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Indicators for the Number of Females Choosing STEM Majors

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Abstract

This paper explores the different variables which may motivate females to choose STEM (science, technology, engineering, and math) majors. Historically, women have been greatly underrepresented in STEM fields for a number of different cultural and economic reasons. However, in order to fully compete in the global economy, the United States must find a way to bolster female participation in these fields. The motivators chosen to explore in this paper are: female faculty numbers, federal financial obligations, early concentration in math, SAT math scores, appropriations through the Women's Educational Equity Act, average salary for STEM occupations, and female unemployment rates. The study found that all variables except federal financial obligations and the female unemployment rate had the expected sign and were statistically significant. The paper proposes that in order to create a more complete model for predicting the number of female STEM majors, cultural trends and attitudes should be an considered.

Introduction:

On June 23, 1972 Title IX was signed into law by President Richard Nixon. This was one of the first federal laws which acknowledged the fact that women were underrepresented in education, but helped to specifically highlight the gender gap in science, technology, engineering, and math (STEM). This underrepresentation of women in STEM fields, though it has improved, has persisted throughout the years and still exists today. Women constitute a dramatically smaller portion of certain STEM-heavy fields than men. In 2009 the Department of Commerce found that, though women constitute close to half of the overall workforce, they hold less than 25 percent of STEM jobs (Beede 1). And in 2011 the Bureau of Labor Statistics cited that women make up 81.7 percent of elementary and middle school teachers, but only 33.9 percent of computer systems analysts and, even more astonishingly, only 4.3 percent of flight engineers.

With an increasing dependence on technology in the workforce, female participation in STEM fields is an essential step towards leadership equality between genders in the workforce. Gaining more women in STEM fields would also increase innovation and accelerate the United States' ability to compete globally in many markets.

The fact that fewer women are receiving bachelor degrees in STEM fields has been cited as a good indicator as to why there are fewer women in STEM occupations because one of the strongest indicators for occupation selection is a person's undergraduate degree (Griffith 1). A study was done by the National Academy of Sciences which found that "education at the undergraduate level is vital to developing a workforce that will allow the United States to remain the leader in the 21st century global economy." This means that in order to remain competitive and productive, we must gain more participation in STEM majors so as to bolster participation in STEM occupations (S. 3475).

In order to explore this dilemma of motivating women to join STEM majors, this paper will look at the different indicators which influence an individual to choose a specific major. The general indicators, chosen from previous academic research on the subject, will be applied to the problem of how to more specifically motivate females to choose STEM majors. It may be helpful to better understand these specific variables so that steps can be taken to further bolster female participation in STEM occupations later in life.

Literature Review:

One factor that is supported by research to have an effect on choice of major by women and which may encourage women to attain degrees in STEM fields is the prevalence of female faculty in those fields. In a study on the effect that having female professors whom students see as role models has on women pursuing science majors, Young and her associates found that "women with a female professor showed a stronger implicit science identity to the extent they viewed her as a positive role model" (Young 288). Similar research has been done in other fields such as mathematics which points to the fact that women and girls who are taught by female instructors identify more with mathematics, earn higher grades in mathematics, and thus have more confidence in the field (Stout 260). Therefore, it will be crucial to explore the change in the number of female faculty members across time in order to determine if an increase in female faculty members in STEM departments had an effect on female STEM graduates.

One variable that will be explored, but which did not have substantial academic literature was the degree to which federal financial obligations to universities for STEM education determines recruitment or retention of women in STEM fields. Because the vast majority of federal initiatives being taken to induce women to join STEM fields are monetarily based in grants, the effects of such grants will be interesting to pursue.

Another factor which greatly affects women's participation in STEM programs during their postsecondary education is the level of interest which they have in those fields when entering college. A person is much more likely to explore a major and furthermore a career in a subject in which they have experience. This theory proves to be especially true for females in quantitative subjects. In their study on expressed interest in STEM fields upon graduation of high school, Amy Bergerson and her colleagues found that early intervention was key to creating interest in quantitative fields in high school females, most specifically in engineering (Bergerson 611). Therefore, studying the effect of concentration on and performance in mathematics in elementary school will be crucial to determining if early intervention helps create more interest in females in STEM degrees.

Another factor which was explored in this same study was the idea that "strong past achievement is likely to be associated with strong positive self-efficacy beliefs, which, according to the literature, are potent determinants of behavioral initiation and persistence" (Bergerson 611). This means that students who do well in a specific subject tend to choose to further their participation in that subject. Another study which echoes this idea that students become more interested in subjects in which they excel was a study done by Lindsay Calkins and Andrew Welki in which they explored the factors which help students decide to major in economics. In their study they found that "positive reinforcement" supplied through the achievement of good grades is a strong motivator for persisting in a major (Calkins 6). By comparing the trend of SAT scores for females on the math portion of the exam, this paper will attempt to determine the effect that higher scores in STEM subjects incentivize women to major in STEM fields while in college.

In a study during which researchers surveyed students to find their expected earnings after graduation with a particular major, economists found that expected earnings do have an effect on college major choice (Arcidiacono 25). They found that students were more likely to choose a major in which the average student is expected to earn more than in other majors (Arcidiacono 25). Additionally, in separate research, economists from Georgetown University found that "majors with high technical, business and healthcare content tend to earn the most among both recent and experienced college graduates" (Carnevale 6). Both of these studies point to the idea that because STEM majors tend to earn higher salaries than other majors, more students may choose STEM degrees. Therefore, the variable of average salary for STEM occupations will be utilized in this paper.

As stated earlier, Title IX exists to protect a person from being discriminated against because of their gender in education programs which receive federal financial assistance ("Title IX and Sex Discrimination"). After Title IX was enacted in 1972, the Women's Educational Equity Act of 1974 was initiated in order to more definitively specify how Title IX would promote gender equity in education (Heston-Demirel). The WEEA was charged with providing financial assistance to educational agencies and programs to help meet certain gender equity requirements laid out in Title IX. Under continued reauthorizations, the WEEA continues to provide funds for equity programs as well as support technical assistance to implement those programs ("Subpart 21 - Women's Educational Equity Act"). Because this is the most substantial piece of federal legislation which exists to promote and protect equality in education for all genders, it will be crucial to include its existence for review in the model.

