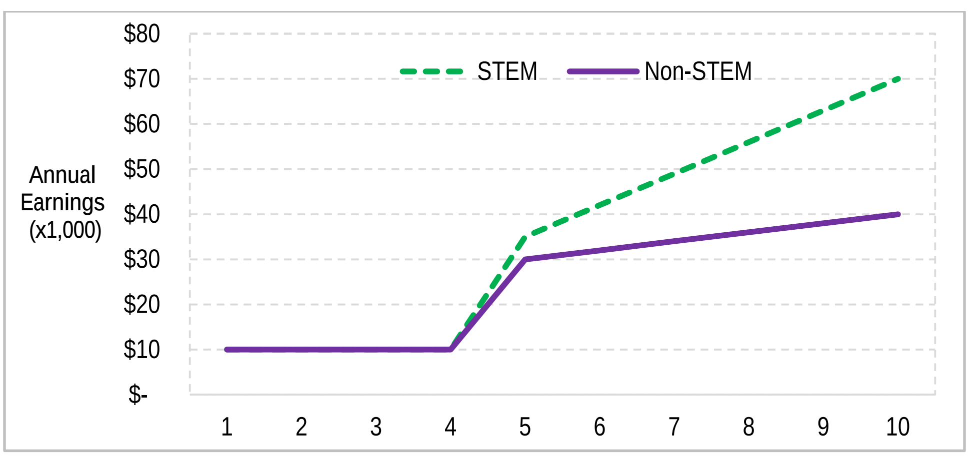
such an approach is generally unavailable for educational research. Like other educational research, this is an observational study based on administrative data. The treatment and comparison groups upon which this study is based are Washington state workers with bachelor's degrees who also graduated from a Washington state high school between 2005 and 2007. These students were not enrolled in a post-baccalaureate program such as graduate school or law school. The data are from the ERDC P-20 Data Warehouse.

We use a propensity score matching (PSM) technique to minimize the effects of selection bias in this study. "The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum and Rubin, 1983, p. 41). This approach matches workers with STEM degrees to workers with non-STEM degrees, based on their respective propensity scores, which are the likelihood of earning a STEM degree. The resulting STEM and non-STEM groups are thus closely matched on the observed characteristics.

While it is not possible to know that selection bias has been eliminated from any observational study, the PSM technique represents the best available method, and is prevalent in the evaluation literature. "Approaches that directly match participants with nonparticipants who have similar observed characteristics have replaced regression as one of the preferred methods for estimating intervention impacts using comparison group data" (Heinrich, Maffioli and Vezquez, 2010, p. 4).

Figure 1 shows the expected (hypothetical) patterns of earnings for the two study groups after high school graduation. Initially, through about year five after high school, both groups have approximately equal earnings as they work part time or for minimum wages while they are in college earning their bachelor's degrees. About five years after high school graduation, the earnings of the workers with STEM degrees should increase relative to those with non-STEM degrees, reflecting the increased human capital, productivity and earnings potential of STEM degrees relative to non-STEM degrees.

Figure 1. Expected patterns of earnings for STEM and non-STEM bachelor's degree graduates



The core hypothesis of this study is represented in Figure 1 by the vertical distance between the earnings of workers with STEM degrees (blue dotted line) and the earnings of workers with non-STEM degrees (red solid line). This difference can be stated as: "The earnings of college graduates with STEM majors exceed the earnings they would have achieved had they taken a non-STEM major." This paper tests this hypothesis for specific groups.

This paper is organized as follows. Section 2 describes previous research assessing the earnings gains associated with a bachelor's degree in a STEM field. Section 3 discusses the paper's analytical approach, including our use of propensity score estimation and matching. Section 4 describes the data used in this study. Section 5 discusses our estimation methodology. Section 6 discusses our findings. We complete the paper with conclusions, observations and a comment on future research.

2. Previous Research

There are relatively few research studies comparing the earnings of workers with STEM bachelor's degrees to those with non-STEM bachelor's degrees. Carnevale, *et. al.*, analyzes the earnings premium attributable to STEM by gender and race, but does not correct for selection bias (Carnevale, et.al., 2011). They use Current Population Survey data combined with projections data from Economic Modeling Specialist Incorporated. Like our current study, Carnevale, *et. al*. find that "on average, STEM workers tend to have higher wages than all other non-STEM workers" (*ibid.*, p. 34*)*. They also find a gender earnings gap, which "starts out small but eventually is larger in STEM than it is in other occupations" (*ibid*., p. 37). Carnevale, *et. al.* also found similar trend effects of race on earnings. "African-Americans and Latinos earn less in STEM than their white and Asian counterparts" (*ibid*., p. 39).

A recent report from the American Institutes for Research provides an analysis of the economic returns to STEM education (Schneider, 2013). While this report does not break out the returns to STEM by gender or race, it does look at returns by educational area. However, it also does not correct for selection bias. The report finds that "graduates in the fields of technology, engineering, and mathematics (or TEM) experience greater labor market success than graduates in other fields and that graduates with degrees in science-related fields (or S) do not generate any greater labor market returns than, for example, the non-STEM field of English Language and Literature" (Schneider, 2013, p. 33).

Using data from Texas, Colorado and Virginia, Schneider finds that STEM fields such as computer and information sciences have first-year earnings between $20,000 to $30,000 greater than the non-STEM field of English language and literature. Unfortunately, Schneider does not correct for selection bias nor break out his STEM findings by gender.

These studies, as is common in educational research reports, make no adjustment for selection bias and thereby are likely to be overstating the earnings premium associated with STEM degrees and STEM jobs. The decision to go into a STEM field in college is correlated with many of the same factors that lead to higher earnings. Thus, selection bias is present in any direct comparison of STEM to non-STEM earnings. Our paper is one of the first both to explicitly recognize this and have access to the data required to make selection-corrected estimates.

