2017

STEM Bachelor's Degrees in Washington State

The Gender Deficit by Major and Race Category

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ABOUT THE ERDC

The research presented here utilizes data from the Education Research and Data Center (ERDC), located within the Washington Office of Financial Management (OFM). ERDC works with partner agencies to conduct powerful analyses of learning that can help inform the decision-making of Washington legislators, parents, and education providers. ERDC's data system is a statewide longitudinal data system that includes de-identified data about people's preschool, educational, and workforce experiences.

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Executive Summary

This study explores the differences between post-graduation earnings of STEM and non-STEM bachelor's degree graduates by gender, by specific college major, and by general race category. We use Propensity Score Matching to correct for selection bias where possible. We find a 65 percent female gender deficit in earnings among all STEM majors.

After selection bias correction, males are found to have a higher STEM premium than females with the difference being a measure of the gender deficit. During the third year after graduation the gender deficit is 65 percent (the male premium is $10,100 and the female premium is $3,600). This implies a 65 percent gender deficit for females (females lose out on 65 percent of the benefit from a STEM degree that males enjoy).

Majors with more females have lower post-graduation earnings. Race has no measureable relationship to the gender deficit. STEM majors in which males have the highest post-graduation earnings are also associated with higher earnings for females, though females select these majors much less frequently than males.

Encouraging students to take a STEM major remains a popular policy prescription. Though simply encouraging females into any STEM major may increase gender deficits. A more promising approach may be to encourage females into more remunerative majors such as computer science and engineering. In addition, effective approaches to counteract gender deficits may involve addressing both constraints and preferences regarding gender choices about STEM majors and earnings. Public policy should seek to remove overt and subtle gender-based discrimination in schools, universities and the workplace. Preference-based gender segregation is a difficult policy issue. Every child should be fully able to pursue their talents and goals, regardless of such superficial characteristics as gender.

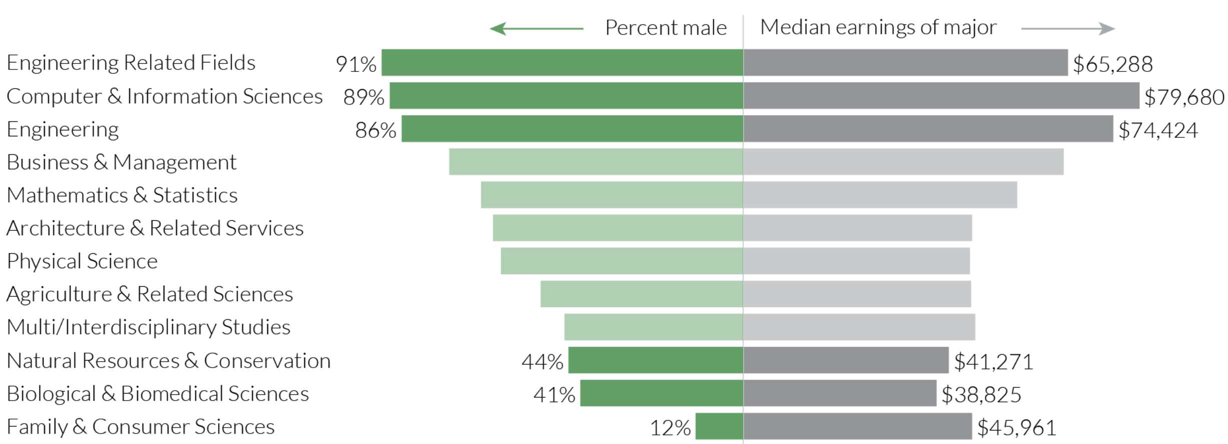

Figure 1. How did the earnings of males and females relate with the proportion of males and females within each STEM major? (Annual real earnings, 2014 dollars, third year after graduation, no selection correction)

Introduction[1]

Encouraging students to study Science, Technology, Engineering and Mathematics (STEM) is a common policy prescription at all levels of education. STEM advocates contend that students with STEM degrees will earn more and better negotiate an increasingly technical and technological world. STEM[2] is defined as a broad category, and encouraging STEM majors has implications that may not increase earnings for all STEM graduates, depending on their choice of specific major.

For example, while women are much less likely than men to earn a STEM degree in college (Hill, et. al. 2010), they are also less likely to work in a STEM occupation (Beede, et. al. 2011). A recent paper suggests that women "may be choosing lower-paying STEM and non-STEM fields, and that may result in lower returns for women in STEM fields" (Olisky, 2013, pp 267). Lordan and Pischke (2016) discuss the role of preference in determining gender segregation in occupations. They hypothesize "…women have different preferences for characteristics and attributes of jobs, as well as the environment in which they work." They point out that traditional analyses of occupational segregation by gender have focused on constraint-based explanations, emphasizing discrimination, human capital and family work (Atoni and Blank, 2008). A thorough explanation of gender differences in STEM education and employment should include both preference-based and constraint-based factors.