It has been found that nontechnical majors have a higher unemployment rate than technical majors. For example, in a study done in 2012 on the different unemployment rates received by different majors, Anthony Carnevale and his colleagues found that "majors… related to technical occupations tend to have lower unemployment rates than more general majors, like Humanities and Liberal Arts, where graduates are broadly dispersed across occupations and industries" (Carnevale 5). They found that because technical degrees such as healthcare and physical sciences are so specifically tied to certain occupations, they tend to have lower unemployment rates. Furthermore, in his research on income and degree choices, researcher Jacopo Mazza found that degrees in the sciences "offer better job security in times of economic uncertainty" (Mazza). Logically, because science degrees offer more stability, it may be assumed that students are more likely to choose STEM majors for an added sense of job security when the unemployment rate is higher. Students wishing to have a stable job after graduation may be more inclined to choose a more technical major in order to increase their chances of getting a job. This feeling may be exacerbated during times of high unemployment rates. Therefore, data for unemployment rates over time will be explored in this paper.

After reviewing the literature on possible factors that can be manipulated in order to incentivize women to major in STEM fields and thus, work in STEM fields, some possible indicators to explore have been narrowed down. These determinants are: the number of female faculty members in STEM fields, the size of federal financial obligations dedicated to university STEM programs, early concentration in mathematics, math SAT scores, average expected salary, appropriations through the WEEA, and unemployment rates.

Model:

The functional form for the linear regression model for determining female STEM majors as a percentage of total female bachelor degree recipients is postulated as follows:

FemSTEM = f (FemProf, FedFin, NAEP, SATMath, AvgSal, WEEA, FemUnemp)

Table 1: Variable Definitions and Sources

Variable	Definition	Data Collected From:
FemSTEM	Female STEM majors as a percentage of total female BA recipients	National Center for Science and Engineering Statistics
FemProf	Number of female professors teaching in STEM fields	National Science Foundation
FedFin	Federal financial obligations designated for promoting STEM majors	National Science Foundation
NAEP	Math score on National Assessment of Educational Progress exam for fourth grade female students	National Center for Education Statistics
SATMath	Average scores for females on SAT math exam	The College Board
AvgSal	Average expected salary for STEM field majors	National Science Foundation
WEEA	Enactment of the Women's Educational Equity Act	U.S. Department of Education
FemUnemp	National unemployment rate	2013 Economic Report to the President

The table below contains the expected affect that each independent variable will have on the dependent variable. Each expected sign also comes with a brief explanation as to why the expected sign was chosen.

Table 2: Expected Variable Effects

Variable	Expected Sign
FemProf	+
FedFin	+
NAEP	+
SATMath	+
AvgSal	+
WEEA	+
FemUnemp	+

The predicted effect of FemProf on FemSTEM is direct. As stated previously, the theory suggests that women are more likely to choose a major when they are able to visualize themselves in that role. Having female faculty members in STEM fields will increase the number of role models for female students, thus increasing the number of female students choosing to major in STEM fields.

The predicted effect of FedFin on FemSTEM is direct. A higher federal financial obligation to STEM programs in universities will provide students with better facilities and training programs and thus a better overall experience in their STEM classes. Included in federal financial obligations is support for research and development facilities, facilities for instruction, fellowships and training grants, among other things. These programs are put in place to bolster the experience of students and encourage further participation in STEM program. I predict that more investment will likely lead more female students to choose to major in STEM.

The predicted effect of NAEP on FemSTEM is direct. As the theory shows, early concentration in a subject is key to sustaining and cultivating that interest further later in life. Early intervention will peak students' interest and build the platform for further achievement in STEM subjects. Because achievement in STEM subjects tends to lead to majoring in the field, more concentration earlier on will lead to more STEM majors. Therefore, I predict that a higher score on the math portion of the NAEP test given to female fourth graders will lead to more female STEM majors.

The predicted effect of SATMath on FemSTEM is direct. Achievement in a subject often leads to concentration in that subject, as supported by theory. Therefore, higher math SAT scores for women will indicate a higher achievement and preparedness in the subject, suggesting an increase in STEM majors.

The predicted effect of AvgSal on FemSTEM is direct. One reason for choosing a major, as found during review of the literature, is the potential earning power of that major. STEM majors tend to earn a higher salary than other majors, such as the humanities. A high expected salary may lead more women to major in STEM fields.

The predicted effect of WEEA on FemSTEM is direct. Providing federal support to the issue of women in education will increase funding to programs that push women to join nontraditional educational programs.

The predicted effect of FemUnemp on FemSTEM is direct. It has been proven that the unemployment rate of recent college graduates differs depending on a student's major choice. Technical majors such as those found in STEM have a lower unemployment rate upon graduation than other majors such as arts and humanities. The national unemployment rate is often called upon as a figure for assessing the health of the nation's economy and workforce. By looking more specifically at the female unemployment rate, we may see an effect on the number of females joining STEM majors. When the female unemployment rate is high, I hypothesize that students will allow the desire to be more hirable affect their decision on what to major in. It is for this reason that I believe that a higher female unemployment rate will cause more women to turn to STEM majors for job security.

Data:

Female STEM Majors

The dependent variable (FemSTEM), Female STEM majors as a percentage of total female BA recipients, has been calculated from a data set provided by the National Center for

Science and Engineering Statistics. This data is available from 1966 to 2010. Because the number of women receiving bachelor's degrees has increased over time due to several different factors, turning the actual number of female STEM majors into a percentage of the total number of female degree recipients will help to correct for this general upward trend. In order to determine that the proposed factors are working, I will thus be looking to see that the proportion of women who are receiving bachelor's degrees in STEM fields is increasing in order to determine an upward trend.