3. Analytical Approach

There is an extensive literature on the topic of correcting selection bias in observational studies. Smith and Todd (2005) refer to articles by Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998) in which the latter authors use non-experimental propensity score techniques to estimate net economic effects from an experimentally designed evaluation study as a way to evaluate the PSM approach. Referring to these authors, Smith and Todd state that:

> "… data quality is a crucial ingredient to any reliable estimation strategy. Specifically, the estimators examined are only found to perform well in replicating the results of the experiment when they are applied to comparison group data satisfying the following criteria: (i) the same data sources (i.e., the same surveys or the same type of administrative data or both) are used for participants and nonparticipants, so that earnings and other characteristics are measured in an analogous way, (ii) participants and nonparticipants reside in the same local labor markets, and (iii) the data contain a rich set of variables that affect both program participation and labor market outcomes" (Smith and Todd, 2005, p. 309).

The data from the ERDC fully meet these requirements. We apply a PSM technique to develop a comparison group to serve as the counterfactual to the treatment group. We use logistic regression to estimate propensity scores for the combined STEM and non-STEM degree groups. The propensity score acts as a single number index of the variables that are used in its estimation.

The primary advantage the present study has over previous studies is our access to individual level data from the high school records of both the STEM and non-STEM groups. Treatment and comparison group members should have the same distributions of observed and unobserved attributes, and come from similar economic environments to effectively reduce the selection bias (Heckman, Ichimura, Todd, 1997, p. 606). To a considerable extent, the STEM group had the same primary and secondary educational experiences and opportunities as the non-STEM group, and had access to the same labor markets during and after high school. These similarities reduce the differences between the two groups and enhance the likelihood that the PSM technique corrects for selection bias.

This reliance on information from the high school records of study participants influences the ways in which outcome (earnings) data are reported. We report earnings as annual median real earnings by year after high school graduation. Table 2 shows that 95 percent of the study population has graduated from college by the fifth year after high school, regardless of gender or STEM degree status.

The PSM reduces the dimensionality of the selection characteristics of sample members. A propensity score is estimated for each member of the study population. Females and males are modeled separately and by race category. The calculation uses a logistic regression technique. The model specification that we use was selected by testing alternative model specifications and evaluating the statistical properties of each specification. The independent variables that compose the characteristics vector of the selected model are high school grade point average, free and reduced-price lunch participation, region of the state of the high school, high school county unemployment rate and whether the worker ever received a Washington state student Need Grant. The binary dependent variable is the attainment of a STEM bachelor's degree or attainment of a non-STEM bachelor's degree. We rely on high school grade point average to serve as a proxy for ability; and free and reduced-price lunch participation, Need Grant receipt, county (of high school) and unemployment rate in the county of high school to serve as proxies

for both family income level and the local labor market. The independent variables are predetermined at the time the student enters postsecondary education.
The propensity scores representing the probability of obtaining a bachelor's degree in a STEM field compared to obtaining a bachelor's degree in a non-STEM field are used to directly match individuals in the STEM degree group to individuals in the non-STEM degree group. We use a one-to-many with replacement matching algorithm, where the non-STEM group members are matched to one or more STEM group members. The matching process minimizes the total distance between propensity scores for the two groups. See Appendix A for a more detailed discussion of these issues.

4. Data

We start with the roster of graduates from public high schools in Washington state, extracted from the annual ERDC High School Feedback Reports (ERDC, 2013). Students who graduated from a Washington state public high school in 2005, 2006 or 2007 and earned a bachelor's degree in a Washington state public university compose the study group. Washington state UI earnings data are used as outcomes for this study. The UI earnings data available to the ERDC at the time of this study covered calendar years 2006 through 2013.

Based on information from the ERDC and the National Student Clearinghouse (NSC), bachelor's degree group members who were attending out-of-state colleges or universities, or attending in-state private colleges or universities, are eliminated from the study population. Also, study group members who were enrolled in post-baccalaureate studies are removed. Finally, because UI wage records are required for in-state employment follow-up, study group members for whom a Social Security number could not be discovered were eliminated from the study. Since UI wage records reflect only those covered by UI in Washington state, we have no means to differentiate non-participation in the labor market from self-employment or out-of-state employment. Also, to ensure the study follow-up represents a significant labor market attachment, any study member without wage data in all quarters of any calendar year is removed from the analysis.[2]

The sources for the data used in this study are administrative data files that are not collected for research purposes, and contain limitations and shortcomings as analytic variables to determine economic impacts. In all the data sources, there may be some institutions not reporting. For example, some private universities in Washington may not share data with the ERDC, or other postsecondary providers nationwide may not share data with the NSC[3]. Also, some data elements may be missing or inaccurate, such as missing earnings in the UI wage record data[4]. The data anomalies and errors compose a small proportion of the information being used, and in the authors' judgment have a minimal impact on the study findings.

[2] See Appendix C for a description of the UI wage record data.
[3] The NSC reports coverage on more than 3,500 public and private U.S. institutions, accounting for more than 98 percent of all enrolled students.
[4] Approximately 0.5 percent of all UI wage records considered for this study have missing data in at least one quarter of any of the analysis years. Missing earnings, either totally or in part, might indicate working out of state or self-employment. We have no way of distinguishing these statuses from employed or not employed.

5. Estimation Methodology

We calculate inflation-adjusted earnings for each calendar year covered by the study. The relevant calendar years for each follow-up year (after high school graduation) for each cohort are then combined (stacked) as illustrated in Table 1. We assess the impact on earnings of obtaining a STEM bachelor's degree by comparing median earnings by year after high school graduation for the workers with STEM and non-STEM bachelor's degrees.

