FEMALE FACULTY IN STEM

FIELDS EFFECT ON STUDENTS'

IMPLICIT ASSOCIATION

by

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TABLE OF CONTENTS

LIST OF TABLES v
LIST OF FIGURES vi
ABSTRACT vii

CHAPTERS

1 INTRODUCTION 1

2 LITERATURE REVIEW 5

3 DATA 10

4 METHOD 14

Materials 14
Implicit Association Test (IAT) 14
Demographic Questions 17
Explicit Measures 18
Qualitative Questions 18
Procedure 19

5 RESULTS 21

Regressions 21
Negative D-Scores 30
Explicit Bias Results 32
Qualitative Results 35

6 CONCLUSION 41

REFERENCES 45

APPENDICES
A Categorizations of STEM, Humanities, and Social Science 48
B Explicit Bias Survey and Pictures 50
C Institutional Review Board Exemption Letter 53

LIST OF TABLES

Table 1 Demographic Information of University of Delaware Undergraduates versus Participants 10

Table 2 Variable Information 12

Table 3 Targets and Categories for IAT 15

Table 4 Results from regressions 24

Table 5 Regression Results With Major Dummy Variables 27

Table 6 Regressions with Differences in Number of Female STEM Professors . 29

Table 7 Differences in Male and Female Evaluations 32

Table 8 Different in Male and Female Evaluations by Student Gender 33

Table 9 Explicit Question Results Separated by Race 34

LIST OF FIGURES

Figure 1 IAT Screenshot 15

Figure 2 Survey Flow 20

Figure 3 Black Female Professor 51

Figure 4 Black Male Professor 51

Figure 5 White Female Professor 52

Figure 6 White Male Professor 52

ABSTRACT

This paper considers whether having female professors in STEM (Science, Technology, Engineering, and Mathematics) fields effects students' implicit associations about women in STEM. This is important because STEM jobs are expected to increase more than other fields in the coming years, yet the number of female STEM majors has been decreasing. The main reason for the decrease is gender stereotypes facing women in STEM. To see if there was a relationship, I administered a survey to 754 undergraduate students where they completed an Implicit Association Test (IAT), answered demographic questions, completed an explicit bias exercise, and answered questions about their experience in STEM. This study found that there was no meaningful relationship between the number of female STEM professor a student has and their implicit associations.

Chapter 1

INTRODUCTION

In 2014 there was a decline in women enrolled in STEM (Science, Technology, Engineering, and Mathematics) Bachelor Degrees when compared to enrollment in 2004 (Rampell, 2015). The study by the National Student Clearinghouse found that enrollment in Engineering, Computer Science, Earth, Atmospheric, and Ocean Sciences, Mathematics, Biological and Agricultural Sciences, and Social Sciences and Psychology have all seen a decrease in the amount of women attaining Bachelor's degrees in those fields. These declines range from 1% to 5%. This contradicts that fact that women are enrolling in colleges at higher rates than men, and the National Center for Education Statistics expected that women would account for the majority of college students by fall 2017 ("The NCES Fast Facts Tool provides quick answers to many education questions (National Center for Education Statistics)," n.d.). Ernesto Reuben, Paola Sapienza, and Luigi Zingales say that this discrepancy is due to the effects of negative sex-based stereotypes. This is a problem because the country is emphasizing the need for STEM education, but the number of women in STEM is dropping. President Barack Obama made STEM education a priority, he called on the nation to develop, recruit, and retain 100,000 teachers over the next 10 years, and emphasized that this needs to include underrepresented groups; however, this will not happen if these underrepresented groups are not majoring in STEM ("Science, Technology, Engineering and Math: Education for Global Leadership | U.S. Department of Education," n.d.). The Department of Education predicts that between 2010 and 2020 that employment in all occupations will increase by 14% but STEM fields, specifically Mathematics, Computer Systems Analysis, Systems Software Developers, Medical Scientists, and Biomedical Engineers, will have increased employment ranging from 16% to 62% ("Science, Technology, Engineering and Math: Education for Global Leadership | U.S. Department of Education," n.d.). Not only are STEM fields expected to see an increase in employment compared to other fields, but on average jobs in STEM fields pay more money than jobs outside STEM fields. A report by Emily Forrest Cataldi, Peter Siegal, Bryan Shepherd, and Jennifer Cooney found that in 2012 STEM majors on average earned $65,000 working full time while non-STEM majors earned $49,500 on average. Despite all these advantages to majoring in STEM, female STEM majors are still in decline.

A report by Catherine Hill, Christianne Crobett, and Andresse St. Rose looked into why there are so few women in STEM. They found that two stereotypes were present to keep women out of STEM: girls are not as good at science as boys are and scientific work is better suited for men. However, this has proven to be false. A study by Ernesto Reuben, Paola Sapienza, and Luigi Zingales found that girls and boys in high school perform just as well on standardized tests, suggesting that they are just as prepared to major in STEM in college. Despite the fact that girls perform just as well as boys on standardized tests in math and science, stereotypes still exist that keep girls out of STEM. Yingyi Ma investigated this question when she inspected the pathways that women and men follow to achieve bachelor's degrees in STEM. She found that women were just as persistent as men in attaining their STEM degree when they declared a major in STEM in college (Ma, 2011). Ma also found that women had lower self-assessment of their math skills than men which plays into whether they decide to major in STEM (Ma, 2011). Even when women decide to major in STEM they are still faced with different biases.

Females in STEM fields face biases in the hiring process, in publishing their scientific work, and in the workplace. A study found that when employers had to choose between a male and female candidate to perform an arithmetic test, and had no information besides the candidates' appearance, they were twice as likely to choose the male candidate (Reuben, Sapienza, & Zingales, 2014). Once female candidates are hired they face biases regarding publishing their research in scientific journals. Studies have found that female abstracts written by women are rated lower than men's, women are less likely to receive funding from government agencies, men publish more papers in STEM fields than women, and women are less likely to be principal investigators (Knobloch-westerwick, Glynn, & Huge, 2013). Another study by Joan C. Williams, Katherine W. Phillips, and Erika V. Hall found that bias, rather than personal choices, are pushing women out of STEM, and they highlighted five key biases that women in STEM face: having to prove themselves over and over again to their colleagues, having to find the balance between being feminine and masculine, having their commitment to their job questioned if they have children, competing with other women for jobs in STEM fields, and feeling isolated from their colleagues.

Since bias in STEM is a persistent problem for women throughout their time in school and in STEM careers, the question is how can we eliminate this bias. This paper questions whether having female faculty in STEM fields affects students' implicit association about women in STEM. Other studies have emphasized the need for female role models in STEM fields (Lockwood, 2006; Marx & Roman, n.d.; Stout, Dasgupta, Hunsinger, & McManus, 2010), but it has not been shown that exposure to female STEM role models can decrease implicit biases toward women in STEM. A study by Jane G. Stout, Nilanjana Dasgupta, Matthew Hunsinger, and Melissa A. McManus found that seeing women in STEM did not change students' biases about STEM being a masculine field. They used three studies to come to this claim: they exposed participants to highly advanced peers, had participants read a biography about female engineers, and tracked students from the beginning to the end of their introductory calculus class (Stout et al., 2010). The current study adds to this literature by looking at undergraduate students at all years to see if the more exposure they have to female faculty changes their implicit associations towards women in STEM. This study goes beyond just looking at exposure to one female STEM professor to see if there needs to be longer exposure in order for implicit association to be affected.

In order to test this hypothesis, I administered a survey to undergraduate students at the University of Delaware. The survey asked for demographic information, had them take an Implicit Association Test (IAT), and asked them to answer questions about the competency of a male and female math professor. The results of this study show that there is not a statistically significant relationship between the number of female faculty in STEM courses that students' have and their implicit association between women in STEM.