Female Faculty

The number of female faculty members teaching in STEM fields (FemProf) was gathered from the National Science Foundation and indicates the number of female science, engineering, and health doctorates who are employed in academia. This data is accountable for women who have earned their doctorate degrees from an American university only. It is available for every other year from 1973 to 2010. It is stated in thousands. In order to allow for the inclusion of this data in the full regression model, the years for which the number of female faculty in STEM fields is missing have been calculate manually as the mean of the years before and after the year in question. For example, the data cited for 1974 is calculated as the mean of the values for 1973 and 1975. This data will be used to determine the degree to which having female role models affects the number of female STEM majors.

Federal Obligations

Federal financial obligations (FedFin) is represented in billions of 2014 dollars by the total federal obligations for science and engineering to universities and colleges. This data was collected from the National Science Foundation and is available from 1963 to 2011. It includes all the aggregated federal obligations, though the data can be split up by activities such as:

research and development, R&D plant, facilities for instruction in science and engineering, fellowships, traineeships, and training grants, general support for science and engineering, and other science and engineering activities. For the purpose of this study, I will be using the aggregate of all of these activities.

Average National Assessment of Educational Progress

The variable EarlyMath will be represented by the mathematics scores for female fourth graders on the National Assessment of Educational Progress. The data was collected from the National Center for Education Statistics. It is available sporadically beginning in 1973 through 2012 and is measured in an averaged test score from 0 to 500. Due to the irregularity of the data, these values will be regressed on their own against the dependent variable rather than including them in the full regression. Though the data is not included in the full regression model, due to theoretical support in the literature review process, it will remain in this paper because it is believed to have a significant effect on female STEM majors.

Furthermore, though the data for the NAEP scores is reported beginning in 1973, each year's score will be matched with the dependent variable value of twelve years later. For example, the 1973 test scores for fourth grade females will be match with the output of 1985 female STEM majors. This is due to the fact that the girls whose tests scores are reported each year, in this example 1973, will be more appropriately matched with the outcome of females graduating college and determining their bachelor degree field, in this example during the year 1985. This will be represented in the data table presented for the regression (Table 6). The NAEP data will be used to test the "early achievement" hypothesis that early focus and achievement in a subject encourages students to major in them.

SAT Math Scores

The variable SATMath is represented by the average yearly score for women on the mathematics portion of the SAT exam. This data was collected from The College Board and is available from 1967 to 2013. Initially this study was going to use data from the ACT test in the subjects of science and math. Data was collected on both portions of the ACT exam, however a test of correlation between ACT math and science test scores revealed a correlation of 0.848 between the two meaning that they were highly correlated. Because skills in mathematics and quantitative knowledge are often required in order to excel in science fields, this paper will omit the ACT science scores. I have chosen to use SAT math scores instead of ACT math scores as an indicator of strong past achievement in STEM subjects because SAT scores available for a larger number of years.

Excepted Salary

The average salary per year for STEM majors, denoted at AvgSal, was collected from a number of reports cited in the Science and Engineering Indicators report put out by the National Science Foundation. The data is reported in 2014 dollars and is calculated for some years based on growth projections of previous years. It is not broken down by gender and thus contains the average salary for both male and female STEM workers.

Women's Educational Equity Act

The variable WEEA is a representation of The Women's Educational Equity Act which began appropriating funds to support women's equality in educational fields in which they are underrepresented in 1976. Though Title IX was enacted in 1972 and the Women's Educational Equity Act was first enacted in 1974, actual funding through this act to educational programs did not begin until the fiscal year of 1976 (U.S. Department of Education). Through reauthorization, this Act has been continually funded since its inception except for during the year 1996. The appropriation amount is used for data here and is listed in millions of dollars. From this variable we will better understand if and to what degree the funding from the WEEA helped motivate women to join STEM majors.

National Unemployment Rate for Females

The national unemployment rate for females, denoted as FemUnemp, was collected from the 2013 Economic Report of the President. The statistics were available from 1966-2012 and were reported as a percentage of civilian labor force in the group specified (in this case the group was females).

The following table contains selected variable statistics:

Table 3: Summary Statistics on Variables

Variable	**Mean**	**Standard Deviation**
FemSTEM (percent)	26.150	1.597
FemProf (thousands)	49.0	27.741
FedFin (billions of 2014 dollars)	21.792	8.174
NAEP	226	5
SATMath	487.263	10.246
AvgSal	82,397	2,806.95
WEEA (millions of 2014 dollars	8.250	8.972
FemUnemp	6.4	1.473

Estimation Results:

Three regressions were run using the data collected for each variable referenced throughout this paper. The reasoning behind running three regressions was because of the unavailability of data for the NAEP test scores as well as limited availability of average salary data for STEM workers.

The NAEP test scores are only available for sporadic periods of time. Therefore, it was difficult to run a regression using the NAEP test scores in a model alongside all of the other variables without losing much of the data for those other variables.

Additionally, salary data was only available for years beginning in 1993 onward. Because of this, it was decided to run a regression which did not include the salary data, but did include all the available data for the rest of the variables which stretched back to 1973. When assessing the model which included the salary data, it was found that the variable AvgSal was statistically insignificant with a p-value of .346. Additionally, many of the variables such as FemProf, FedFin, WEEA, FemUnemp became statistically insignificant when regressed in a model with AvgSal. It is for these reasons that the model run with the salary data will not be discussed further in this paper[1] and the variable of average salary will not be included in the Regression One.

[1] The data table including average salary data is available in Appendix A. The regression results for the regression run including salary data are included in Appendix C.