Table 1. Follow-up years after high school graduation

		Cohort Follow-up Dates (available earnings data in bold) Years After High School Graduation Calendar Year (CY)							
	High School Graduation	1	2	3	4	5	6	7	8
Cohort 1	*2005*	2006	2007	2008	2009	2010	2011	2012	2013
Cohort 2	*2006*	2007	2008	2009	2010	2011	2012	2013	2014
Cohort 3	*2007*	2008	2009	2010	2011	2012	2013	2014	2015

As indicated in Table 1, for the fifth follow-up year, earnings information is combined from cohort one, CY 2010; cohort two, CY 2011; and cohort three, CY 2012. This procedure is applied separately for both genders for each follow-up year. Currently, data are available for eight years of follow-up after high school graduation. The eighth year includes only one year of data for cohort one, as shown in Table 1. Our inflation adjustment converts all earnings data to 2013 dollars[5]. We use median earnings instead of average earnings throughout to limit the influence of extreme values. Also, median is the better measure of central tendency for earnings because the distribution of earnings is typically positively skewed.

Table 2 shows the number and percentage of the study population graduating from college by year after high school. For female and male STEM and non-STEM graduates, more than 95 percent had graduated by the fifth year after high school. Non-STEM females graduate a little earlier than the other groups, with 77.4 percent graduating by the fourth year after high school. STEM male graduates achieve their bachelor's degree a little later than the other groups, with 64.8 percent completing their degrees by the fourth year after high school.

Table 2. College graduates, STEM and non-STEM, by year after high school graduation

	Females			Males		
Years after HS	non-STEM	STEM	Total	non-STEM	STEM	Total
Year 1	5	1	6	9	1	10
% Graduating	0.0%	0.1%	0.0%	0.1%	0.0%	0.1%
Year 2	306	23	329	131	32	163
% Graduating	2.7%	1.1%	2.4%	1.9%	1.0%	1.6%
Year 3	1,205	206	1,411	472	204	676
% Graduating	10.5%	9.7%	10.4%	6.8%	6.3%	6.7%

[5] Bureau of Labor Statistics, Consumer Price Index- All Urban Consumers, Not Seasonally Adjusted, Seattle-Tacoma-Bremerton, WA, All Items, Series Id: CUURA423SA0.

Year 4	7,335	1,347	8,682	4,119	1,854	5,973
% Graduating	64.2%	63.7%	64.1%	59.7%	57.5%	59.0%
Year 5	2,223	471	2,694	1,865	977	2,842
% Graduating	19.4%	22.3%	19.9%	27.0%	30.3%	28.1%
Year 6	360	66	426	303	155	458
% Graduating	3.2%	3.1%	3.1%	4.4%	4.8%	4.5%
Total	11,434	2,114	13,548	6,899	3,223	10,122
% Graduating	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

6. Findings

The primary results of this research are presented below in chart form. For Figures 2 through Figure 5, earnings are the real median earnings by calendar year. All earnings are expressed in 2013 dollars. Workers are included only if they had earnings in the UI wage record in all four quarters for a given calendar year.

Figure 2 shows the earnings premium associated with a STEM degree expressed as the difference between the STEM degree group earnings and the non-STEM degree earnings for males and females. During the years in which both groups are attending college (years one through five after high school), the difference between the two genders is minimal, though the male STEM earnings premium begins to increase by year five (to about $9,600 more than female earnings). In year 6, the payoff to male STEM degrees relative to non-STEM degrees rises to $14,400 while female STEM degree holders earn about $300 more than females with non-STEM degrees. The STEM earnings premium for males rises to $15,700 in the seventh year after high school and continues to grow to $18,300 for the eighth year after high school graduation.

In stark contrast, the female earnings premium associated with STEM degrees remains at or below zero until the eighth year after high school graduation, when it rises to $2,800, $15,600 below the eight year male STEM earnings premium.

Figure 2. Male and female STEM earnings premiums in 2013 dollars, follow-up years 1-8.