Paterson and Weeks (2015a) have previously speculated about the reasons for the gender deficit in the economic benefits from STEM degrees:

Constraint-based

- 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.

Preference-based

- Tastes and preferences of female students may lead them to select STEM fields that are less remunerative than male students (perhaps related to the first and second bullet above).

1 We would like to acknowledge the expert assistance and advice from Tim Norris, George Hough, Vivien Chen and numerous other ERDC colleagues. Meaghan Weherell and Darby Haikkonen also made insightful and useful comments. The paper is better because of all these contributions. Remaining shortcomings and errors are the responsibility of the authors.

2 There are several alternative definitions of STEM fields. This paper uses a definition of STEM that includes any field designated as STEM by the major STEM definitions.

- Combinations of any and all of these.

The goal of this study is to improve an understanding of the gender deficit for STEM degrees through an exploration of the differences between post-graduation earnings of STEM and non-STEM bachelor's degree graduates by gender as well as by general race category.

Analytical Approach

This study examines the relationship between students' majors and post-graduation earnings by gender. Because this is an observational study, selection bias plays a role in the measurement of outcomes. That is, STEM majors may be different from non-STEM majors in unmeasurable ways. Propensity Score Matching (PSM) methods are used to correct for selection bias. The uncorrected treatment (STEM major) effect is made up of two components, one resulting from the student's personal characteristics (ability, persistence, etc.) and the other effect attributable to the treatment itself. PSM isolates the impacts attributable to the treatment alone, assuming the matching process matches treatment group members to similar comparison group members, eliminating the portion of the treatment effect attributable to personal characteristics.

Data

This study is based on two related sets of data housed in the Washington state Education Research and Data Center (ERDC)[3] data warehouse. These ERDC data are uniquely suited to the purposes of this study and is the source for both study samples, the PSM sample and the College Graduate Population (CGP) sample.

The *PSM sample* begins with graduates from public high schools during the years 2005-2010. Their K-12 data are merged with a list of bachelor's degree earners from Washington state public universities and colleges during the years 2006-2015. Graduate students are removed from the study sample, as are out-of-state students. The National Student Clearinghouse is used to identify students who attend school out-of-state.

The *College Graduate Population sample* does not require the college graduates be graduates of Washington public high schools, we use this in order to maximize the number of observations for analysis. The data set starts from a list of graduates from the state public four year colleges and universities. These graduates are restricted to bachelor's degree earners.

For both samples, unemployment insurance earnings data are merged with the multi-sector student data to provide earnings, industry of employment and hours worked for the calendar years after graduation. These data cover in-state workers covered by the unemployment insurance system (See Appendix D). Also, in order to ensure earnings reflect a strong labor market attachment, our analyses require working in all four quarters of a calendar year, with calendar year earnings above $15,600 in 2014 dollars ($10/hour for 30 hours per week).

3 A description of the ERDC can be viewed here: http://www.erdc.wa.gov/about-us-0

Findings

Who earns degrees in STEM fields?

Overall, more females than males earn bachelor's degrees. During 2007 through 2015, the percentage of all Washington state public college graduates that were female fluctuated between 55 and 56 percent. Male graduates, however, are much more likely to have earned a STEM degree than female graduates.

There is considerable gender segregation within STEM majors. Male students are more likely to select STEM majors in engineering and computer science, while female students are more likely to select biology, agriculture and human sciences.

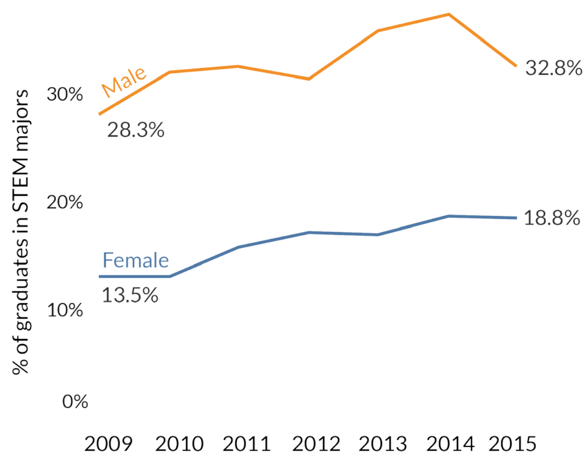

Figure 1. What percent of bachelor's degree graduates pursued STEM majors? (Selection corrected)

Table 1. Percent of female graduates by two digit CIP code, STEM majors, no selection correction.