Regression One: FemProf, FedFin, SATMath, WEEA, FemUnemp

Table 4: Regression One Data

Year	FemSTEM	FemProf[a]	FedFin[b]	SATMath	WEEA[c]	FemUnemp
1973	23.486%	10.7	$13.031	489	$0.000	6.0
1974	24.223%	12.2	$13.034	488	$0.000	6.7
1975	24.292%	13.6	$12.244	479	$0.000	9.3
1976	24.401%	15.1	$12.212	475	$25.871	8.6
1977	24.468%	16.5	$12.983	474	$28.165	8.2
1978	24.518%	18.0	$14.268	474	$29.113	7.2
1979	24.428%	19.4	$14.446	473	$29.105	6.8
1980	24.536%	21.3	$13.650	473	$28.492	7.4
1981	24.509%	23.1	$13.076	473	$20.985	7.9
1982	24.954%	24.8	$12.601	473	$14.013	9.4
1983	24.773%	26.5	$13.390	474	$13.577	9.2
1984	25.047%	28.8	$14.254	478	$13.015	7.6
1985	25.559%	31.1	$15.836	480	$13.091	7.4
1986	25.617%	32.6	$15.919	479	$12.296	7.1
1987	25.369%	34.0	$17.708	481	$7.233	6.2
1988	24.949%	36.4	$18.135	483	$6.650	5.6
1989	24.600%	38.7	$19.086	482	$5.583	5.4
1990	24.725%	40.3	$18.809	483	$3.768	5.5
1991	24.764%	41.9	$20.526	482	$3.438	6.4
1992	25.531%	44.4	$21.483	484	$0.836	7.0
1993	25.823%	46.9	$20.852	484	$3.223	6.6
1994	26.464%	49.7	$21.968	487	$3.143	6.0
1995	27.349%	52.4	$22.277	490	$3.178	5.6
1996	27.820%	55.8	$21.622	492	$0.000	5.4
1997	28.279%	59.2	$22.082	494	$4.388	5.0
1998	28.254%	61.8	$23.179	496	$4.321	4.6
1999^	28.110%	64.4	$25.446	495	$4.227	4.3
2000	27.966%	67.5	$27.101	498	$4.090	4.1
2001	28.035%	70.5	$29.833	498	$3.979	4.7
2002	28.050%	74.6	$31.883	500	$3.915	5.6
2003	28.337%	78.7	$34.017	503	$3.802	5.7
2004	28.290%	84.4	$33.978	501	$3.681	5.4
2005	28.209%	87.3	$33.710	504	$3.553	5.1
2006	27.798%	90.1	$32.916	502	$3.408	4.6
2007	27.538%	92.2	$31.911	499	$2.128	4.5
2008	27.514%	94.2	$30.996	499	$2.013	5.4
2009	27.457%	99.7	$39.578	498	$2.615	8.1
2010	27.677%	105.2	$38.037	499	$2.608	8.6
Mean	26.150%	49.0	$21.792	487.263	$8.250	6.4
StdDev	1.5967%	27.7414	$8.174	10.246	$8.972	1.473

[a]in thousands, every other year starting with 1974 is an average

[b]in billions, converted to 2014 dollars

[c]in millions, converted to 2014 dollars

The functional model for this linear regression is stated as follows:

FemSTEM = *ƒ* (FemProf, FedFin, SATMath, WEEA, FemUnemp)

Table 5: Regression One Estimates (Dependent Variable: FemSTEM)

Independent Variable	Expected Sign	Estimated Coefficient	*t*-statistic	P-value
Intercept		-0.276	-1.559	0.129
FemProf	+	0.000658	3.536	0.00126
FedFin	+	-0.00160	-2.232	0.0327
SATMath	+	0.00111	3.025	0.00487
WEEA	+	0.000369	2.099	0.0438
FemUnemp	+	-0.000574	-0.541	0.592
R^2		.864		
Adjusted R^2		.843		

Based on the R^2 value of this model of .864, this regression is a good fit. Generally speaking, an R^2 value of above a .7 can be considered a "good fit." The R^2 value of a regression represents the proportion of the variation in the dependent Y variable explained by the set of independent X variables. An R^2 of .864 suggests that 86.4% of the percentage of females in STEM majors is explained by the set of independent variables used in the model (number of female professors, federal financial obligations, SAT math scores, WEEA appropriations, and female unemployment rate).

In order to test further the usefulness of this model, a test was run using the calculated R^2 value of .864 to calculate the overall F statistic of 40.659[2]. The critical F value for a model with a numerator of 5 degrees of freedom and denominator of 32 degrees of freedom is $F_{(5,32)}$: 2.05 at a significance level of 10 percent. The calculated F value for this model is larger than the critical F value, meaning that it has statistical significance and the independent variables do have an effect the dependent variable.

[2] Equation used to find overall F value: $(R^2/k-1)/((1-R^2)/(n-k))$

In addition to the R^2 value, the p-values can be used to show the strength of the individual independent variables on the dependent variable. A p-value that is very small (generally, less than .05) usually indicates a stronger relationship with the dependent variable. In this regression, the variables FemProf, FedFin, SATMath, and WEEA have very small p-values and thus can be seen as having a strong relationship with the Y variable of FemSTEM. The intercept value and the variable FemUnemp, however, have larger p-values (.129 and .592 respectively) and therefore can be seen as having weaker relationships with the dependent Y variable.

The estimated coefficient for FemProf is approximately 0.000658 resulting in a positive relationship between the number of female faculty members in STEM fields and the percentage of women choosing STEM majors. This coefficient means that an increase in 1,000 female professors will lead to a 0.000658 percent increase in female STEM majors. This result is consistent with the model prediction. It supports the theory that more women in faculty roles in STEM fields allows more female students to see women in these skilled positions, allowing female students to more easily picture themselves in those roles and causing them to stick with, or choose, STEM majors more frequently.

The estimated coefficient for FedFin is approximately -0.00160 resulting in a negative relationship between the amount of federal financial obligations designated for promoting STEM fields in universities and the percentage of women choosing STEM majors. This result is not consistent with the model prediction. It was predicted that there would be a positive relationship between the amount of money provided by the federal government and the number of female STEM majors. This finding of a negative relationship between FedFin and FemSTEM could be caused by a number of things. First, the data for FedFin may be regressed against the wrong values and years for FemSTEM. It may be possible that the money dispensed each year towards

STEM fields does not take effect on female major choices until a year or two later. Therefore, it may be more statistically correct to attribute the amount of money dispensed one year, on the FemSTEM percentage outcome of the following year[3]. A second item that may be throwing off the sign for FedFin is the large jump in funding from $30.996 in 2008 to $39.578 in 2009. This is due to the fact that the data used for the regression includes funding dispersed in 2009 that was designated under the American Recovery and Reinvestment Act of 2009. This stimulus package put forth a total of $1 billion towards education alone, some of which was further designated specifically for STEM fields, causing the large jump from 2008 to 2009. This is a small bump in the trend, however, and most likely does not account for the full error in prediction. Though it does not have the expected sign, because it is statistically significant, it will remain in the model.