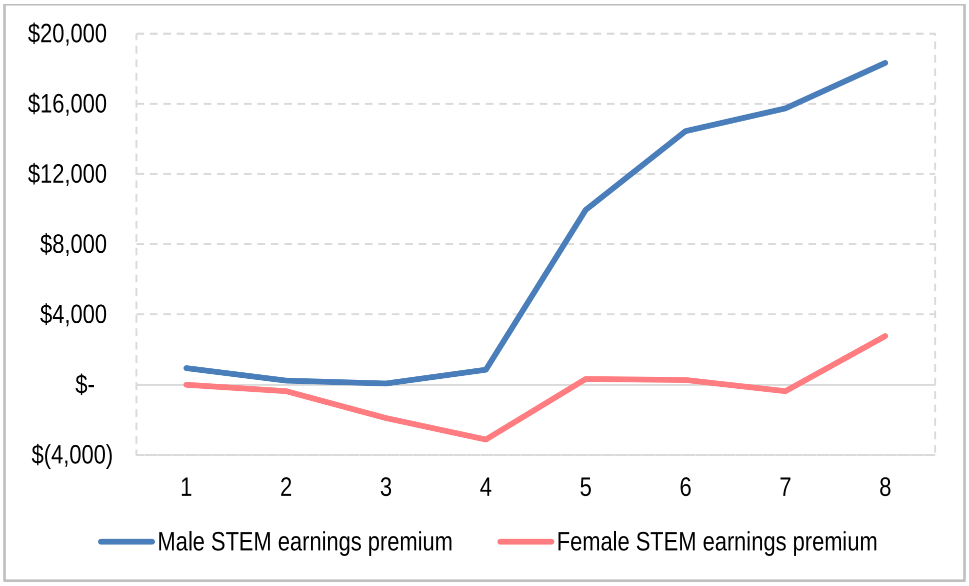
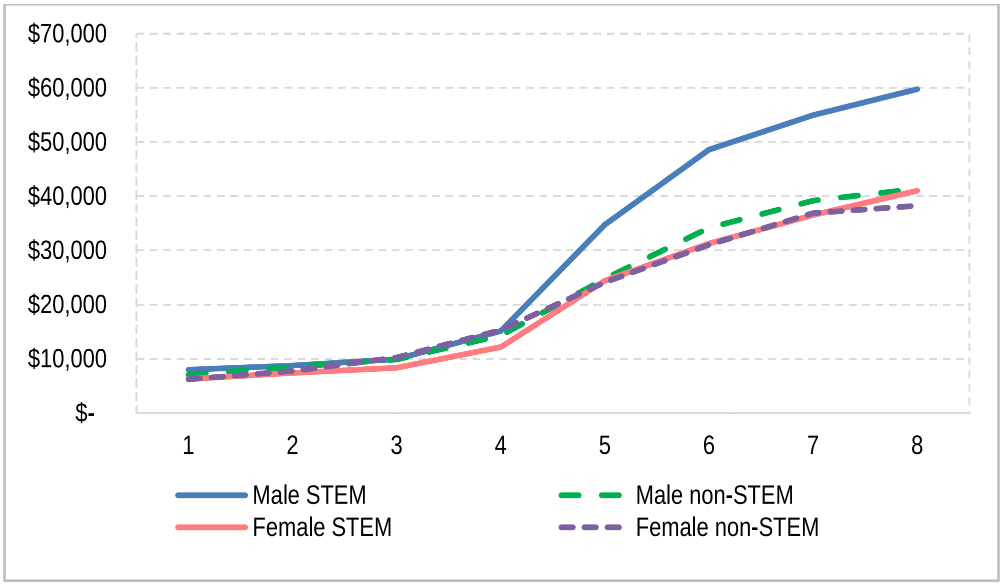


Figure 3 shows the earnings trajectories for males and females in STEM and non-STEM degree fields in one chart. Reflecting the findings from Figure 2, males with STEM degrees have substantially higher annual real earnings than females with STEM degrees and both males and females in non-STEM fields. By the eighth year after high school graduation, the median real annual earnings for male workers with STEM bachelor's degrees are nearly $60,000 ($59,700), while the male non-STEM workers median real annual earnings are $18,300 less, at $41,400. For females the earnings situation is worse. Median real annual earnings for female workers with STEM degrees in the eighth year after high school graduation are $41,000. For females with non-STEM degrees, the median real annual earnings in the eighth year after high school graduation are $38,200, $2,800 less.

Females gain little advantage from earning a STEM degree, in terms of median real annual earnings. Also, female workers with STEM degrees earn slightly less than males with non-STEM degrees, in median real annual earnings.

Figure 3. Median real earnings trajectories, STEM and non-STEM, by gender, 2013 dollars



These findings indicate a very substantial differential in earnings gains from STEM degrees by gender. To explore this further, we analyze the effects of race categories on STEM earnings premiums. To preserve sample size, we consolidated African-American, Native American and Pacific Islander race designations into a single category, which we call ANP.

Table 3 shows the distribution of our sample by race category and STEM degree status. Only about 6 percent of the study population is in the ANP race category: about 900 females and 600 males. About 14 to 15 percent of the study population is Asian: 1,900 females and 1,500 males. Whites compose nearly 80 percent of the study population (10,700 females and 8,000 males).

Table 3: Distribution of analytical sample by race category and gender

	Female			Male		
Race Category	non-STEM	STEM	Total	non-STEM	STEM	Total
ANP	763	97	860	417	147	564
Row %	88.7%	11.3%	100.0%	73.9%	26.1%	100.0%
Column %	6.7%	4.6%	6.4%	6.0%	4.6%	5.6%
Asian	1,451	441	1,892	868	612	1,480
Row %	76.7%	23.3%	100.0%	58.7%	41.4%	100.0%
Column %	12.7%	20.9%	14.0%	12.6%	19.0%	14.6%
White	9,172	1,569	10,741	5,581	2,450	8,031
Row %	85.4%	14.6%	100.0%	69.5%	30.5%	100.0%
Column %	80.6%	74.5%	79.6%	80.9%	76.0%	79.3%
Total	11,386	2,107	13,493	6,899	3,223	10,122
Row %	84.4%	15.6%	100.0%	68.2%	31.8%	100.0%
Column %	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Figure 4 shows the STEM and non-STEM earnings trajectories of males in the three race categories: white, Asian and ANP. The three lines bunched together at the top right of the chart show the earnings trajectories of males with STEM degrees in the three race categories. While white males with STEM degrees have the highest median real annual earnings in the eighth year after high school graduation at $60,500, Asian males with STEM degrees are a close second at $58,900, with ANP males having the lowest STEM median real annual earnings at $52,900 in the eighth year after high school graduation.

While the differences between the race categories are striking among workers with STEM degrees, they are dwarfed by the STEM-to-non-STEM differences in earnings between workers of any race. White male workers with non-STEM degrees have the highest median real annual earnings in the eighth year after high school at $44,200. This is $16,300 below the median earnings of white male workers with STEM degrees. Asian workers with non-STEM degrees are well below the median earnings of white male non-STEM workers with median real annual earnings of $37,000, which is $21,900 below the median earnings for Asian male workers with STEM degrees. As with males with STEM degrees, ANP males with non-STEM degrees have the lowest median earnings with median real annual earnings of $34,800, $18,100 below ANP workers with STEM degrees. All comparisons are made at the eighth year after high school. For males, the differences in earnings by race category persist for both STEM and non-STEM workers throughout the follow-up period[6].