Major Category	Percent Female
Engineering Technologies and Engineering-Related Fields	8.3%
Engineering	18.5%
Computer and Information Sciences and Support Services	18.6%
Business, Management, Marketing and Related	29.4%
Mathematics and Statistics	33.5%
Physical Sciences	36.0%
Architecture and Related Services	42.0%
Natural Resources and Conservation	55.4%
Multi/Interdisciplinary Studies	55.8%
Biological and Biomedical Sciences	57.4%
Agriculture, Agriculture Operations, and Related Sciences	64.0%
Family and Consumer Sciences/Human Sciences	87.8%

PSM Sample, PSM-Selection Corrected Earnings

Figure 2 shows the selection-corrected post-graduation annual earnings for STEM and non-STEM majors by gender. Males with STEM degrees earn more than males with non-STEM degrees, and females with STEM or non-STEM degrees. For example, in the third year after college graduation (see Figure 2), males with STEM degrees earn 33 percent than males with non-STEM degrees, while females with STEM degrees earn 12 percent more than females with non-STEM degrees.

This implies a 65 percent gender deficit for females (females lose out on 65 percent of the benefit from a STEM degree that males enjoy). Three years after graduation, females who earn a STEM degree earn about three percent less than males with a non-STEM degree. In addition, males with STEM degrees earn 27 percent more than females with STEM degrees.

College Graduate Population, Earnings Not Corrected for Selection Bias

Figure 3 shows the post-graduation earnings for the uncorrected CGP sample. While the earnings are slightly lower and the gender deficit is also correspondingly lower, the pattern of post-graduation earnings remains very similar to the PSM results. Males with STEM majors have the highest earnings, followed by males with non-STEM majors. The next high-

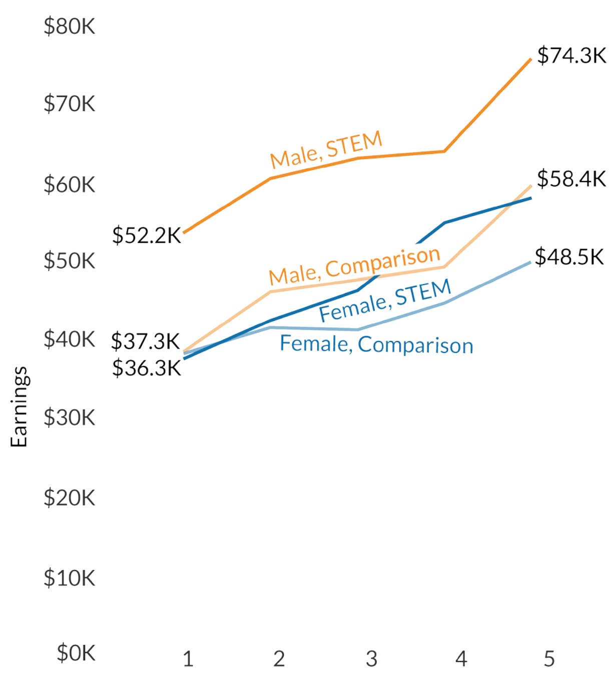

Figure 2. What did STEM graduates earn, compared with non-STEM graduates? (Annual real earnings, 2014 dollars, selection corrected)

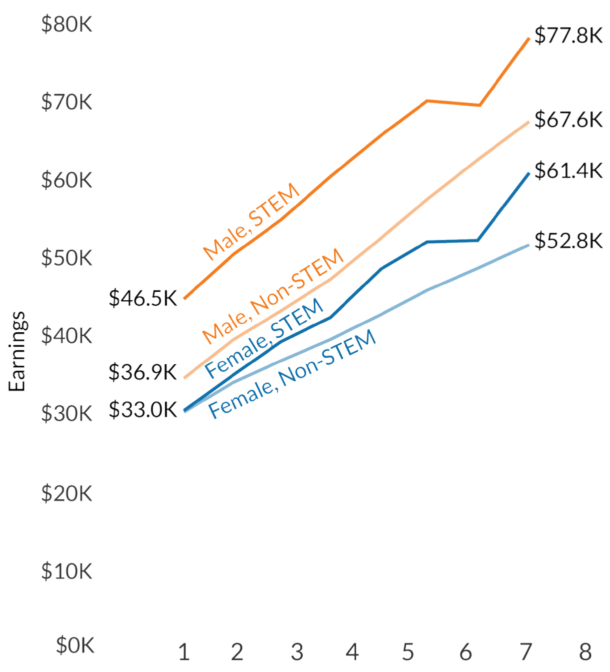

Figure 3. What did STEM graduates earn, compared with non-STEM graduates? (Annual real earnings, 2014 dollars, no selection correction)

est is female STEM major earnings, followed by female non-STEM major earnings.