The estimated coefficient for SATMath is approximately 0.00111, resulting in a positive relationship between the average math SAT scores for females and the percentage of women choosing STEM majors. This means that a one point increase in the average math score for females will lead to a .00111 increase in the percent of female STEM majors. This supports the theory that achievement in a subject will encourage students to focus on that subject. Thus, a higher score on the math portion of the SATs can lead to a higher percentage of females choosing STEM majors.

The estimated coefficient for WEEA is approximately 0.000369, resulting in a positive relationship between the appropriations set for the Women's Educational Equity Act and the percentage of women choosing STEM majors. This means that a $1 million increase in WEEA appropriations will lead to a 0.000369 increase in the percent of female STEM majors. This

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[3] For example, the 2008 value for FedFin of $30.996 may be more useful if it were regressed against the 2009 value for FemSTEM of 27.457%.

coefficient supports the model predictions and the theory that higher appropriations that promote women specifically in education will lead to more women in STEM fields.

The estimated coefficient for FemUnemp is approximately -0.000574, resulting in a negative relationship between the female unemployment rate and the percentage of women choosing STEM majors. This does not correspond with the expected sign. It should also be noted, however, that the p-value of .592 renders the variable statistically insignificant in this model. One reason that the predicted sign may be wrong and the variable may be statistically insignificant could be that the reported annual unemployment rates may not affect actual behavior until years later. When a person is laid-off it may take some time for them to go back to school, potentially holding previous years of unemployment responsible for current years STEM rates[4]. Because theory strongly suggests that in times of high unemployment people tend to choose STEM majors for their stability and strong job opportunities, this variable will remain in the model.

Regression Two: NAEP Scores

Table 6: Regression Two Data

Year for STEM Majors	FemSTEM	Year Test Taken	NAEP
1985	25.559%	1973	220
1990	24.725%	1978	220
1994	26.464%	1982	221
1998	28.254%	1986	222
2002	28.050%	1990	230
2004	28.290%	1992	228
2006	27.798%	1994	230
2008	27.514%	1996	229

[4] This concept is similar to that discussed with FedFin. Some of the females choosing STEM majors in 2010 may be attributable to female unemployment rates from 2006, for example.

The functional model for this linear regression is stated as follows:

FemSTEM = *f* (NAEP)

Table 7: Regression Two Estimates (Dependent Variable: FemSTEM)

Independent Variable	Expected Sign	Estimated Coefficient	*t*-statistic	P-value
Intercept		-0.211	-1.164	0.289
NAEP	+	0.00214	2.658	0.0376
R^2		.541		
Adjusted R^2		.464		

As stated earlier, due to the fact that the NAEP test has been administered sporadically for the past thirty years, it was necessary to regress, or correlate, the NAEP math scores alone for each of the available years to the percentage of females in STEM majors. The NAEP math scores listed here are the average for females in fourth grade. In Table 6, it can be seen that the values for FemSTEM in each year are matched with the NAEP math scores for twelve years prior. This is so that the female students who took the NAEP in fourth grade would be the traditional age of graduating seniors in college. By regressing the numbers this way the NAEP scores are more closely attributed to the class that took them.

Though the R^2 value is .541, this is a suitable number for a regression with only one variable. The p-value for the NAEP scores is .0376, making it statistically significant.

The estimated coefficient for NAEP is approximately 0.00214, resulting in a positive relationship between the scores achieved by female students on the math portion of the NAEP and the percentage of females choosing STEM majors twelve years later. This finding supports the model prediction that early achievement in math, recorded by higher test scores in the math NAEP by females, will lead to more females choosing to focus on STEM subjects in college.

Standardized Coefficient Model

Table 8: Standardized Coefficient Estimates

Independent Variable	Standardized Coefficient[5]
FemProf	1.144
FedFin	-.821
SATMath	.712
WEEA	.208
FemUnemp	-.0529

In Table 8, the standardized coefficients for each variable are listed. These new beta coefficients are helpful for comparing multiple regressors to each other without the confusion of different units and measurements of the previous models. Instead, each of these coefficients deals in standard deviations. If the X variable increases by one standard deviation, the Y variable will increase by the amount of the coefficient (Gujarati 158). A larger coefficient in comparison to another means that the former contributes more to the explanation of the Y variable than the latter (Gujarati 158).

It is interesting to compare the relative strength of each variable to the others, especially considering the wide breadth of measurements (from percentages to dollars) and units (from decimals to billions) that the variables take on in their unstandardized forms.

When comparing these standardized variables it appears that female professors have the greatest relative strength. Given the extremely low p-value for FemProf of 0.00126, it makes sense that it would be a strong regressor when compared to the other variables with slightly higher p-values. Female unemployment rates have the lowest relative strength. This is not surprising considering female unemployment rates were found to be statistically insignificant in Regression One.

[5] Standardized coefficients were found by translating the data into standardized variables using the equation: $Y_i^* = (Y_i - \bar{Y})/S_Y$ and $X_i^* = (X_i - \bar{X})/S_x$. These new data points were regressed to give the standardized betas above.

Possible OLS Assumption Errors

According to the table in Appendix B, there appears to be some multicollinearity amongst a number of the explanatory variables in the model. Multicollinearity arises when there are linear relationships among the X variables (Gujarati 321). In order to define two variables as being highly correlated, the absolute value of their correlation coefficients must be above .7.

Multicollinearity is undesirable in a model because it is difficult to make precise estimations of the betas when it is present (Gujarati 327). This can lead to the variables presenting as statistically insignificant and also creating an artificially high goodness of fit measurement (Gujarati 327).

By examining the table in Appendix B, it is clear that there are a number of relationships which show multicollinearity. For example, in the correlation coefficients for Regression One, the variable FemProf is highly correlated with FedFin with a correlation coefficient of .979 and SATMath with a correlation coefficient of .889. Additionally, FedFin is highly correlated with SATMath with a correlation coefficient of .900 and WEEA is highly correlated with SATMath with a correlation coefficient of -.708.