[6] We thank ERDC colleague Vivien Chen for this observation.

Figure 4. Male STEM and non-STEM median earnings by years after high school, by race category, 2013 dollars

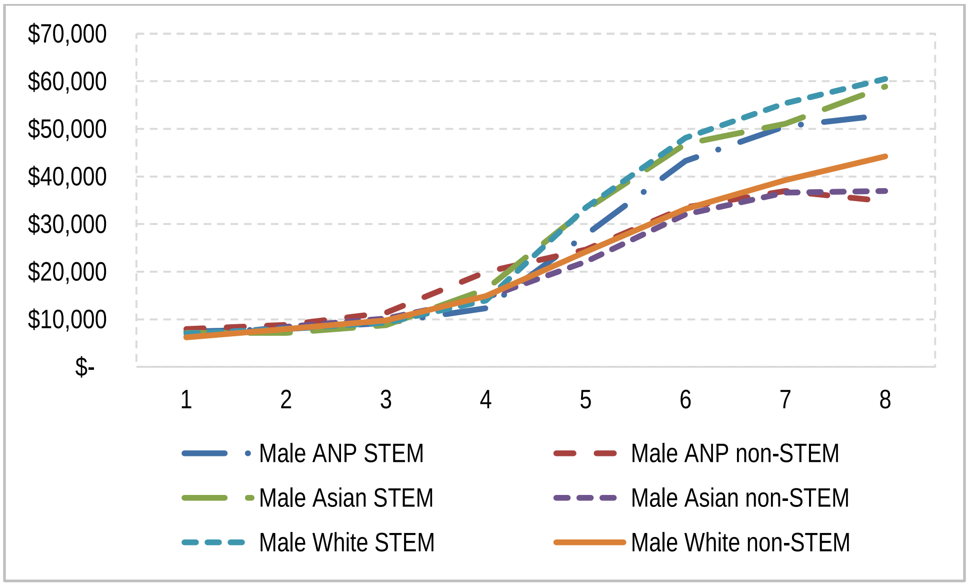


Figure 5 shows the earnings trajectories of female workers by STEM and non-STEM degree and by race categories. As is evident from the figure, the female earnings are tightly bunched throughout the follow-up period. This is consistent with the initial results for all races combined. The dispersion by race category exceeds the dispersion based on STEM or non-STEM status. Eight years after high school graduation, white females with a STEM degree have median real annual earnings of $40,000, while white females with a non-STEM degree have median real annual earnings of $38,600, a $1,400 difference. Asian females have the highest median real annual earnings in the eighth year after high school graduation. Asian female workers with STEM degrees earn $46,900 and Asian female workers with non-STEM degrees earn $39,500, a STEM to non-STEM differential of $7,400, the largest among female workers. ANP female workers earn the least, in terms of median real annual earnings. ANP female workers with STEM degrees have eighth-year median real annual earnings of only $29,500, while ANP female workers with a non-STEM degree have median real annual earnings of $34,700, a STEM to non-STEM differential of -$5,200. This negative differential may reflect the small sample size for ANP workers in the study.

The female STEM to non-STEM differential ranges from -$5,200 to +$7,400 and the male STEM to non-STEM differential ranges from +$18,100 to +$21,900. It is clear that STEM degrees have a much higher payoff in terms of earnings for males than for females.

Figure 5. Female STEM and non-STEM median earnings by years after high school, by race category, 2013 dollars