Table 2 compares the annual earnings of males and females during the third year after graduation by STEM and non-STEM major for both samples. Both samples exhibit very similar gender deficits.

Table 2. STEM and non-STEM Median, real (2014 dollars) annual earnings and Gender deficits, third year after graduation, PSM and CGP samples.

	PSM sample (selection corrected)		CGP sample (Not selection corrected)	
	STEM	Non-STEM	STEM	Non-STEM
Female	$44,885	$39,942	$41,223	$38,865
Male	$61,744	$46,385	$56,162	$44,974
Gender Deficit	-38%	-16%	-36%	-16%

Figure 4 depicts the post-graduation earnings of STEM graduates in computer science and engineering majors by gender. These majors have the highest post-graduation STEM earnings for males and the lowest proportions of female STEM graduates. For comparison purposes, male and female graduates with other STEM majors are included in the chart. The post-graduation annual real earnings of males and females with STEM majors in computer science and engineering are virtually identical for the first five years after grad-

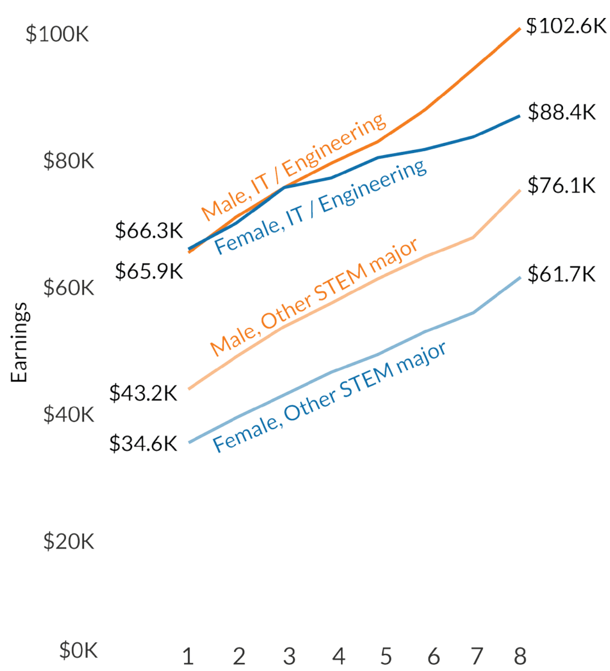

Figure 4. How did the earnings of males and females compare within the highest-earning STEM majors, compared with other majors? (Annual real earnings 2014 dollars, no selection correction)

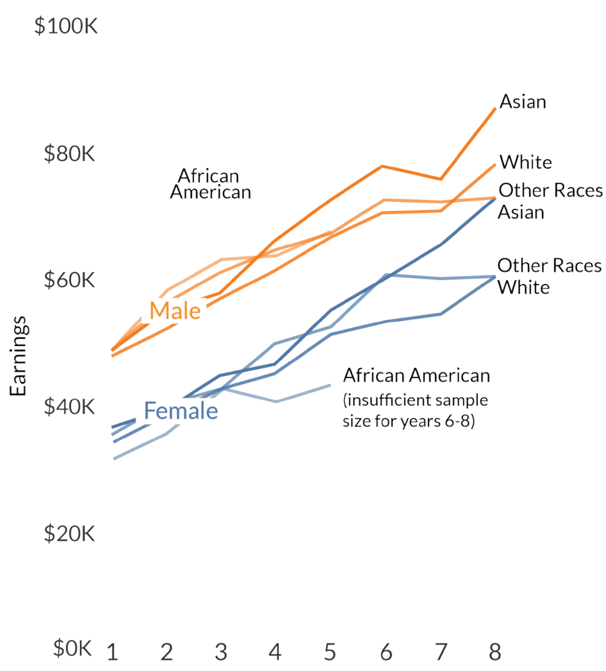

Figure 5. How did the gender deficit compare across racial categories? (Annual real earnings, 2014 dollars, no selection correction)