Chapter 2

LITERATURE REVIEW

Several studies have found that having female role models is important for female. A study by Penelope Lockwood explored if students need role models of the same gender. She tested this through two different studies. First, she exposed college age students to mentors who are advanced in their careers, and she varied whether the student and mentor were of the same or opposite sex. She then had the students complete a self-evaluation. The results were that after female participants interacted with a female mentor they viewed themselves as being more able to be successful, while male mentors had no effect. Lockwood states that this is because seeing women in high level positions proves to younger women that they too can overcome gender discrimination. In the second study Lockwood had male and female undergraduate students describe the ideal role model who would inspire them to achieve their goals. She found that female undergraduates were more likely to choose a female as their role model than a man, and they indicated that the role model's gender was a motivating factor (Lockwood, 2006).

Another study by David M. Marx and Jasmin S. Roman found that having female role models had an effect on women's performance on a math test. They used three studies to support their conclusion. In the first study they had male and female students take a math test that was either administered by a male or female experimenter, and the proctor told them that they were about to take a difficult exam that they created to show that the proctor was competent in their math ability. They found that female students performed just as well as male students and had higher self-esteem scores when a female administered the test, but when a male administered the test they had lower performance and self-esteem scores. In the second study they were testing whether a female role model needs to be present to have an effect on the students' math performance and self-esteem. For this study, they had the students enter the testing center where they found a note on the door explaining that the female proctor would be late and they should begin the exam anyway. Unlike the other two studies, the results of study 2 were not as clear. They found that having a competent female proctor did help the female students' test scores, but did not help their self-esteem. For the third study they wanted to test if the female proctor's math ability had an effect on the students' test and self-esteem scores. This study was performed the same as study 2, but the students were told whether or not their proctor was good at math. Results showed that female students reported high self-esteem scores when they were told the proctor was competent in math (Marx & Roman, n.d.).

Other research on women and STEM has looked at the impact that female role models in STEM have on girls in the field or looking to enter the field. Dasgupta and Asgari found that women who encounter more women who embody counterstereotypic behavior are more likely to join STEM fields (Dasgupta & Asgari, 2004). They tested whether exposure to women in leadership positions undermined women's automatic gender stereotypic beliefs. Dasguta and Asgari found that women who encountered mostly male faculty in STEM related fields were more likely to hold stereotypes about women, but if they were exposed to more female faculty, these stereotypes that they held decreased. Similarly, Cheryan, Siy, Vichayapa, Drury, and Kim found that the when trying to recruit more women in STEM fields the gender of the role model does not matter. Instead, it matters whether these role models fit stereotypes that do not match up with female stereotypes. For example, a stereotype about women is they are helpful and socially skilled, while a stereotype about computer scientist is that they are computer nerds and socially awkward. If a role model shows themselves to be antisocial and unhelpful, going against a female stereotype, this will prevent women from entering the STEM field, whether the role model is male or female (Cheryan, Siy, Vichayapai, Drury, & Kim, 2011). Therefore, previous research has shown that the gender of the role model does not matter when it comes to getting more women to enter STEM fields.

Another group of papers exploring the role of women in STEM has investigated the stereotypes that women, men, STEM majors, and non-STEM majors hold about women in STEM. Smeding studied whether implicit associations about women and math would be weaker among female engineering students compared to female humanities students, male engineering students, and male humanities students. She found that female engineering students had weaker gender-math implicit associations than the other three groups, and that all groups assumed that the female humanities students would have lower grades in math (Smeding, 2012). A similar study completed by Steffens and Jelenec found that males had a stronger math-male stereotype, while women held a stronger female-language stereotype. Also, this study showed that females were more aware of the math-male stereotypes than their male counterparts (Steffens & Jelenec, 2011). Both of these studies are important because they both utilized implicit association tests. Smeding's research used the Implicit Association Test (IAT), which is the same association test that I utilize in my research, while Steffens and Jelenec used the Go/No-go Association Task (GNAT).

A paper by Lynn Farrell and Louise McHugh titled, "Examining gender-STEM bias among STEM and non-STEM students using the Implicit Relation Assessment

Procedure" tested whether male STEM, male non-STEM, female STEM, and female non-STEM majors had the same bias towards women in STEM. To test this they utilized an Implicit Relational Assessment Procedure (IRAP) which has participants sort phrases into true or false. Participants are presented with the phrase "Men/women are more suited for arts/STEM" and had to sort them into true or false depending on the instructions for that round. One round they had to say that men were suited for STEM and women were suited for arts, and then it switched the next round. The results were that all four groups had a significant bias towards men in STEM, but there was evidence of positive bias towards females in STEM from the female STEM majors (Farrell & McHugh, 2017).

The research most similar to this paper is by Beaman, Chattapadhyay, Duflo, Pande, and Topalova. They looked at the gender quota system in India to determine if having more exposure to female leadership decreased constituents' bias about women in leadership positions (Beaman et al.). They found that "although deep preferences and social norms remain difficult to erode, beliefs on effectiveness are much more malleable, and they play a role in the voting decision. In the setting we study, we see an improvement in voter perceptions of female leaders, followed by electoral gains for women" (Beaman, Chattopadhyay, Duflo, Pande, & Topalova, 2009). To complete their study they utilized an IAT to measure gender-occupation stereotypes and to study the association with female and bad and male with good traits.

I will be contributing to this body of research to see if bias can be reduced by exposure to female professors in STEM fields, in the same way that it reduces bias for women in political leadership positions. My research will be similar to others in this area because I am looking at implicit associations by using an IAT; however, I am not looking at female versus male perceptions of women in STEM, I am instead looking to see if female professors can help diminish these harmful stereotypes. This research is useful to universities and school districts because it provides policy recommendations to decreases harmful stereotypes about women in STEM which will increase women's self-esteem and feeling as if they belong in STEM fields (Murphy, Steele, & Gross, 2007) and cause more women to get involved in STEM fields (Cheryan, Plaut, Davies, & Steele, 2009).

Chapter 3

DATA

For this paper I am using cross-sectional data obtained from a survey distributed to undergraduate students at the University of Delaware during spring of 2018. 754 students participated in the survey and 95 were excluded. 55 (38 females, 14 males, and 3 did not provide a gender) were excluded because they did not fill out all parts of the survey, and 40 (31 females, 8 males, and 1 no gender given) were excluded because they did not score high enough on the IAT which will be addressed later. This survey was sent to undergraduate students in the Alfred Lerner College of Business and Economics, the College of Engineering, the College of Arts and Sciences, the College of Health Sciences, the College of Agriculture and Natural Resources, and the College of Earth, Ocean, and Environment. Since each school sent this survey out to every undergraduate in their list-serve, which includes majors and minors, some students received the survey multiple times. The only undergraduates who did not receive the survey are those who are only in the School of Education. Due to this I will be comparing the statistics of my response rate to that of the entire undergraduate population at the University of Delaware. Table 1 shows demographic information about the participants in this study compared to undergraduates at the University of Delaware based on 2017 statistics (Campus, 2017).

Table 1 Demographic Information of University of Delaware Undergraduates versus Participants

	UD 2017	Participants
Female	57.6%	73.7%
White	72.3%	84.2%

Table 1 continued

African-American	5.2%	2.0%
Hispanic	7.9%	3.4%
Asian	5.1%	4.8%
Other Race	9.4%	5.3%

There is a difference of 16.1% between the percentage of women who completed the survey and the percentage of women at the University of Delaware. This could be explained by the fact that in the email recruiting participants to take part in the survey it mentioned that it was looking at the association between students' implicit associations and the number of female faculty in STEM fields they have had. The fact that it mentioned female faculty could have made this survey appeal more to female students than male students. The biggest discrepancy in percentage based on race is that 11.9% more white students completed the survey than the percentage of white students at the University of Delaware.