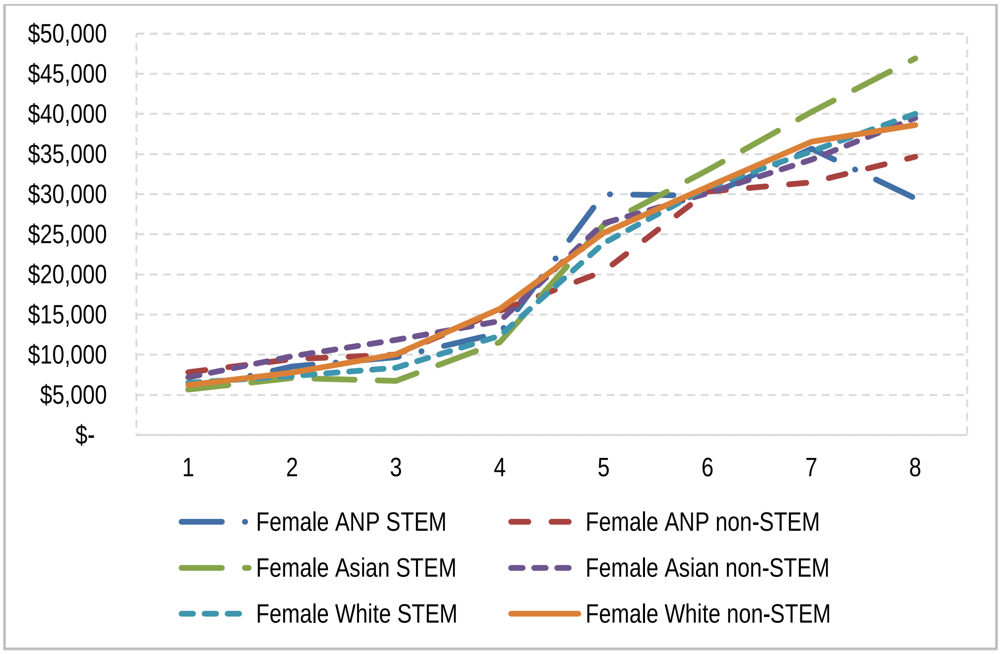
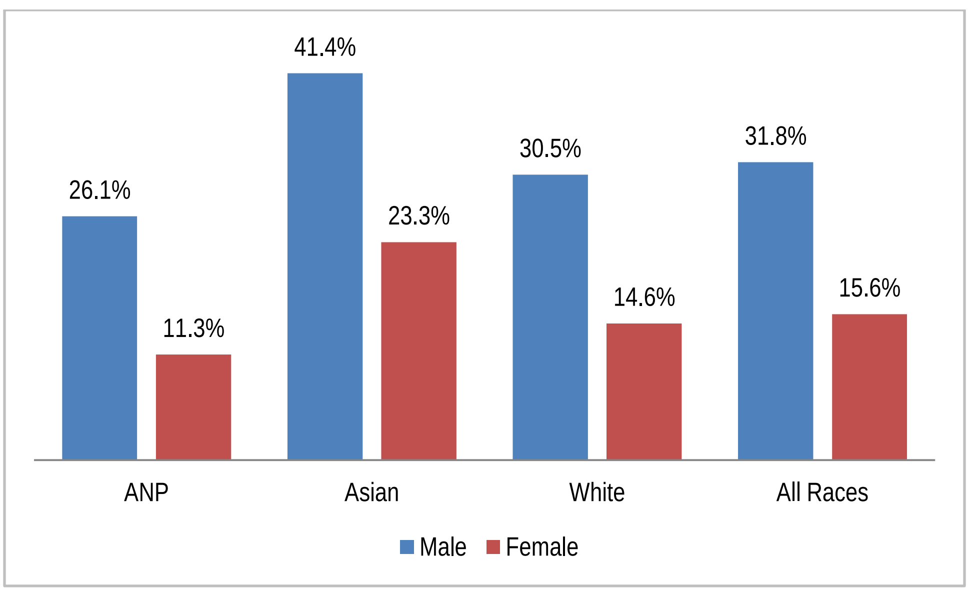


Figure 6 shows the differences in the percentage of STEM and non-STEM degree attainment in our study population. The large differences in STEM earnings premiums between the genders may also influence their choices about whether to pursue a STEM degree. Females are about half as likely to have a STEM major field of study as males. This finding is generally consistent across the race categories.

Figure 6. Percentage of STEM and non-STEM major choices by gender and race category



7. Conclusion

The results of this study show a substantial gender-based earnings gap for workers with STEM bachelor's degrees. The next step in this line of inquiry is to understand the reasons for the earnings gap. There are many possible explanations for the STEM earnings gap, including:

- Gender-based discrimination in the educational system and labor market
- A male-oriented culture in high-technology organizations, leading to less hiring and advancement for female job applicants and workers
- Child-bearing and family responsibilities requiring women to periodically withdraw from the workforce, leading to reduced job tenure, missed promotions and lower earnings over their careers
- Tastes and preferences
  - Female students may select STEM fields that are less remunerative than male students (perhaps related to the first and second bullet above)
  - Female workers may select occupations that are less remunerative (perhaps related to the first and second bullet above)
- Combinations of any and all of these

We only start an exploration of these reasons for the STEM gender gap. First, we look at the STEM majors for male and female graduates. Also, please recall that these workers earned their bachelor's degree but have no additional postsecondary education. It should also be noted that there are inherent differences in earnings due to the differing distribution of majors between men and women. We do not have access to occupational information and therefore do not know if an earnings gap within occupations exists. The study population was not sufficient to compare male and female STEM and non-STEM graduates by major.

Table 4 shows the top 20 college majors of male and female STEM graduates from our treatment group. For both genders, the top 20 majors compose about three-quarters of all majors. Despite 12 majors (in bold type) appearing on both lists, there are differences between the genders in terms of reported college majors. The top six female majors are in the biological sciences or an environmental area. The top three majors for females compose a full one-third of all female majors, all in the biological sciences. The male majors are a little more dispersed, with the top three accounting for about one-fifth of all male majors, two of which are in engineering.
Of those majors that are unique to their gender, the eight female majors that are not shared in the male list are in the biological or environmental sciences, food and nutrition, or geology. For males, the majors that are not on the female list are all in types of engineering, computer or information sciences, or physics. The information presented in Table 4 clearly indicates that having a STEM major has quite different meanings for females and for males.

Table 4. Top 20 majors by percentage reported, male and female

Female Major	Percent	Cumulative Percentage	Male Major	Percent	Cumulative Percentage
cell/cellular and molecular biology	15.7%	15.7%	mechanical engineering	8.1%	8.1%
biology/biological sciences, general	11.6%	27.3%	**civil engineering, general**	6.5%	14.6%
biochemistry	7.1%	34.4%	**cell/cellular and molecular biology**	6.0%	20.6%
environmental studies	5.0%	39.4%	electrical and electronics engineering	5.9%	26.5%
biological and physical sciences	5.0%	44.4%	**biochemistry**	5.7%	32.3%
environmental science	4.7%	49.1%	**biology/biological sciences, general**	5.2%	37.5%
chemistry, general	4.2%	53.3%	computer and information sciences, general	5.1%	42.6%
mathematics, general	3.2%	56.5%	**computer science**	4.8%	47.4%
civil engineering, general	2.8%	59.3%	**management information systems general**	4.7%	52.1%
zoology/animal biology	2.5%	61.8%	**chemistry, general**	3.4%	55.5%
animal sciences, general	2.4%	64.1%	**mathematics, general**	3.3%	58.8%
microbiology, general	2.3%	66.5%	**biological and physical sciences**	2.5%	61.2%
management information systems, general	2.1%	68.6%	**chemical engineering**	2.5%	63.7%
computer science	1.8%	70.4%	information technology	2.4%	66.0%
foods, nutrition and wellness studies	1.7%	72.1%	computer engineering, general	2.2%	68.2%
bioengineering and biomedical engineer	1.7%	73.8%	**architecture**	2.1%	70.4%
nutrition sciences	1.7%	75.4%	physics, general	2.0%	72.3%
architecture	1.6%	77.0%	**environmental studies**	1.9%	74.2%
geology/earth science, general	1.4%	78.3%	applied mathematics, other	1.8%	76.0%
chemical engineering	1.3%	79.6%	aerospace, aeronautical and astronautical engineering	1.7%	77.7%