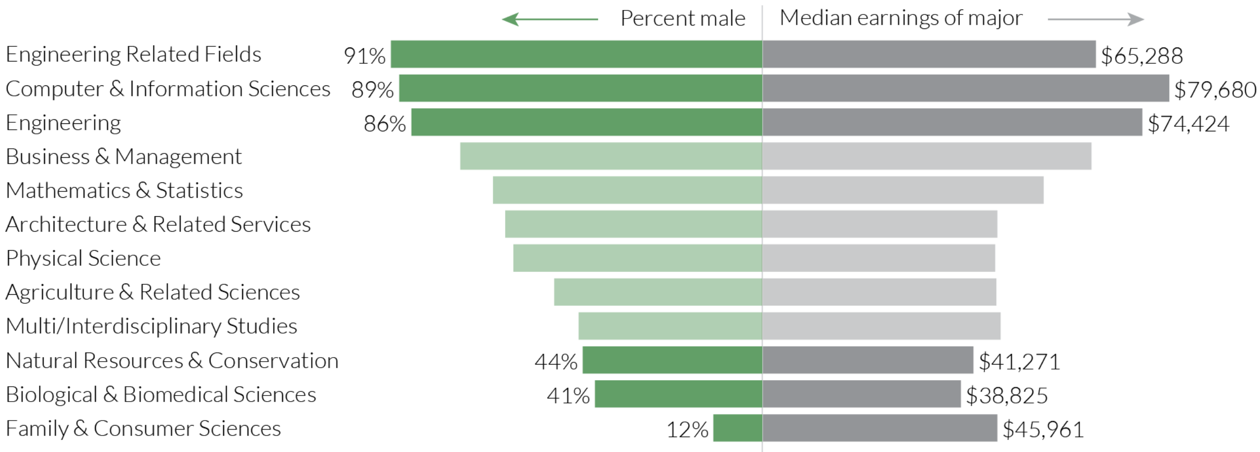

Figure 6. How did the earnings of males and females relate with the proportion of males and females within each STEM major? (Annual real earnings, 2014 dollars, third year after graduation, no selection correction)

uation. After five years, male graduates with these majors begin to earn more than female graduates with these same majors. For STEM graduates with other majors, the female post-graduation earnings deficit appears constant throughout the follow-up period.

Figure 5 (on the following page) shows a consistent gender deficit across racial categories. Throughout the follow-up period the earnings of males with STEM majors exceeds the earnings of females with STEM majors for all racial categories. The impact of gender **overwhelms the impact of race.**

Figure 6 (on the following page) shows the median earnings of males and females within individual STEM majors, compared with the proportion of graduates from each major that are male and female. We can see that in the three highest earning STEM majors, males and females earned comparably. In other words, when females who choose majors where males have high earnings, they also have high earnings. However, those are also the **majors where most graduates are males**. Majors with lower earnings have a higher percent of females in the major.

Discussion

Our analysis suggests systematic gender segregation among STEM majors. We find majors with **higher concentrations** of males are associated with higher post-graduation earnings, while those with more females are associated with lower earnings. We use PSM selection correction to account for **selection bias** (unmeasured heterogeneity). Females with STEM majors have higher post-graduation earnings than females with non-STEM majors; they also earn less than males with non-STEM majors. These differences in choice of major and earnings persist when we use uncorrected data (the CGP sample). However, our analysis provides no direct evidence about the causes of linkages between gender segregation and gender deficits, nor provide direct evidence about why females and males select different majors. No matter the reason, it is clear that female STEM students select less remunerative majors than male students in STEM majors.

Encouraging students to take a STEM major is a common policy prescription. Unfortunately, simply encouraging females into any STEM majors may increase gender deficits. A more promising approach may be to encourage females into more remunerative majors such as computer science and engineering. In addition, effective approaches to counteract gender deficits may involve addressing both constraints and preferences regarding choices about STEM majors and earnings. Certainly public policy should seek to remove overt and subtle gender-based discrimination in schools, universities and the workplace. Preference based gender segregation is a more difficult policy issue. Every child should be fully able to pursue their talents and goals, regardless of such superficial characteristics as gender.

References

American Association of University Women Educational Foundation. (2008), "Where the Girls Are: The Facts About Gender Equity in Education," Washington, DC: AAUW Educational Foundation.

Arcidiacono, P. (2004), "Ability Sorting and the Returns to College Major," Journal of Econometrics, 121, 343-375.

Abadie, A., and Imbens, G. (2012), "Matching on the Estimated Propensity Score," Submitted.

Baum, S., Ma, J., Payea, K. (2013), "Education Pays 2013," The College Board.

Brand, J., Xie, Y. (2010), "Who Benefits Most from College? Evidence for Negative Selection in Heterogeneous Economic Returns to Higher Education," American Sociological Review, 75 (2), 273-302.

Bijsterbosch, J., Volgenant, A. (2010), "Solving the Rectangular assignment problem and applications," Annals of Operations Research, Vol. 181, 443-462.

Caponi, V., Plesca, M. (2007), "Post-secondary Education in Canada: Can Ability Bias Explain the Earnings Gap Between College and University Graduates?" Canadian Journal of Economics, 42 (3), 1100-1131.

Card, D. (2001), "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," Econometrica, Vol. 69, No. 5, 1127-1160.

Carnevale, A., Rose, S., Cheah, B. (2011), "The College Payoff," Georgetown University Center on Education and the Workforce.

Coca-Perraillon, M. (2006), "Matching with Propensity Scores to Reduce Bias in Observational Studies," North East SAS Users Group 2006.