There are a number of reasons that multicollinearity may appear. It may be that there is a model specification error. This means that the linear model chosen to estimate the dependent variable in this paper is not the best model to choose for the data set. However, because the data used in this paper is time series data, it is very likely that multicollinearity is present simply due to the fact that many of the variables follow similar trends. A number of the variables chosen for this model have trended upward and thus will appear to be related to one another because they are moving in the same direction. This may not mean that they have any bearing on each other;

it may simply be that because the data is moving in similar directions, they only appear to be related.

Forecasting

One reason for developing an economic model is to use it for forecasting and prediction. The resulting forecast can aid in developing policy and making decisions about the future.

It is important, however, to keep in mind that forecast error can occur for many reasons when using an estimated model for forecasting. There may have been an error that occurred when developing the model, leading any predictions formulated by that model to be skewed. There may also be errors in the values used to represent the X independent variables. It is difficult to accurately predict what will happen in the future, therefore predicting the exact correct values for every independent variable in a model can be unlikely.

Another potential problem to consider when using an estimated model for forecasting is that the potential for forecast error grows the further in the future you try to predict. Because a model, and especially in this case of a single-equation regression model, is developed using specific points, using the same model for points outside of the calculated region will naturally produce some level of forecast error.

With all of this in mind, I will attempt to use the model found in Regression One stated in the functional form:

FemSTEM = *f* (FemProf, FedFin, SATMath, WEEA, FemUnemp)

to predict the percentage of females in STEM majors for the years 2011 and 2012. To do this I found the known and forecasted values for each of the independent variables for the years 2011 and 2012. These values are displayed in Table 9.

Table 9: Forecasted Values for Regression One

	FemProf[a]	FedFin[b]	SATMath	WEEA[c]	FemUnemp
2011	110.5*	$33.013	500	$2.521	8.5
2012	116*	$32.188*	499	$2.470	7.9

[a]in thousands
[b]in billions, converted to 2014 dollars
[c]in millions, converted to 2014 dollars
*these values were speculated using research, all other values are known

The predicted FedFin value for 2012 was formulated through a number of assumptions. The final funds from the American Recovery and Reinvestment Act were distributed in 2010. Due to the absence of ARRA funding, a large decrease in funding of about 11 percent from 2010 to 2011 is visible ("Federal Science and Engineering Obligations…"). Prior to this abnormally large drop in funding, federal obligations towards science and engineering support had been decreasing at a rate of about 2 to 3 percent every year from 2006 to 2010, not including the large spike in 2009 explained by the ARRA stimulus. Therefore, the value speculated for 2012 reflects a 2.5 percent decrease in funding from 2011 to follow the general decreasing trend of the previous years.

The number of female professors has been increasing by varying degrees every year since 1973. The values for FemProf for 2011 and 2012 were calculated by following the trends from 2009 and 2010 of approximately a 5 percent increase.

The values from Table 9 were plugged into the equation using the coefficients from Regression One[6]. The forecast for the percent of females who choose to major in STEM fields in 2011 is 29.494 percent. The forecast for the percent of females who choose to major in STEM fields in 2012 is 29.909 percent. Comparing these numbers to the previously known values used

[6] FemSTEM = -.0276 + .000658FemProf – 0.00160FedFin + 0.00111SATMath + 0.000369WEEA – 0.000574FemUnemp

for the regression equations, the percent of females who will choose to major in STEM fields is predicted to increase.

In 2011 there is predicted to be a 1.82 percent increase in female STEM majors from 27.677 percent in 2010 to the predicted 29.494 percent in 2011. This is due in part to the predicted increase of female faculty members in both 2011 and 2012. It may also be due to the fact that federal funding is expected to continue decreasing and because the relationship found between FedFin and FemSTEM is negative, the double negative causes a positive increase in FemSTEM.

In 2012 there is predicted to be a .41 percent increase in female STEM majors from the forecasted 29.494 percent in 2011to 29.909 percent in 2012. The small change is due to the fact that SAT math scores decrease and offset some of the increase gained by the predicted rising number of female faculty members as well as the further decrease predicted for federal funding. A decrease in WEEA appropriations also contributes to the low level of increase in female STEM majors from 2011 to 2012.

Summary

Based on the two regressions, it is can be seen that five of the seven variables tested were statistically significant[7] when regressed with the percentage of females in STEM majors. Average salary and female unemployment rates were found to be statistically insignificant to the explanation of the dependent variable. Additionally federal financial obligations, though statistically significant, had a negative relationship with the dependent variable which was opposite of the predicted model.

This model may be useful for policy in the future when legislators are looking for ways to bolster female participation in STEM fields as a way to boost gender equity and the economy.

[7] Those variables which were statistically significant were: FemProf,FedFin, NAEP, SATMath, and WEEA.

As seen in the section on forecasting, female STEM majors are expected to have increased in 2011 and 2012.

It will be important for legislators to note that federal funding must be timed correctly and administered to the appropriate sectors in order to make the desired impact. This implication can be seen in the negative relationship found between the FedFin variable and FemSTEM. The negative relationship between these two variables indicates that more federal funding towards STEM fields in universities may actually decrease the number of females choosing STEM majors. Though this outcome may be due to errors in the regression model, it is still an interesting and worrisome outcome which should not be taken lightly.

Additionally, policymakers should note that early concentration in mathematics is a statistically significant indicator of female STEM majors. By building a foundation of quantitatively-literate female students, the United States may then be able to increase the number of females in STEM majors and thus in STEM occupations.

If given more time and resources, I would like to improve this study through a number of methods. First, I would like to find a different, more consistent set of data for the AvgSal variable. The data available to me for this variable was limited and therefore required that I pull data points from a number of different reports. This could mean that the different data points were not measured or collected in the same way and could have resulted in the outcome of statistical insignificance. With a consistent set of data from one report, there may be a different regression outcome.