Source: ERDC

To examine whether female workers with STEM degrees are working in different occupations than male workers, we used data from the American Community Survey, conducted by the U.S. Census Bureau. Table 5 shows the top 10 occupations for workers with bachelor's degrees in STEM fields, though the table represents the population of Washington workers with STEM degrees at any age and is not cohort-based.

For male workers, one in five with STEM degrees works as software developers, with the other nine male occupations ranging from 3.9 to 2.3 percent of all male workers with STEM degrees. For females, the occupational distribution is very different. Only 3.2 percent of female workers with STEM degrees are software developers, while the leading occupation at 9 percent is registered nurses, which is not a STEM occupation. Second is the category “no occupation,” which may reflect temporary or permanent absence from the workforce. Civil and mechanical engineers makes the male list of top 10 occupations, while there are no engineering occupations in the female list. The male list also includes accountants and two additional computer-related occupations, all of which are absent from the female list of occupations. The female list of occupations of workers with STEM degrees in Washington state also includes secretaries, counselors and customer service representatives, all of which are absent in the male list. Also, the male list of occupations is more concentrated in these top 10 occupations compared to the female list of occupations of STEM degree holders. The listed top 10 occupations account for 45 percent of male workers with STEM degrees in Washington state, while the top 10 occupations for females with STEM degrees accounts for only 37 percent of female workers. The table suggests that the distribution of occupational choices and opportunities of male and female workers with STEM degrees are quite different.

Table 5. American Community Survey top 10 occupations for workers with STEM degrees, by gender

Male		Female	
Software developers, applications and system software	20.9%	Registered nurses	9.0%
Civil engineers	3.9%	No occupation	5.0%
Postsecondary teachers	3.3%	Customer service representatives	3.5%
Accountants and auditors	2.7%	Software developers, applications and system software	3.2%
Computer programmers	2.5%	Postsecondary teachers	3.2%
Computer support specialists	2.4%	Counselors	3.1%
Managers, all other	2.4%	Secretaries and administrative assistants	2.8%
Sailors and marine oilers	2.3%	Miscellaneous life, physical and social science technicians	2.5%
Mechanical engineers	2.2%	Managers, all other	2.4%
Carpenters	2.2%	Physical therapists	2.2%
Total top 10	44.8%	Total top 10	36.9%

Source: U.S. Census Bureau, American Community Survey

Table 6 shows the median earnings for the occupations listed in Table 5. The earnings come from a BLS survey and are not gender specific. Occupations common to both genders show the same wage rate in both lists.

Three occupations are common to male and female workers with STEM degrees in Washington state: software developers, postsecondary teachers and managers, all other. The other 14 occupations are unique by gender. The top 10 male occupations, when weighted by the proportion of the workforce with STEM bachelor’s degrees they compose, average an hourly wage rate of $44, or about $91,500 per year, full time. The top 10 female occupations for workers with STEM bachelor's degrees in Washington state have a weighted average hourly wage rate of $28, or about $59,400 per year, full time. The difference between male and female earnings for workers with STEM bachelor's degrees in Washington state is approximately $32,100, assuming full-time, full-year work at the median occupational wage rate. This differential is even larger than our findings discussed earlier in this paper.

Table 6. American Community Survey median hourly wage rate for top 10 occupations of workers with STEM degrees, by gender

Male		Female	
Software developers, applications and system software	$52.70	Registered nurses	$36.74
Civil engineers	$39.15	No occupation	
Postsecondary teachers	$39.09	Customer service representatives	$17.48
Accountants and auditors	$32.16	Software developers, applications and system software	$52.70
Computer programmers	$53.66	Postsecondary teachers	$39.09
Computer support specialists	$25.32	Counselors	$21.47
Managers, all other	$50.48	Secretaries and administrative assistants	$17.75
Sailors and marine oilers	$22.77	Miscellaneous life, physical and social science technicians	$30.25
Mechanical engineers	$42.68	Managers, all other	$50.48
Carpenters	$22.68	Physical therapists	$17.48
Weighted average hourly wage rate	$44.23	Weighted average hourly wage rate	$28.12

Source: U.S. Census Bureau, American Community Survey

The differences between the STEM majors of females and males as well as the differences in the rates at which male and female students achieved bachelor's degrees in STEM fields may partly reflect a sorting process throughout the educational system in which girls are viewed by elementary school teachers as less skilled in mathematics than male students (Riegle and Humphries, 2012). Recent research on high school credits earned indicates that "Compared to males, higher percentages of females earned credits in algebra II, pre-calculus, advanced biology, chemistry and health science/technologies. However, higher percentages of males earned credits in physics, engineering, engineering/science technologies, and computer/information science" (National Center for Educational Statistics, 2015, p. 7). Female high school students take STEM classes less frequently than males.