Another discrepancy in the data is that STEM was narrowly defined in the survey. The survey defined STEM as Science, Technology, Engineering, and Mathematics so it left a lot up to interpretation of the participant. For example, there is a debate about whether economics and nursing are considered part of the STEM field. This affects whether students said they were going into a STEM field, how many STEM courses they have taken, and how many female STEM professors they have had. In the appendix I provide a list of what I consider to be STEM, humanities, and social science majors for this paper.

Table 2 gives information about the variables used in the study.

Table 2 Variable Information

Data	Variable Name	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
D-score	D	753	.302	.4208	-.873	1.392
Percentage of Female STEM faculty	PFF	753	.431	.413	0	9
Year in school	Year	753	1.523	1.127	0	4
Major	Maj	753	.920	1.149	0	6
Do they plan to attend graduate school	GS	753	.348	.477	0	1
Do they plan to go into the STEM field	STEM	753	.428	.495	0	1
Career Field they aspire for	CF	753	13.337	4.987	0	19
Do they prefer math or English	Eng	753	.458	.499	0	1
Do they prefer science or humanities	Hum	753	.380	.486	0	1
Confidence in math	CM	753	2.788	.889	1	4
Confidence in science	CS	753	2.831	.885	1	4
Gender of advisor(s)	GA	753	.595	.670	0	2
Age	Age	753	20.260	2.631	18	68

Table 2 continued

Gender	Gender	753	.270	.459	0	2
Race	Race	753	.673	1.804	0	9
Religion	Rel	753	7.367	6.293	0	16
Zip code of hometown	Zip	753	17943.78	28272.03	1022	518000
Percentage of women in family	PWF	753	.536	.178	0	1
Parents' marital status	MS	753	.304	.641	0	3
Parents' highest education level	HE	753	2.317	1.240	0	5
Mother's field of work	FM	753	11.770	4.230	0	20
Father's field of work	AB	753	11.770	5.440	0	20
Step-mother's field of work	FSM	753	20.465	2.261	2	21
Step-father's field of work	FSF	753	20.486	2.517	2	21
Family income	FI	753	3.438	1.336	0	5

Chapter 4

METHOD

Ethical approval was obtained for this study from the University of Delaware's Institutional Review Board and all participants gave their consent to participate in this study.

Materials

The survey was conducted using Qualtrics and emailed out to participants. Participants had to take the survey on a computer because the IAT portion of the survey does not work on a mobile device.

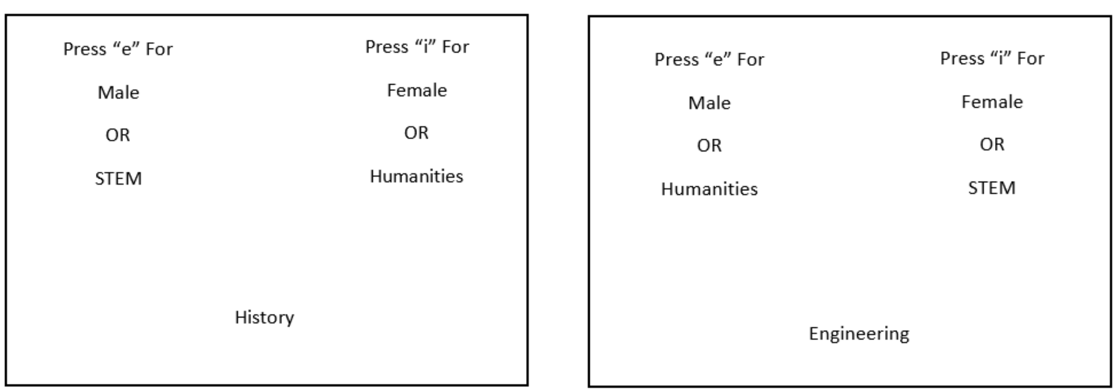
Implicit Association Test (IAT)

Implicit attitudes are thoughts that are automatic and occur without our awareness. In order to measure these implicit attitudes, the Implicit Association Test (IAT) is often used. It was created by Anthony G. Greenwald, Debbie E. McGhee, and Jordan L. K. Schwartz, and the scoring algorithm was improved in a later paper (A. G. Greenwald et al., 2002; A. G. Greenwald, McGhee, & Schwartz, 1998; A. G. Greenwald, Nosek, & Banaji, 2003). The IAT works by assessing the association between target pairs and categories, in this case men and women and STEM and Humanities. Table 3 shows the stimuli that participants had to sort in their IAT. For this survey I used the IAT developed by Iatgen which can be used in Qualtrics (Carpenter et al., 2018). Figure 1 shows an image of the IAT to better explain it. First, the participants are given instructions which tells them to sort the terms as quickly as they can making as few mistakes as possible. They will hit the "e" button to sort words to the left side of the screen and the "i" button to sort things to the right side of the screen. Next, they are shown a screen with male and female in the top corners. Then, target words are displayed in the middle of the screen one after the other, and the participants need to sort them properly. They are then told whether to pair male and STEM words or female and STEM words together. Next, target and category words appear in the middle of the screen and the participants have to sort them properly. If they make a mistake, an "X" appears on the screen and they have to re-sort it. Whether the participants are asked to sort male and STEM or male and humanities first varies each time, and then they will be switched. There are seven blocks to complete.

Table 3 Targets and Categories for IAT

Male	Female	STEM	Humanities
Boy	Girl	Science	Arts
His	Hers	Math	English
He	She	Physics	Drama
Him	Her	Chemistry	Music
Mr	Mrs	Computing	French
Men	Women	Engineering	History

Figure 1 IAT Screenshot



The idea behind the IAT is that participants will have an easier time matching targets and categories that they mentally associate with each other. For example, if they associate vegetables with healthy and ice cream with unhealthy then they will have faster responses matching vegetables with healthy categories as opposed to unhealthy categories. The IAT is measured using a D-score where a score of 0 means that the participant has no association, a positive score means that they have an association between the compatible block (male and STEM), and a negative score means they have an association with the incompatible block (female and STEM). The following scoring algorithm was created by Greenwald, Nosek, and Banaji and outlined by Kristin Lane, Mahzarin Banaji, Brian Nosek, and Anthony Greenwald:

1. Delete trials greater than 10,000 msec
2. Delete subjects for whom more than 10% of trials have latency less than 300 msec
3. Compute the “inclusive” standard deviation for all trials in Stages 3 and 6 and likewise for all trials in Stages 4 and 7
4. Compute the mean latency for responses for each of Stages 3,4,6 and 7
5. Compute the two mean differences ($\text{Mean}_{\text{Stage6}}$ – $\text{Mean}_{\text{Stage3}}$) and ($\text{Mean}_{\text{Stage7}}$ – $\text{Mean}_{\text{Stage4}}$)
6. Divide each difference score by its associated “inclusive” standard deviation
7. D = the equal weight average of the two resulting ratios (Lane, Banaji, Nosek, & Greenwald, 2007)

Due to this scoring algorithm 40 responses were deleted because they did not fit the criteria to receive a proper D-score. These consisted of 31 responses from females, 8 responses from males, and 1 response without a gender given.

A study by T. Andrew Peohlman, Eric Luis Uhlman, Anthony G. Greenwald, and Mahzarin R. Banaji conducted a meta-analysis of 61 studies that used the IAT to determine the extent to which the IAT measures were predictive. They found that the IAT was the most significant measure, over explicit measures, when the study involved stereotyping (A. G. A. Greenwald et al., 2009). Since this study deals with stereotyping, the IAT is the better measure to use instead of using explicit measures.