Dadgar, M., Weiss, M. (2012), "Labor Market Returns to Sub-Baccalaureate Credentials: How Much Does a Community College Degee or Certificate Pay?" Community College Research Center.

Dehejia, R., Wahba, S. (2002), "Propensity Score-Matching Methods for Nonexperimental Causal Studies," *Review of Economic Studies*, 84(1): 151-161.

ERDC, (2011), "Research Brief 2011-02," ERDC, April 2011, retrieved from: http://www.erdc.wa.gov/briefs/pdf/201102.pdf.

ERDC (2013), "Key Education Indicators," ERDC, April 2013, retrieved from: http://www.erdc.wa.gov/indicators/pdf/12_degree_completion.pdf.

ESD, (2011), "Unemployment Insurance Tax Information: A handbook for Washington state employers," January 2011, Employment Security Department. www.esd.wa.gov/uitax/formsandpubs/tax-handbook.pdf

Fan, W. (2011), "Estimating the Return to College in Britain Using Regression and Propensity Score Matching," UCD Centre for Economic Research, Working Paper

Series 2011.

Golding, C., Katz, L. (2008), "The Race Between Education and Technology," The Belknap Press of Harvard University Press.

Heckman, J., and Todd, P. (2009), "A Note on Adapting Propensity Score Matching and Selection Models to Choice Based Samples," Econometrics Journal, vol. 12(s1), pages S230-S234, 01.

Heckman, J., Ichimura, H., and Todd, P. (1997), "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," *Review of Economic Studies*, 64, 605-654.

Heckman, J., Ichimura, H., and Todd, P. (1998), "Matching as an Econometric Evaluation Estimator," *Review of Economic Studies*, 65, 261-294.

Heinrich, C., Maffioli, A., Vasquez, G. (2010), "A Primer for Applying Propensity-Score Matching," Inter-American Development Bank.

Hollenbeck, K. (2004), "Some Reflections on the Use of Administrative Data to Estimate the Net Impacts of Workforce Programs in Washington State," Upjohn Institute, Working Paper No. 04-109.

Imbens, G., Wooldridge, J. (2008), "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature*, vol. 47(1), 5-86.

Jonker, R. and Volgenant, A. (1987), "A Shortest Augmenting Path Algorithm for Dense and Sparse Linear Assignment Problems," *Computing*, 38, 325–340.

James, J. (2012), "The College Wage Premium," Economic Commentary, 2012-10.

Leaper, C. and Friedman, C. "The Socialization of Gender". Chapter 22 in Handbook of Socialization: Theory and Research, edited by Joan E. Grusec and Paul D. Hastings, Guilford Publications. 2007 pp 561-587.

Leslie, S., Cimpian, A., Meyer, M., Freeland, E. (2014) "Expectations of Brilliance Underlie Gender Distributions Across Academic Disciplines," Science, 347, 6219, 262-265.

Melguizo, T. and Wolniak, G (2011) "The Earnings Benefits of Majoring in STEM Fields Among High Achieving Minority Students", Review of Higher Education, 53, 383-405.

National Center for Educational Statistics, (2015) "Stats in Brief: Gender Differences in Science, Technology, Engineering, and Mathematics (STEM) Interest, Credits Earned, and NAEP Performance in the 12th Grade," (NCES 20150075) U.S. Department of Education, Washington DC. Retrieved from: http://nces.ed.gov/pubs2015/2015075.pdf on February 12, 2015.

Olitsky, N. (2014) "How Do Academic Achievement and Gender Affect the Earnings of STEM Majors? A Propensity Score Matching Approach", Review of Higher Education, 55, 245-271.

Paterson, T. and Weeks, G. (2016). "A Comparison of Pathways to a Bachelor's Degree in Washington State," Education Research and Data Center, Office of Financial Management, State of Washington. April, 2016. Retrieved from: http://www.erdc.wa.gov/sites/default/files/publications/CompPathwaysBachDegreesWashState.pdf

Paterson, T. and Weeks, G. (2015a). "Earnings Premium Estimates by Gender and Race Category for STEM Bachelor's Degrees in Washington," Education Research and Data Center, Office of Financial Management, State of Washington. July, 2015. Retrieved from: http://www.erdc.wa.gov/sites/default/files/publications/EarningsPremiums-STEMBachelorDegrees.pdf

Paterson, T. and Weeks, G. (2015b). "Postsecondary Education Assessment in Washington State: Earnings Premium Estimates for Associate Degrees," Education Research and Data Center, Office of Financial Management, State of Washington. March, 2015. Retrieved from: http://www.erdc.wa.gov/sites/default/files/publications/201501.pdf

Paterson, T. and Weeks, G. (2014). "Earnings Premium Estimates for Bachelor's Degrees in Washington State," Education Research and Data Center, Office of Financial Management, State of Washington, 2014. Retrieved from: http://www.erdc.wa.gov/sites/default/files/publications/201403_0.pdf

Penner, A., (2014) "Gender Inequality in Science. How Should a Better Gender Balance be Achieved," Science, 347, 6219, 234-235.