Second, I would like to attempt to rerun Regression One, offsetting the variables of FedFin and FemUnemp in order to try to correct for the unpredicted sign and statistical insignificance, respectively. Perhaps by correlating one year's data to the FemSTEM data of a number of years later, I would receive the expected results.

Lastly, I would like to explore the effect that cultural trends and attitudes have on the number of females choosing STEM majors. Historically, there have been cultural pressures for females to focus on softer subjects such as the humanities and for males to focus on the hard sciences such as chemistry and mathematics. The lasting effect that these pressures have on females' choice of major is difficult to quantify, especially with macro data like the sets that I was using for this study. Many of the studies that I came across which discussed the social and cultural factors in choice of major were pursued with data collected from personal surveys rather than aggregated, impersonal data. If given the time and resources, I would like to attempt to capture and quantify such variables as public attitude towards genders in specific fields, parental support for females in STEM subjects, and personal perception of ability to achieve in STEM subjects among women.

Appendix A

Percentage of Female Stem Majors

Source: National Science Foundation/National Center for Science and Engineering Statistics; data from Department of Education/National Center for Education Statistics: Integrated Postsecondary Education Data System Completions Survey

Year	FemSTEM[8]
1973	23.486%
1974	24.223%
1975	24.292%
1976	24.401%
1977	24.468%
1978	24.518%
1979	24.428%
1980	24.536%
1981	24.509%
1982	24.954%
1983	24.773%
1984	25.047%
1985	25.559%
1986	25.617%
1987	25.369%
1988	24.949%
1989	24.600%
1990	24.725%
1991	24.764%
1992	25.531%
1993	25.823%
1994	26.464%
1995	27.349%
1996	27.820%
1997	28.279%
1998	28.254%
1999	28.110%
2000	27.966%
2001	28.035%
2002	28.050%
2003	28.337%
2004	28.290%
2005	28.209%
2006	27.798%
2007	27.538%
2008	27.514%
2009	27.457%
2010	27.677%
Mean	26.150%
StdDev	1.5967%

[8] Calculated by dividing females receiving bachelor degree in STEM fields by total number of females receiving bachelor degrees.

Female Professors

Source: National Science Foundation, National Center for Science and Engineering Statistics, special tabulations (2013) of the Survey of Doctorate Recipients (various years).

Year	FemProf[9]
1973	10.7
1974	12.2
1975	13.6
1976	15.1
1977	16.5
1978	18.0
1979	19.4
1980	21.3
1981	23.1
1982	24.8
1983	26.5
1984	28.8
1985	31.1
1986	32.6
1987	34.0
1988	36.4
1989	38.7
1990	40.3
1991	41.9
1992	44.4
1993	46.9
1994	49.7
1995	52.4
1996	55.8
1997	59.2
1998	61.8
1999	64.4
2000	67.5
2001	70.5
2002	74.6
2003	78.7
2004	84.4
2005	87.3
2006	90.1
2007	92.2
2008	94.2
2009	99.7
2010	105.2
Mean	49.0
StdDev	27.7414

[9] In thousands, every other year beginning 1974 is an average

Federal Financial Obligations

Source: National Science Foundation/National Center for Science and Engineering Statistics, Survey of Federal Science and Engineering Support to Universities, Colleges, and Nonprofit Institutions.

Year	FedFin[10]
1973	$13.031
1974	$13.034
1975	$12.244
1976	$12.212
1977	$12.983
1978	$14.268
1979	$14.446
1980	$13.650
1981	$13.076
1982	$12.601
1983	$13.390
1984	$14.254
1985	$15.836
1986	$15.919
1987	$17.708
1988	$18.135
1989	$19.086
1990	$18.809
1991	$20.526
1992	$21.483
1993	$20.852
1994	$21.968
1995	$22.277
1996	$21.622
1997	$22.082
1998	$23.179
1999	$25.446
2000	$27.101
2001	$29.833
2002	$31.883
2003	$34.017
2004	$33.978
2005	$33.710
2006	$32.916
2007	$31.911
2008	$30.996
2009	$39.578
2010	$38.037
Mean	$21.792
StdDev	$8.174

[10] In billions, converted to 2014 dollars

Average NAEP Math Scores for Fourth Grade Females

Source: U.S. Department of Education, National Center for Education Statistics, National Assessment of Educational Progress (NAEP), NAEP 2012 Trends in Academic Progress; and 2012 NAEP Long-Term Trend Mathematics Assessment, retrieved August 29, 2013, from Long-Term Trend NAEP Data Explorer.

Year taken	Score
1973	220
1978	220
1982	221
1986	222
1990	230
1992	228
1994	230
1996	229
1999	231
Mean	226
StdDev	5

Average SAT Math Scores for Females

Source: College Board: 2013 College-Bound Seniors Total Group Profile Report

Year	SATMath
1973	489
1974	488
1975	479
1976	475
1977	474
1978	474
1979	473
1980	473
1981	473
1982	473
1983	474
1984	478
1985	480
1986	479
1987	481
1988	483
1989	482
1990	483
1991	482
1992	484
1993	484
1994	487
1995	490
1996	492
1997	494
1998	496
1999	495
2000	498
2001	498
2002	500
2003	503
2004	501
2005	504
2006	502
2007	499
2008	499
2009	498
2010	499
Mean	487.263
StdDev	10.246

Median Salary for STEM Occupations

Source: National Science Foundation, Division of Science Resources Statistics, Scientists and Engineers Statistical Data System (SESTAT), http://sestat.nsf.gov.