Demographic Questions

In the second part of the survey, participants were asked to answer different demographic questions. One block of questions asked for their year in school, major(s), whether they plan on attending graduate school, whether they want to enter a STEM field, what field they aspire to have a career in, whether they prefer math or English, whether they prefer science or humanities, rank their confidence in math on a scale from 1 (not confident) to 4 (really confident), rank their confidence in science on the same scale, how many STEM courses they have taken, how many of those courses were taught by female faculty, and the gender of their academic advisor(s). In the next block of questions they were asked their age, gender, race, religion, zip code of their hometown, the number of women in their immediate family, the number of men in their immediate family, their parents' marital status, their parents' highest education level, the field their mother, father, step-mother, and step-father work in, and their family income. The categories for careers were taken from the North American Industry Classification System ("North American Industry Classification System," 2017).

Explicit Measures

The last part of the survey measured students' explicit associations which are associations that they are aware of. Utilizing the survey from Pasha-Zaidi and Afari students were asked to rate a professor's teaching effectiveness. They were first shown a picture of either a black male, a black female, a white male, or a white female, and told that this was their math instructor for the next semester. Next, they were asked 14 questions about the teacher and asked to rate each question on a scale of 1 (strongly disagree) to 4 (strongly agree) (See appendix) (Pasha-Zaidi & Afari, 2016). They were then shown the corresponding picture and asked the same questions (if they were first shown a black male then they were shown a black female).

To evaluate the data I will be taking the difference between the score that the participant gave to the female professor and the male professor for each question. Then, I will take the average of all the differences for each participant to create an explicit bias score. This score will then be incorporated into the regressions. In the study by Poehlman, Uhlmann, Greenwald, and Banaji they found considerable promise that using the IAT along with self-report measures would improve predictions. Due to this I will be adding the explicit measures of each participant into the regressions.

Qualitative Questions

At the end of the survey students were given the option to answer 5 questions:

1. Have you experienced prejudice/discrimination in STEM fields? If so how?
2. Have you witnessed prejudice/discrimination in STEM fields? If so how?

3. How have professors impacted your career goals and aspirations?

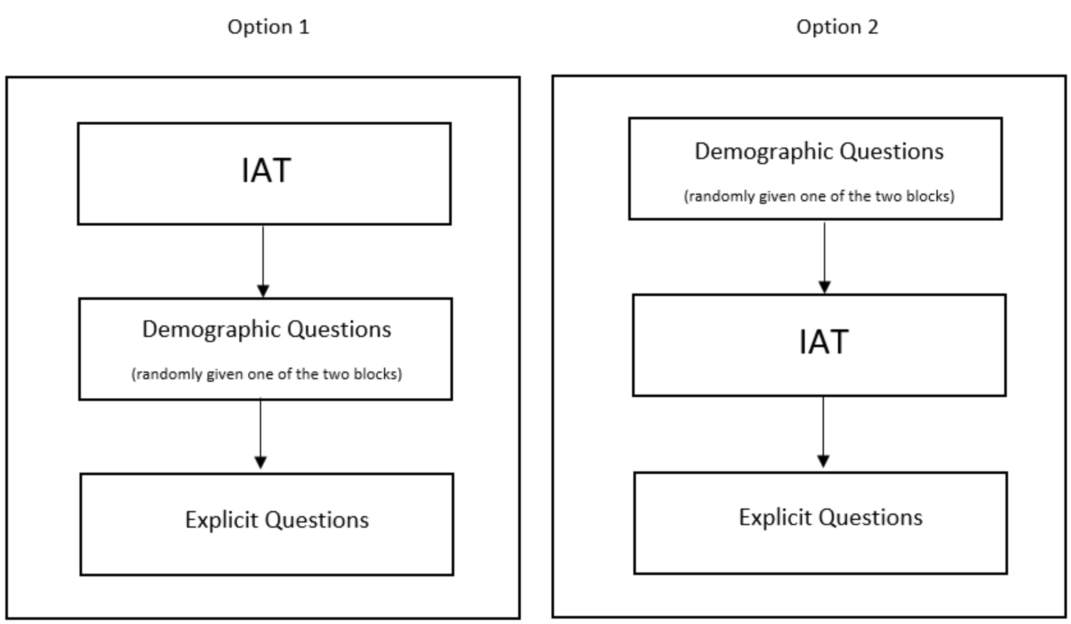
4. How have professors impacted your self-esteem as a student?

5. Do you think the University of Delaware has gender equality in STEM fields?

Procedure

The survey was set up to give participants different parts of the survey randomly. Figure 2 illustrates how the participants were given the survey. First, the participants were randomly given either the IAT or the demographic questions. The demographic questions were split into two blocks: one focused on individual questions (year, major, do you plan to attend graduate school, do you want to go into the STEM field, what career do you aspire to be in, do you prefer math or English, do you prefer science or humanities, rank your confidence in math, rank your confidence in science, how many STEM courses have you taken, how many STEM courses were taught by female professors, and what gender is your academic advisor(s)), and the second block focused more on questions pertaining to the family (age, gender, race, religion, zip code of your hometown, number of women in your immediate family, parents' marital status, parents' highest education level, what field do your mother, father, step-mother, and step-father work in, and family income). These two blocks were also presented to the participants in a random order. After completing both the IAT and demographic questions the participants were given the explicit part of the survey, and then at the end they were asked questions about their experience in STEM at the University of Delaware.

Figure 2 Survey Flow



Questions have been raised in the past about whether it matters how closely administered the IAT and explicit measures are to each other and whether this will affect scores. The meta-analysis by Poehlman, Uhlmann, Greenwald, and Banaji found no evidence that the ordering of the IAT and explicit measures affected the correlation between the two scores.

Chapter 5

RESULTS

Regressions

I will now investigate if there is an effect on implicit associations based on the percentage of female STEM faculty that a student has had. In order to do this I considered eight different regression models. First, I created a dummy variable, Male, which equals 1 if the person is a male and 0 otherwise. The first regression, Equation 1, is used to see the relationship between the independent variable, the D-score, and the main variable of interest, the percentage of female faculty. There is not a problem with endogeneity between D and PFF because out of all the STEM courses offered at the University of Delaware only about 7% give students the option to choose between a male or female professor. A majority of the time the class is only taught by one professor or the different professors that teach different sections are the same gender.

$$D_i = \alpha + \beta_1 PFF_i + e_i \tag{1}$$

As Table 4 shows there is a negative relationship between the D-score and the percentage of female faculty; however, this result is statistically insignificant and there is a lot of omitted variable bias. Therefore, I added more variables to control for this bias. For Equation 2 I added variables of interest including gender, age, and major.

$$D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + e_i \tag{2}$$

In this regression the PFF stays negative and insignificant while both the coefficients on the male and major coefficients is significant (at 10% and 1% respectively). Although these two coefficients are significant there is still a lot of omitted variable bias since we are not controlling for demographic or academic information, so in the third equation I added demographic information.

$$(3)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + e_i$$

After running this regression the coefficients for male and major still stayed statistically significant. For the fourth regression I added academic variables including their year in school, if they want to attend graduate school, if they want to pursue a career in STEM, what career field they want to go into, the gender of their academic advisor(s), and the number of STEM courses they have taken. These variables were added to control for a student's academic preferences. Whether they want to pursue a career in STEM may affect their bias because as Lynn Farrell and Louise McHugh found females in STEM, unlike other gender-major combinations, are likely to have a positive female STEM association. Also, the gender of their advisor(s) was added to make sure that the results on the D-score had to do with the female STEM professors they had not the gender of their advisor(s).

$$(4)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + \beta_7 Year_i + \beta_8 GS_i + \beta_9 STEM_i + \beta_{10} CF_i + \beta_{11} GA_i + \beta_{12} NSTEM_i + e_i$$

For the fifth regression I added their preferences towards STEM or non-STEM fields including if they prefer mathematics or English, if they prefer science or humanities, their confidence in math, and their confidence in science. These were added because this can affect how they view people's abilities both in and outside their own gender. For example a female student who has high confidence in their math and science ability may have a positive association between females in STEM.