Riegle-Crumb, C. and Humphries, M. (2012). "Exploring Bias in Math Teachers' Perceptions of Students' Ability by Gender and Race/Ethnicity," *Gender & Society April 2012 26: 290-322.*

Rosenbaum, P., and Rubin, D. (1983), "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrica*, 70, 1, 41-55.

Schneider, M. (2013), "Higher Education Pays: But a Lot More for Some Graduates Than for Others," College Measures.

Smith, J. and Todd, P. (2005), "Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?," Journal of Econometrics, 125, 1-2, 305-353.

Zimmerman, S. (2011), "The Returns to Four-Year College for Academically Marginal Students," IZA, Discussion Paper 6107.

Appendices

Appendix A: Data and sample characteristics

Table 1 shows the sizes of the two analysis samples by STEM major and gender. Though there are more female college graduates, there are fewer female STEM majors in both samples.

Table 1A. PSM and CGP sample sizes by STEM major and gender.

PSM sample	Male	Female	Total
Non-STEM majors	6,175	9,681	15,856
STEM majors	3,244	1,951	5,195
All majors	9,419	11,632	21,051
CGP sample			
Non-STEM majors	58,463	90,537	149,000
STEM majors	26,949	16,585	43,534
All majors	85,412	107,122	192,534

Table 2A breaks the samples into graduation year and gender. For the PSM sample, there are fewer graduates before 2009 because the first high school graduation year is 2005.

Table 2A. Full Sample and PSM Sample Counts by College Graduation Year.

	PSM sample			CGP sample		
Graduation Year	Male	Female	Total	Male	Female	Total
2006	19	11	30	8,450	10,769	19,219
2007	32	28	60	8,730	11,150	19,880
2008	73	139	212	8,860	11,147	20,007
2009	550	908	1,458	8,867	11,086	19,953
2010	1,280	1,584	2,864	9,305	11,650	20,955
2011	1,624	2,084	3,708	9,489	11,883	21,372
2012	1,868	2,181	4,049	9,901	12,587	22,488
2013	1,906	2,190	4,096	10,163	12,573	22,736
2014	1,819	2,211	4,030	10,138	12,344	22,482
2015	248	296	544	1,509	1,933	3,442
Total	9,419	11,632	21,051	85,412	107,122	192,534

Table 3A provides an example of how the outcomes are "stacked" to maximize the number of observations.

Table 3A. College Graduation Year and Earnings Stacking Example.

	Calendar years after college graduation						
College Graduation Year	1	2	3	4	5	6	7
2007	2008	2009	2010	2011	2012	2013	2014
2008	2009	2010	2011	2012	2013	2014	
2009	2010	2011	2012	2013	2014		
2010	2011	2012	2013	2014			
2011	2012	2013	2014				
2012	2013	2014					
2013	2014						

For a 2007 graduate, for example, the first year after graduation earnings are from calendar year 2008. The second post-graduation year earnings are from calendar year 2009 and the third from 2010. Calendar year 2014 earnings are the most current available, so the latest available earnings data for graduation year 2007 is the seventh year post-graduation.

Table 4A illustrates the precipitous drop in available sample when full year (worked in all four quarters) annual earnings are required for inclusion in the sample. We also filter observations for labor market attachment which only includes observations with at least $15,600 in earnings per year. It shows the sample sizes by follow up year after graduation by gender.

The PSM STEM sample diminishes quickly by the fifth year after college graduation to 22 males and 8 females with earnings that meet our labor market attachment criteria. For the College Graduate STEM population, with the larger sample size, there are 180 females and 400 males remaining by the eighth follow up year.

Table 4A. Sample sizes with earnings in 2014 dollars, years after college graduation, PSM and CGP samples.

PSM sample	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Male - All majors	1,611	1,026	575	1,068	82			
Female - All majors	2,107	1,401	851	1,446	138			
All majors	3,718	2,427	1,426	2,514	220			
Male - STEM	472	293	160	72	22			
Female - STEM	222	137	69	30	8			

All STEM majors	694	430	229	102	30

CGP sample	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Male - All majors	13,764	11,379	9,421	7,720	6,160	4,547	2,944	1,400
Female - All majors	16,977	14,098	11,639	9,513	7,350	5,308	3,476	1,665
All majors	30,741	25,477	21,060	17,233	13,510	9,855	6,420	4,411
Male - STEM	4,045	3,242	2,642	2,156	1,755	1,327	850	400
Female - STEM	1,906	1,495	1,216	976	768	561	371	180
All STEM majors	5,951	4,737	3,858	3,132	2,523	1,888	1,221	580

Table 5A shows the percent of female STEM bachelor's degree graduates by two digit CIP. Engineering majors have the lowest proportion of female graduates at 8.3 percent, while Family and Consumer Sciences and Human Sciences have the highest proportion of females at 87.8 percent. This table indicates a substantial degree of gender segregation by college major.