Year	Salary[11]
1993	$77,989
1994	$77,626
1995	$77,027
1996	$78,559
1997	$80,454
1998	$82,821
1999	$84,554
2000	$84,259
2001	$84,433
2002	$85,565
2003	$86,134
2004	$84,491
2005	$84,173
2006	$83,990
2007	$81,528
2008	$81,730
2009	$83,828
2010	$83,983
Mean	$82,397
StdDev	$2,806.95

[11] In 2014 dollars

Appropriations to Women's Educational Equity Act

Source: U.S. Department of Education

Year	WEEA[12]
1973	$0.000
1974	$0.000
1975	$0.000
1976	$25.871
1977	$28.165
1978	$29.113
1979	$29.105
1980	$28.492
1981	$20.985
1982	$14.013
1983	$13.577
1984	$13.015
1985	$13.091
1986	$12.296
1987	$7.233
1988	$6.650
1989	$5.583
1990	$3.768
1991	$3.438
1992	$0.836
1993	$3.223
1994	$3.143
1995	$3.178
1996	$0.000
1997	$4.388
1998	$4.321
1999	$4.227
2000	$4.090
2001	$3.979
2002	$3.915
2003	$3.802
2004	$3.681
2005	$3.553
2006	$3.408
2007	$2.128
2008	$2.013
2009	$2.615
2010	$2.608
Mean	$8.250
StdDev	$8.972

[12] In millions, in 2014 dollars

Female Unemployment Rates

Source: 2013 Economic Report of the President

Year	FemUnemp
1973	6.0
1974	6.7
1975	9.3
1976	8.6
1977	8.2
1978	7.2
1979	6.8
1980	7.4
1981	7.9
1982	9.4
1983	9.2
1984	7.6
1985	7.4
1986	7.1
1987	6.2
1988	5.6
1989	5.4
1990	5.5
1991	6.4
1992	7.0
1993	6.6
1994	6.0
1995	5.6
1996	5.4
1997	5.0
1998	4.6
1999	4.3
2000	4.1
2001	4.7
2002	5.6
2003	5.7
2004	5.4
2005	5.1
2006	4.6
2007	4.5
2008	5.4
2009	8.1
2010	8.6
Mean	6.4
StdDev	1.473

Appendix B

Simple Correlation Coefficients among Variables

Regression One: Correlation coefficients between variables

	FemSTEM	*FemProf*	*FedFin*	*SATMath*	*WEEA*	*FemUnemp*
FemSTEM	1					
FemProf	0.885182	1				
FedFin	0.853025	0.978654	1			
SATMath	0.875535	0.88666	0.900483	1		
WEEA	-0.50119	-0.54425	-0.53971	-0.70815	1	
FemUnemp	-0.60816	-0.49743	-0.47854	-0.67068	0.474385	1

Regression Two: Correlation coefficients between variables

	NAEP	*STEM*
NAEP	1	
STEM	0.735345077	1

Correlation coefficients including AvgSal

	FemSTEM	*FemProf*	*FedFin*	*SATMath*	*WEEA*	*FemUnemp*	*Salary*
FemSTEM	1						
FemProf	0.334491	1					
FedFin	0.337673	0.937851	1				
SATMath	0.759997	0.783752	0.793543	1			
WEEA	0.29071	-0.15304	-0.02275	0.165071	1		
FemUnemp	-0.39378	0.329634	0.405831	-0.14596	-0.30304	1	
Salary	0.690664	0.621215	0.723629	0.856353	0.426234	-0.08967	1

Appendix C

Final Regression Results

SUMMARY OUTPUT: **Regression One**

Regression Statistics	
Multiple R	0.929438546
R Square	0.863856012
Adjusted R Square	0.842583513
Standard Error	0.006420133
Observations	38

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	0.008369142	0.001673828	40.60905323	6.11075E-13
Residual	32	0.001318979	4.12181E-05		
Total	37	0.009688121			

2.021

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.275894178	0.17688016	-1.559780235	0.128648275	-0.636187274	0.084398918	-0.636187274	0.084398918
FemProf	0.000658454	0.000186217	3.535949866	0.001263473	0.000279142	0.001037766	0.000279142	0.001037766
FedFin	-0.001603741	0.000718547	-2.231922864	0.032747961	-0.003067373	-0.000140109	-0.003067373	-0.000140109
SATMath	0.001109658	0.000366833	3.024968422	0.004873387	0.000362444	0.001856872	0.000362444	0.001856872
WEEA	0.000369661	0.0001761	2.099159358	0.043779685	1.0958E-05	0.000728365	1.0958E-05	0.000728365
FemUnemp	-0.000573986	0.001061248	-0.54085961	0.592349722	-0.002735679	0.001587706	-0.002735679	0.001587706

SUMMARY OUTPUT: **Regression Two**

Regression Statistics	
Multiple R	0.735345077
R Square	0.540732382
Adjusted R Square	0.464187779
Standard Error	0.009869705
Observations	8

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.000688139	0.000688139	7.064278362	0.037630853
Residual	6	0.000584466	9.74111E-05		
Total	7	0.001272605			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.2111025	0.181351628	-1.164050759	0.28859314	-0.654853947	0.232648947	-0.654853947	0.232648947
NAEP	0.002141867	0.000805858	2.657871021	0.037630853	0.000170003	0.00411373	0.000170003	0.00411373

SUMMARY OUTPUT: **Regression Including Average Salary**

Regression Statistics	
Multiple R	0.910342625
R Square	0.828723696
Adjusted R Square	0.735300257
Standard Error	0.003403204
Observations	18

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	0.000616426	0.000102738	8.870618621	0.001087901
Residual	11	0.0001274	1.15818E-05		
Total	17	0.000743826			
			2.11		

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.72723457	0.234573224	-3.100245448	0.010099715	-1.243526756	-0.210942385	-1.243526756	-0.210942385
Faculty	-3.61839E-05	0.000159363	-0.227053482	0.82454673	-0.000386939	0.000314572	-0.000386939	0.000314572
FedOb	-0.001371798	0.000638484	-2.148522865	0.054787512	-0.002777093	3.34964E-05	-0.002777093	3.34964E-05
SAT Math	0.001962511	0.000527865	3.717828363	0.003394582	0.000800688	0.003124333	0.000800688	0.003124333
WEEA	-0.000221824	0.001055672	-0.210126124	0.837410633	-0.002545342	0.002101693	-0.002545342	0.002101693
FemUnemp	0.002178751	0.001397604	1.558918392	0.147304125	-0.000897355	0.005254858	-0.000897355	0.005254858
Salary	7.39735E-07	7.51269E-07	0.984647756	0.345959614	-9.13796E-07	2.39327E-06	-9.13796E-07	2.39327E-06

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