$$(5)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + \beta_7 Year_i + \beta_8 GS_i + \beta_9 STEM_i + \beta_{10} CF_i + \beta_{11} GA_i + \beta_{12} NSTEM_i + \beta_{13} Eng_i + \beta_{14} Hum_i + \beta_{15} CM_i + \beta_{16} CS_i + e_i$$

In the sixth regression family information is added to ensure that the implicit association is due to the percentage of female faculty that a student has had not based on family information such as the career field of their parents or the number of women in their family.

$$(6)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + \beta_7 Year_i + \beta_8 GS_i + \beta_9 STEM_i + \beta_{10} CF_i + \beta_{11} GA_i + \beta_{12} NSTEM_i + \beta_{13} Eng_i + \beta_{14} Hum_i + \beta_{15} CM_i + \beta_{16} CS_i + \beta_{17} PWF_i + \beta_{18} MS_i + \beta_{19} HE_i + \beta_{20} FM_i + \beta_{21} FF_i + \beta_{22} FSM_i + \beta_{23} FSF_i + \beta_{24} FI_i + e_i$$

The seventh regression added the explicit bias variable.

$$(7)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + \beta_7 Year_i + \beta_8 GS_i + \beta_9 STEM_i + \beta_{10} CF_i + \beta_{11} GA_i + \beta_{12} NSTEM_i + \beta_{13} Eng_i + \beta_{14} Hum_i + \beta_{15} CM_i + \beta_{16} CS_i + \beta_{17} PWF_i + \beta_{18} MS_i + \beta_{19} HE_i + \beta_{20} FM_i + \beta_{21} FF_i + \beta_{22} FSM_i + \beta_{23} FSF_i + \beta_{24} FI_i + \beta_{25} Exp_i + e_i$$

The last regression absorbed the zip codes of all the participants to serve as a proxy for socioeconomic status.

$$(8)\quad D_i = \alpha + \beta_1 PFF_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Maj_i + \beta_5 Race_i + \beta_6 Rel_i + \beta_7 Year_i + \beta_8 GS_i + \beta_9 STEM_i + \beta_{10} CF_i + \beta_{11} GA_i + \beta_{12} NSTEM_i + \beta_{13} Eng_i + \beta_{14} Hum_i + \beta_{15} CM_i + \beta_{16} CS_i + \beta_{17} PWF_i + \beta_{18} MS_i + \beta_{19} HE_i + \beta_{20} FM_i + \beta_{21} FF_i + \beta_{22} FSM_i + \beta_{23} FSF_i + \beta_{24} FI_i + \beta_{25} Exp_i + e_i, \text{ absorb (Zip)}$$

The results of these regressions are presented in Table 4.

Table 4 Results from regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8a)
PFF	-.01336 (.03720)	-.02606 (.03692)	-.02365 (.03707)	-.02921 (.0377)	-.03347 (.03756)	-.04181 (.04358)	-.04637 (.04405)	-.05235 (.06592)	-.01810 (.04973)
Male		.08138** (.03471)	.08558** (.03519)	.09438*** (.03545)	.11182*** (.03548)	.11889*** (.03685)	.12040*** (.03739)	.08555 (.05407)	.09256** (.04138)
Maj		.06174** (.01320)	.06044*** (.01321)	.03516** (.01728)	.02581 (.01751)	.02796 (.01761)	.02809 (.01771)	.03634 (.02727)	.02714 (.02054)
Year				.03822** (.01823)	.02968* (.01825)	.03058* (.01843)	.03039* (.01859)	.00356 (.02727)	.01853 (.02124)
CM					-.00789 (.021940)	-.00936 (.02209)	-.00878 (.02235)	-.01051 (.03377)	-.02688 (.02648)
CS					-.04426*** (.02378)	-.04651** (.02392)	-.04879** (.02415)	-.04374 (.03645)	-.04092 (.02862)
intercept	.30813*** (.02205)	.28030** (.12074)	.26464** (.12273)	.33280** (.14155)	.43570*** (.16544)	.32852 (.25283)	.35166 (.25478)	.26548 (.33305)	.28128 (.28916)
R-squared	-.0012	0.0308	0.0323	0.0362	0.0530	.0553	.0538	.1051	.0189

Significant at 10% level = * | Significant at 5% level = ** | Significant at 1% level = ***

This table shows that the coefficient for percentage of female faculty is statistically insignificant throughout all the regressions, and gender, year, major, and confidence in science remain statistically significant up until the last regression. Interpreting the coefficients in regression 7 shows that for each additional year, holding everything else constant, the D-score increases by 0.03039 points and is significant at 10%. Holding everything else constant, as a student's confidence in science increases, their D-score decreases by 0.04879 points, which is significant at the 5% level. Lastly, holding everything else constant, male students have D-scores 0.12040 points higher than female students, which is significant at 1% level. Another interpretation is that increasing year by one standard deviation increases the D-score by 0.08523 standard deviations, and increasing a student's confidence in science by one standard deviation decreases their D-score by 0.09774 standard deviations.

In the eighth regression there were a total of 414 zip codes absorbed, which greatly increased the degrees of freedom. To account for this, I then ran the same regression, but only used the first three digits of the zip codes as a proxy for socioeconomic status. This regression used a total of 187 zip codes. The results of this regression are shown in Table 4 under column (8a). The only coefficient that stayed significant was male. This means, holding everything else constant, male students have D-scores 0.09256 points higher than female students, and this is significant at 5% level. Also, this regression had an adjusted R^2 of 1.89% while the R^2 for the 7th regression was 5.38%. Since using zip codes as a proxy for socioeconomic status muddied up the results, and since I am already controlling for family income and parents' highest education level for the rest of the regressions I will not be using zip codes.

Seeing that major stayed statistically significant up until the last regression, I decided to separate major into three different dummy variables: STEM_Major, Non_STEM_Major, and STS_Major. STEM_Major equals 1 if the person is a STEM major and 0 otherwise; Non_STEM_Major equals 1 if the person is a humanities, social science, a double major between humanities and social sciences, or undeclared and 0 otherwise; and STS_Major equals 0 if the person is a STEM and humanities double major or a STEM and social science double major. I then ran the same 7 regressions (leaving out regression 8) above but replaced Maj with STEM_Major and STS_Major, Non_STEM_Major was the omitted variable in these regressions. The results are in Table 5.

Table 5 Regression Results With Major Dummy Variables

Variables	(2)	(3)	(4)	(5)	(6)	(7)
PFF	-.03335 (.03691)	-.03084 (.03705)	-.02962 (.03772)	-.03385 (.03757)	-.04272 (.04361)	-.04719 (.04408)
Male	.08596*** (.03474)	.09011*** (.03521)	.09369*** (.03551)	.10994*** (.03557)	.11700*** (.03691)	.11843*** (.03746)
Maj						
STEM_Major	- .16534*** (.03112)	- .16307*** (.03112)	- .12583*** (.05054)	-.08519 (.05332)	-.08433 (.05387)	-.08430 (.05428)
STS_Major	-.04243 (.09580)	-.05444 (.09598)	-.03089 (.10051)	.01225 (.10158)	.02990 (.10263)	.03148 (.10318)
Year			.03642** (.01825)	.02907 (.01826)	.02997 (.01844)	.02981 (.01861)
CM				-.00710 (.02387)	-.00862 (.02211)	-.00805 (.02237)
CS				-.04269* (.02387)	-.04528* (.02400)	-.04758** (.02423)
intercept	.45313*** (.12360)	.43373*** (.12563)	.47341*** (.15300)	.52302*** (.17419)	.40084 (.25684)	.42400* (.25886)
R-squared	0.0379	0.0394	0.0379	0.0529	0.0550	0.0535

Significant at 10% level = * | Significant at 5% level = ** | Significant at 1% level = ***

These results also show that the coefficient on percentage of female faculty in STEM fields is statistically insignificant. The coefficients for male and confidence in science are statistically significant. Interpreting the male coefficient means that males, controlling for everything else, have a .1184317 higher D-score than females. The coefficient on confidence in science means that, holding everything else constant, if a student's confidence in science increases by one scale (say 1 to 2) their D-score decreases by -.047575 points. Another interpretation is increasing a student's confidence in science by one standard deviation decreases their D-score by 0.09502 standard deviations.