This "sorting" by gender begins early in the educational process and continues through postsecondary and graduate level schooling. Penner, citing the work of Leslie, *et. al.*, observes that in "philosophy and physics, which are dominated by men, ability is considered to be innate. In molecular biology and psychology, in which women are well-represented, effort is viewed as important" (Penner, 2015, p. 235). He continues to discuss the goal of encouraging women in STEM fields. "Given that women have been graduating at higher rates than men for over three decades, the idea that men's curricular choices should be used as a baseline for women to emulate seems problematic" (*ibid*.).

Gender disparities in college achievement, major selection and ultimately employment opportunities are complex and reflect a wide range of social and economic phenomena. It is difficult to develop criteria that would unambiguously indicate progress in this area. For example, Penner concludes his article with the observation that "Given the importance of having talented men and women in education, health care and throughout the economy, it seems important to take a broader perspective on issues of gender equality. Perhaps it is time to ask a new question about gender representation in STEM: Would society be better off if men were more like women?" (*ibid*.)

8. Future research

As more data become available, we will continue to add years of follow-up information to this analysis. More years of data will permit additional selection-corrected PSM analyses using larger groups of workers with bachelor's degrees in STEM fields. A more-detailed analysis of the specific courses in high school and college, majors and industry of employment of male and female workers may reveal aspects of educational and labor market choices and opportunities available to female and male workers in STEM fields.

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Appendix

Appendix A: Matching

This study uses a one-to-many matching with replacement algorithm. This approach permits non-STEM-only group members to be matched to more than one STEM degree group member. We found this approach minimized the total distance between treatment and comparison group propensity scores. When we tested a one-to-one match without replacement, we found the total distance to be more than 1,000 percent larger than the one-to-many matching with replacement approach.

Appendix B: Enrollment Data Sources & Definitions[7]

Enrollment Data Sources

Enrollment data for this study came from the following sources:

High school graduates: Annual summary data files (P-210) for high school enrollment and completion from the Office of Superintendent of Public Instruction. This file identifies regular high school graduates, their graduation date, school district and school, low-income status, gender, grade point average and race/ethnicity. The P-210 record for a student is referred to as the student's "graduation record" in the discussion that follows.

Washington public four-year higher education enrollment: Enrollment data for the state's six public baccalaureate higher education institutions from the Public Centralized Higher Education Enrollment System maintained by OFM.

Enrollment data for private and out-of-state higher education institutions: Enrollment data for institutions other than the Washington public institutions was obtained from the NSC, which captures 92 percent of postsecondary enrollment nationally. At this time, it is the best source of information about postsecondary enrollment in private higher education institutions in Washington and for all out-of-state institutions.

Administrative data from Washington state's UI program: Provided by the Employment Security Department. This data source is described in the main body of the report.

[7] ERDC Research Brief 2011-02. (2011), "Workforce Participation: Washington High School Graduates, 2009-09." Appendix A, pp A1. Retrieved from: http://www.erdc.wa.gov/briefs/pdf/201102.pdf.

Appendix C: Unemployment Insurance

The UI program is a federal-state program financed by payroll taxes paid by employers. The U.S. Department of Labor sets broad criteria for eligibility and coverage, but states determine the specifics of the implementation. In Washington, the Employment Security Department is responsible for the administration of the UI program.

Employers must participate in the UI program if they pay wages to employees, regardless of the dollar amount. Participating employers are called “covered employers.” Participation includes registering, reporting wages and paying unemployment taxes or reimbursing the department for benefits paid for all part-time or full-time employees. There are exceptions to this, including the following:

- Small farm operators — those with payroll less than $20,000 and fewer than 10 employees — do not cover spouse, children under 18 or student workers.
- Employees performing domestic services in a private home, college club, fraternity or sorority are not covered if the total wages paid are less than $1,000 per quarter. If payroll exceeds $1,000 in any quarter, wages must be reported for the entire year and the following year.
- Nonprofit preschool staff if fewer than four staff.
- Business owners are not reported. Sole proprietors do not report their spouses or unmarried children under 18.
- Corporate officers are required to cover themselves for UI unless they opt out by January 15 each year.
- There are additional types of employees that an employer may not be required to report, depending upon the circumstances. Those most pertinent to this study include the following:
    - self-employed workers
    - religious employees
    - Work-Study students, as long as the employer is a non-profit 501(c)(3), state government or local government

More complete information on the UI program is available from the Employment Security Department.

In addition to the above categories, federal civilian employees and both active duty and retired military are not reported in the state-level UI program administrative records.

Nationally, the UI program includes 98 percent of all employers (ERDC, 2011).

Data Elements and Timing

In Washington state, employers file a quarterly wage detail report that includes the following elements:

- year
- quarter
- employer account number
- employee Social Security number
- name
- wages paid during quarter
- hours worked during quarter

Employer characteristics can be added to the wage record. These are:

- industry — North American Industry Classification System code
- ownership — private or public (federal, state, local governments)
- size of firm (monthly)

There is a lag between the time the employer files the report and the time the associated administrative data become available for research use. Both UI tax payments and wage reports are due by the last day of the month following the last day of each quarter. Incorporating the wage data in administrative databases takes the remaining two months of the quarter. Data are ready for use for research purposes early in the subsequent quarter. The process is summarized in Figure C1:

Figure C-1: Timing of collection and availability of UI wage data

Current Year

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Quarter 1			Quarter 2			Quarter 3			Quarter 4		
Prior year Quarter 4 data submitted by employer and processed by ESD			Current year Quarter 1 data submitted by employer and processed by ESD			Current year Quarter 2 data submitted by employer and processed by ESD			Current year Quarter 3 data submitted by employer and processed by ESD		
Prior year Quarter 3 data available for research			Prior year Quarter 4 data available for research			Current year Quarter 1 data available for research			Current year Quarter 2 data available for research		

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