Computer Science and Engineering majors attain the highest post-graduation earnings among the two-digit STEM majors. Figure three utilizes the CGP sample to show that gender-based segregation occurs in these fields. More than two-fifths of the males with STEM majors are in these fields while for female graduates, the proportion is less than one-fifth. These proportions are similar across all race categories.

Tables 6A and 7A show the proportion of 2010 and 2011 graduates from the PSM sample with earnings in follow-up years. Table 1A shows the follow-up proportions for STEM graduates of whom about one fifth have covered earnings in Washington by the fourth year after graduation. Some of the missing workers may be working in other states, be working in uncovered employment, primarily self-employed, or be out of the labor force. Table 2A shows the same information for non-STEM majors. The follow-up rates are slightly higher for non-STEM majors, but remain relatively low, about one-third.

Table 6A. Percent of 2010 and 2011 STEM graduates with earnings in follow up years, PSM Sample.

	Year 1	Year 2	Year 3	Year 4
Female (2010 grad.)	28.0%	23.7%	21.3%	21.7%
Male (2010 grad.)	22.9%	20.4%	18.2%	18.0%
Female (2011 grad.)	28.0%	26.1%	24.3%	
Male (2011 grad.)	25.3%	24.4%	24.2%	

Table 7A. Percent of 2010 and 2011 Non-STEM graduates with earnings in follow up years, PSM Sample.

	Year 1	Year 2	Year 3	Year 4
Female (2010 grad.)	39.2%	36.1%	34.6%	33.6%
Male (2010 grad.)	32.4%	28.8%	28.2%	28.6%
Female (2011 grad.)	43.2%	40.1%	38.4%	
Male (2011 grad.)	33.6%	31.2%	29.7%	

These low follow up rates mean that cell sizes become small as shown in Table 4. This leads to the development of the CGP sample, which is much larger, but without the benefit of the PSM-based selection bias correction.

Table 8A compares the PSM sample race categories to the race categories reported in the American Community Survey (ACS), conducted by the US Census Bureau. In general, across genders, the sample shows higher rates in the "other race" category. In the PSM sample, the ethnicity Hispanic is included as a separate race, so that may explain the higher rates of "other race".

Table 8A. Percent distribution by race category, ACS data, US Census Bureau.

		Female	Male	All
White	Sample	72%	72%	72%
	State	77%	77%	77%
Other	Sample	15%	15%	15%
	State	6%	6%	6%
Asian / Pacific Islander	Sample	6%	6%	6%
	State	10%	9%	10%
African American	Sample	3%	4%	4%
	State	4%	5%	5%
Native American / Alaska Native	Sample	3%	3%	3%
	State	2%	2%	2%

Appendix B: Matching

A propensity score is estimated and assigned to each Treatment and Comparison group member and used to match for comparison purposes. One Comparison group member may be matched assigned to more than one Treatment group member, a with replacement selection algorithm. Using the with replacement selection method helps to minimize the overall distance between propensity scores, and thus increases the selection correction accuracy.

Appendix C: Enrollment Data Sources & Definitions

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 (OSPI). This file identifies regular high school graduates, their graduation date, school district and school, low-income status, gender, grade point average (GPA), 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 4-Year Higher Education Enrollment: Enrollment data for the state's six public baccalaureate higher education institutions from the Public Centralized Higher Education Enrollment System (PCHEES) maintained by the Office of Financial Management (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 National Student Clearinghouse (NSC). The National Student Clearinghouse captures 92 percent of post-secondary enrollment nationally. At this time it is the best source of information about post-secondary enrollment in private higher education institutions within Washington and for all out-of-state institutions.

Administrative data from state's Unemployment Insurance (UI) Program: Provided by the Employment Security Department. This data source is described in the main body of the report.

Appendix B: Unemployment Insurance

The Unemployment Insurance (UI) Program is a federal-state program financed by payroll taxes paid by employers. The U.S. Department of Labor sets broad criteria for the 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.

- Non-profit 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 15th 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
  - Church employees
  - Work-study students, as long as the employer is a non-profit 501(c)(3), state government or local government

More complete information regarding the Unemployment Insurance Program in Washington is available from the Employment Security Department ESD, 2011).

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 include:

- Industry – North American Industry Classification System (NAICS) 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 into 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 D1.

Figure D1: 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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