Next, I wanted to see if it matters how many female STEM faculty a student has. To test this I made 4 variables: Fem_Fac_0, Fem_Fac_1, Fem_Fac_2, and Fem_Fac_3. Fem_Fac_0 equals 1 if they have had 0 female STEM professors, Fem_Fac_1 equals 1 if they have had 1 female STEM professor, Fem_Fac_2 equals 1 if they have had 2 female STEM professors, and Fem_Fac_3 equals 1 if they have had 3 or more female STEM professors. I then ran the same seven regressions above, changing PFF for Fem_Fac_1, Fem_Fac_2, and Fem_Fac_3, Fem_Fac_0 was the omitted variable in these regressions. The results are in Table 6.

Table 6 Regressions with Differences in Number of Female STEM Professors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fem_Fac_1	-.02069 (.06339)	-.02267 (.06260)	-.02571 (.06236)	-.02539 (.06289)	-.03154 (.06253)	-.02950 (.06338)	-.02837 (.06391)
Fem_Fac_2	-.07695 (.06252)	-.03152 (.06246)	-.03674 (.06254)	-.04639 (.06290)	-.05203 (.06249)	-.05209 (.06356)	-.05573 (.06403)
Fem_Fac_3	-.12079** (.05692)	-.04297 (.05949)	-.04439 (.05972)	-.04964 (.06162)	-.05158 (.06130)	-.05573 (.06854)	-.05969 (.06924)
Male		.08591*** (.03488)	.09000*** (.03537)	.09193*** (.03565)	.10808*** (.03572)	.11454*** (.03704)	.11532*** (.03758)
Maj							
STEM_Major		-.15123*** (.03495)	-.14959*** (.03497)	-.11907** (.05122)	-.07797 (.05384)	-.07526 (.05424)	-.07425 (.05470)
STS_Major		-.02994 (.09648)	-.04309 (.09673)	-.02511 (.10086)	.01853 (.10190)	.03723 (.10341)	.03923 (.10372)
Year				.03910** (.01835)	.03181* (.01836)	.03338* (.01846)	.03361* (.01863)
CM					-.00652 (.02202)	-.00826 (.02218)	-.00768 (.02244)
CS					-.04238* (.02405)	-.04445* (.02413)	-.04659* (.02436)
intercept	.38498*** (.05282)	.44053*** (.12818)	.42644*** (.12981)	.49282*** (.15979)	.54038*** (.17985)	.41885 (.26221)	.44045* (.26434)
R-squared	.0077	0.0350	0.0367	0.0355	0.0504	0.0522	0.0506

Significant at 10% level = * | Significant at 5% level = ** | Significant at 1% level = ***

This table shows that no matter how many female STEM professors a student has it does not affect their D-score. These regressions do show that for every additional year, a students' D-score increases by 0.03361 points, as their confidence in science increases their D-score decreases by 0.04659 points, and males have D-scores 0.11532 points higher than female students. These are significant at 10%, 10% and 1% levels respectively. This also means that increasing year by one standard deviation increases the D-score by 0.09368 standard deviations, and increasing a student's confidence in science by one standard deviation decrease their D-score by 0.09303 standard deviations.

One thing to note about all these regressions is they have lower R^2. Most of the R^2s are around 5%. In the literature around IATs and STEM the R^2s are generally around 18 or 22% (Dasgupta & Asgari, 2004; Nosek & Smyth, 2011). The R^2s in this study are low because they do not take into account variables from the students' high school years, such as how many female STEM teachers they had in high school, whether their school promoted STEM, and their math SAT scores. These regressions also do not take into account the number of males and females in different majors. For example, since nursing is a female dominated field, this may affect students' implicit associations because they see females as being more competent in STEM since that is what they are exposed to.

Negative D-Scores

The majority of participants in this study had positive D-scores meaning that they have a positive association between men and STEM; however, 23.08% of respondents had a negative D-score, meaning they have a positive association between females and STEM. Of these respondents with negative D-scores, 67.63% were STEM majors, 2.89% were humanities majors, 27.17% were social science majors, and 2.31% were STEM and social science majors. Also, 65.90% of the respondents preferred math to English and 73.40% preferred science to humanities. Similarly, 71.09% of respondents ranked their confidence in math as 3 or 4, and 73.41% ranked their confidence in science as 3 or 4. Finally, 78.03% of the respondents with negative D-scores were female.

Next, I wanted to see what percentage of the participants with negative D-scores were both female and a STEM major because Lynn Farrell and Louise McHugh found that female STEM majors tended to have a positive association between women and STEM, and I wanted to see if the same held true in this study. Of all the people who took part in the survey, 311 were female STEM majors, 9 were female STEM and humanities majors, and 4 were female STEM and social science majors. Of the participants with negative D-scores 101 were female STEM majors, 0 were female STEM and humanities majors, and 3 were female STEM and social sciences majors. Similarly, 108 people who completed the survey were male STEM majors, 1 was a male STEM and humanities major, and 9 were male STEM and social science majors. Of the participants with negative D-scores 14 were male STEM majors, 0 were male STEM and humanities majors, and 1 was a male STEM and social science major. This means that 32.48% of female STEM majors have a positive association between females and STEM compared to 12.96% of male STEM majors. Female STEM majors are more likely to have a negative D-score compared to male STEM majors. Similary, 75% of female STEM and social science majors have a negative D-score compared to 11.11% of males; however, this is a very small sample of STEM and social science majors so it would be interesting to see if the result holds with a larger sample size.

These results confirm Farrell and McHugh's study that female STEM majors have more of a possibility of a positive association between women and STEM. Also, people with negative D-scores prefer math and science and have high confidence in math and science. This is especially important for females because it shows a possible way to decrease the strong association between males and STEM. If we can increase girls' confidence in math and science we may be able to change their implicit associations between men and STEM. This is something that will need to be looked into further.

Explicit Bias Results

For the most part there was little difference between the rankings of male and female professors. Overall between 74.24% and 82.47% of respondents had no difference between the rating of the male or female professor. Questions 1, 2, 4, 6, 7, 9, and 13 measured the professor's professionalism while questions 3, 5, 7, 10, 11, and 12 measured the professor's warmth. The difference for each question are presented in Table 7.

Table 7 Differences in Male and Female Evaluations

Question	Preferred Female Professor	Preferred Male Professor
Professionalism		
1	13.55%	4.38%
2	11.82%	4.52%
4	15.27%	2.79%
6	15.01%	1.59%
7	16.33%	4.12%
9	14.48%	2.79%
13	13.94%	2.52%
Warmth		

Table 7 continued

3	23.51%	4.78%
5	18.06%	1.73%
8	15.67%	3.32%
10	18.59%	4.52%
11	21.51%	3.19%
12	19.79%	4.25%
14	19.12%	2.66%

This table shows that the female professor was preferred more than the male professor for each question. Female professors were preferred more for question 3: “The instructor will motivate me to succeed in the class”, and question 11: “The instructor is interested in student success”. The fewest people preferred the male professor for question 6: “The instructor will treat me fairly”, and question 5: “The instructor will treat me with respect”. These results are interesting because they contradict the fact that most of the respondents have a positive association between men and STEM, but more people rated the female professor higher than the male professor.

Next, I wanted to see if there was a difference in how the male and female professors were evaluated based on the student’s gender. The results are shown in Table 8.

Table 8 Different in Male and Female Evaluations by Student Gender

	Female Students		Male Students	
Question	Preferred Female Professor	Preferred Male Professor	Preferred Female Professor	Preferred Male Professor
Professionalism				
1	15.69%	5.11%	8.33%	2.60%
2	11.50%	5.29%	11.98%	2.60%
4	15.69%	2.37%	14.58%	4.17%

Table 8 continued

6	15.69%	1.28%	13.54%	2.60%
7	15.88%	4.74%	17.19%	2.60%
9	14.23%	3.28%	15.10%	1.04%
13	13.32%	3.10%	16.15%	1.04%
Warmth				
3	23.91%	4.38%	23.44%	5.21%
5	18.43%	1.82%	17.71%	1.56%
8	15.88%	3.28%	15.63%	3.65%
10	18.25%	3.65%	19.79%	6.77%
11	21.35%	3.83%	22.92%	1.04%
12	20.80%	4.56%	17.71%	3.65%
14	18.98%	2.55%	19.79%	2.60%

This table shows that both male and female students rated the female professor higher. One of the largest differences between male and female students was in question 1, "The instructor is an expert in his/her field." 15.69% of female students said that the female professor was more of an expert while 8.33% of male students said the female professor was more of an expert. For question 13, "This person will be an excellent instructor for this course," 2.83% more male students than female students ranked then female professor higher.

In Table 9 I break down the difference between male and female professors based on the professors' race.

Table 9 Explicit Question Results Separated by Race

	Black Professors		White Professors	
Question	Preferred Female Professor	Preferred Male Professor	Preferred Female Professor	Preferred Male Professor
Professionalism				
1	11.65%	3.79%	15.69%	5.05%
2	8.94%	4.87%	14.89%	4.26%
4	11.92%	3.25%	18.88%	2.39%

Table 9 continued

6	9.76%	1.08%	20.48%	2.13%
7	13.55%	3.79%	19.41%	20.21%
9	8.94%	2.98%	20.21%	2.66%
13	11.65%	1.90%	16.49%	3.19%
Warmth				
3	15.99%	4.87%	31.38%	4.79%
5	13.28%	1.90%	23.14%	1.60%
8	11.38%	3.52%	20.21%	3.19%
10	12.73%	4.34%	24.73%	2.66%
11	14.09%	3.79%	29.26%	2.66%
12	14.09%	3.52%	25.80%	5.05%
14	14.63%	2.17%	23.94%	3.19%

This table shows that female professors are preferred regardless of race. Regardless of looking at professionalism or warmth female professors are rated higher.

Qualitative Results

The last question of the survey asked whether they thought that the University of Delaware has gender equality in STEM fields? I coded the responses into yes, no, or unsure/no opinion. Of the 681 students who answered this question, 47.72% said yes, 29.36% said no, and 22.90% were unsure or had no opinion. The other four questions asked about their specific experiences, or the experiences of people they know, in STEM fields.

Question 4 asked how professors have impacted their self-esteem as a student. The majority of responses pointed to the fact that the more positive and accessible a professor was the more it helped their self-esteem, but if the professor was unapproachable or the class was difficult it hurt their self-esteem. Some notable responses are listed below:

- “When they recognize what you've done well and give you constructive criticism on what you need to work on”
- “Some made me feel stupid and just like a number, but some do value me and that definitely boosted my self-esteem. I also like when professors are just as nerdy as I am. It makes me feel less alone when I end up just wanting to learn a lot about a really specific subject for no reason, but then I realize that’s EXACTLY what professors do and its totally normal and its actually great to really like something, even if people think your ridiculous and weird”
- “I have had professors that work hard to make sure I understand concepts that are applicable to the real world, which has made me confident in my knowledge and in my studying”
- “When I speak out in class and they degrade what I have to day my self-esteem is lower. When I am praised for what I volunteer I am more likely to speak out again”
- “Some professors build it up by showing you the steps to take to keep working hard, while others can limit self-esteem by harshly grading with no explanations and talking down to students with lower grades”
- “If they don’t allow room for confusion or questions, I feel like a failure. Professors need to be more understanding and reliable. I was only in high school a few months ago and now you treat me as a colleague and yet a child all at once”

A student’s academic self-esteem is related to the difficulty of the class and their relationship with the professor.

The first and second question asked if they experienced or witnessed prejudice or discrimination in STEM fields. Respondents who did not have a direct experience to pull from either did not answer the question or talked about how there are more male STEM professors and students than female STEM professors and students. They also commented that females in STEM are paid less than males in STEM. Out of the students who have experienced or witnessed prejudice in STEM fields, mostly talked about how being a female in STEM meant they had to work harder to prove themselves, their knowledge was questioned by their male professors and classmates, and how people question if they are capable of being in STEM.

- “I have had my reasoning and thoughts disregarded by males”
- “Yes, was in an Honors section of the class and the (male) professor (and department chair) walked in late and said something along the lines of, ‘I thought I had the wrong room because there were so many females.’ Section of 18, 15 were women in engineering . . .”
- “Yes. When I was a TA in a computer science course, the first day I walked in, I went to the front of the room to join the other TAs, who I hadn’t met. One of them, a male, gestured towards the student seats and said, ‘please take a seat’ as if I wasn’t supposed to be up front. He clearly thought I was not a TA, and was surprised when I informed him I was.”
- “The boys in STEM classes generally treat us like were incompetent until we prove we’re not”
- “Just male professors pairing me up with a male student when I have trouble”
- “Yes, being a woman in a STEM field, I have often been discriminated by male classmates who do not want to be lab partners because ‘it isn’t a place for a girl to be in STEM’ as I have been told”
- “Male teachers never assisted me one-on-one and I didn’t feel comfortable staying after class”
- “Yes. My advisor in the past has encouraged me to take less challenging coursework because he didn’t believe that I could handle a more difficult course”
- “Yes, my male professors have less patience in answering questions when I ask them vs when my male classmates ask them”
- “The other day, I was in ISE lab, studying with a friend, and she was reading a book for her grammar course. We were sitting across

> from two boys who were talking about how men should be engineers and women should be teachers"

- "During an ANFS lab, our male professor told the male TAs to 'keep an eye on the girls because they'll need extra help'"
- "One example is in a class I took, we were told by the class above us to only put our 1st initial and last name on our test because the professor was biased against girls and this way he would not be able to tell if you were a girl when he was grading your exam"

These examples point out some of the experiences that people have faced.

Another theme that occurred in these responses points to typical gender norms that are imposed on females. One person explained how women are asked to do the writing portions of the assignment while men do the technical side. This supports the belief that women are better at humanities and men better at STEM. Another stereotype exposed in these comments was that women are expected to only want jobs that are nurturing, such as being a vet. Also, one respondent pointed out how "research jobs are assumed for the men, and I am assumed for education", while another was told that women lacked the emotional control to be doctors or engineers. The most surprising response involved a lead researcher being sexist towards the female research assistant: "I have experienced small differences working in a lab. The lead researcher often asked me to fetch things [or] wash dishes, where as he rarely asked my male equals to do so."

One response illustrated that the issue may be in regards to gender expression as opposed to sex or gender.

> "More often than not because of my gender expression (which comes off as androgynous or feminine), I am often seen as the 'lost humanities major.' Along with this, white professors tend to talk to me as if I do not understand them and tend to take a certain tone with me that professors of color have never taken. The fact that I am seen as a

> woman by many also leads to treatment as such and in so I am treated like I'm not as intelligent as my peers"

Even though this person does not identify in the gender binary since their gender expression is often more feminine they face the same stereotypes that people who identity as female do. Further research needs to be done to see if a students' implicit associations are affected by their professors' gender expression instead of by their gender. Perhaps if professors, regardless of gender, are more feminine in nature they will be seen as breaking stereotypes since STEM is viewed as a more masculine field.

The remaining responses pointed out discrimination occurring in STEM outside of sexism. One student commented on feeling like he cannot come out as a gay man and still feel comfortable with his bosses in his lab. Some pointed to the additional prejudice that women of color face in STEM fields. One women of color says her intelligence is often seen as less than others, while another said that they were given an extension on an assignment without question while a woman of color was questioned extensively about the same extension. A third student noticed that as the female faculty's skin gets darker the more they have to prove their worth. Another student recounted, "My white female math professor (who was generally great) once divided the room into having bad students up front, then we realized they were all non-white." The students who were labeled as "bad" (the respondent did not clarify what this means) were all people of color, and the professor signaled them out in class. One student stated that English as a second language students have lower expectations compared to other students. Another issue that was raised was about professors and students with disabilities when a student acknowledged that one of their professor's thought two girls had severe mental disabilities because they had DSS accommodations. A final comment was the most surprising:

> “Chinese kids and Chinese professors can’t speak English well so their courses are far worse. In general white professors, particularly female white professors are the best because they had bad experiences and want to do better”

This comment needs to be taken into consideration because it presents a discrepancy in the explicit bias part of the survey. For this survey I only looked at racial differences between black and white professors, not taking into account that many professors and students in STEM fields are Asian and how that plays into students’ perceptions. Further research will need to be done to see if there is a difference in students’ perceptions of professors looking at different races and ethnicities besides just black and white.

Lastly, a number of students commented that they do not like being characterized as having made a huge accomplishment because they are majoring in STEM. One student stated, “Either I get special recognition for being a girl in STEM because it is considered uncommon, or I get treated as if I am unqualified because I’m a girl in what is considered a man’s field.” Another mentioned that their professor made a big deal about the fact that their teaching assistants were females and that he had complete confidence in their abilities. This is not just an issue that women face because another response pointed out that in their major men are the minority so they are often tokenized. Theses biases in STEM will persist if women keep being treated as though it is surprising and a huge accomplishment that they are in STEM. Studies have shown that women are just as successful in STEM as males, so it should not be surprising that they are pursuing careers in STEM fields.

Chapter 6

CONCLUSION

Through completing an undergraduate thesis I have learned a lot. This was my first time putting together a survey to be sent out on such a large scale, and I learned the importance of testing the survey before you send it out. Before I sent it out I had a group of people read over it and provide feedback if anything was unclear, but I forgot to test out to see if everything was working properly. Also, through this process I learned how to get a survey approved by the Institutional Review Board and what that process looks like. My research exposed me to many interesting papers about gender and STEM and different stereotypes, and I learned a little about psychology, specifically about implicit associations. Finally, I learned how to write an economics paper and what separates it from other disciplines.

Gender bias in STEM fields is a major issue affecting females in STEM fields. Although girls have shown in high school that they are just as prepared as males to major in STEM, the number of female STEM majors has decreased in recent years. Research indicates that this is mainly due to gender stereotypes about women in STEM. This is important because employers in STEM fields are expected to be recruiting more people than other industries in future years, and STEM jobs on average pay more than non-STEM jobs. When women graduate with a STEM degree and get a job, they are still faced with biases in the workplace ranging from a lower chance of being hired, a lower change of having their research published, and less of a chance of being the primary investigator for a study. All of these are reasons why biases facing women in STEM need to be better understood and addressed.

For this project I administered a survey to undergraduate students at the University of Delaware to test if having female faculty in STEM fields effects students' implicit associations between women in STEM. After collecting the data, I then ran multiple regressions. I used several different regression specifications to test the impact of female STEM faculty on student implicit associations. While I hoped the results would identify clear steps to address bias amongst students, it turns out that having more female faculty in STEM fields has no meaningful impact on reducing or increasing this bias. The regressions, however, did show significant relationships between a students' year in school, their confidence in science, and their gender on their D-score. For the final set of regressions which included major dummies and female faculty dummies, it showed that, holding everything else constant, for every additional year a student attends school, their D-score increases by 0.03361 points. This means that the environment at the University of Delaware is causing them to have a stronger implicit association towards men and STEM. Also, as their confidence in science increases their D-score decreases 0.04659 points, and males have D-scores 0.11532 points higher than females. Despite, there being no significant relationship between the number of female STEM faculty a student has and their implicit associations, the qualitative results from this study do show that gender bias in STEM is a problem at the University of Delaware, and it presents some keys to fixing this problem.

The qualitative results of this study point to a number of problems in STEM departments at the University of Delaware, but they also present solutions. The majority of students who participated in the survey stated that their self-esteem increased the more accessible their professor was, and the more the professor allowed room for confusion and questions. This can be used to address the fact that increasing students' confidence in science decreases their D-scores. If STEM professors make themselves available to answer their students' questions and make their questions feel important, and not like a waste of time, students' self-esteem and confidence will increase, thus, decreasing their D-scores. Also, since the coefficient on year is positive and significant this means that students' D-scores are increasing for each additional year they attend the University of Delaware. One reason for this may be that female STEM professors are teaching introductory courses, while only male STEM professors are teaching upper level courses. This signals to students that female STEM professors are qualified to a fault. Further research needs to be conducted to see if this holds true. To address this, there needs to be a universal message that STEM departments are communicating to indicate that they are unbiased. This message needs to be communicated through STEM professors. First, professors cannot be surprised by the makeup of their classroom (i.e. if there are a lot of female or a lot of people of color). Acting surprised by the makeup of the class communicates to students that this is abnormal, which reinforces that certain students are better at STEM. It is also important for professors to treat all students that same. One way for this to be accomplished is by ensuring that when students are put into groups for projects that the females in the group are not just doing the writing portion while the males do the technical side of the assignment. Steps should be taken to ensure that all the work is divided evenly by tasks, not by the overall project. Also, it is important that faculty be educated on other biases that exist in STEM besides sexism, like homophobia, ableism, and racism. Finally, the most important thing for departments, faculty members, and professors to do is stop tokenizing underrepresented students in STEM.

Treating female STEM majors like they are an anomaly suggests to everyone that females are less qualified to be STEM majors, thus reinforcing gender STEM stereotypes. All in all, gender bias in STEM fields is a major problem, but my research suggests that exposing students to more female faculty in STEM courses alone will do little to address this problem, however, there are steps that STEM departments can take to help address this bias.

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Appendix A

Categorizations of STEM, Humanities, and Social Science

STEM
- Actuarial Science
- Athletic Training
- Biology
- Chemical Engineering
- Civil Engineering
- Computer Science
- Dietetics
- Environmental Engineering
- Exercise Physiology
- Food science
- Geology
- Health Behavior Science
- Insect ecology
- Mathematics Education
- MIS
- Nursing
- Nutrition
- Physics
- Pre-vet
- Wild life ecology

Humanities
- Anthropology
- Art
- Classics
- History
- Law
- Literature/English
- Performing Arts
- Philosophy

Social Sciences
- Accounting
- Agriculture and natural resources
- Communication

- Economics
- Education
- Environmental Studies
- Finance
- Geography
- HRIM
- Human Services
- International Relations
- Linguistics
- Management
- Marketing
- Political Science
- Psychology
- Public Policy
- Sociology
- Spanish
- Women and Gender Studies

Appendix B

Explicit Bias Survey and Pictures

Imagine that next semester you are assigned to a math class that is taught by the professor in the photo. This professor has recently joined from another university. Although you do not know this person, please rate your level of agreement with the statements below.

1. The instructor is an expert in his/her field
2. The instructor will speak clearly and use precise English
3. The instructor will motivate me to succeed in class
4. The instructor will access my work fairly
5. The instructor will treat me with respect
6. The instructor will treat me fairly
7. The instructor will explain the lessons clearly
8. The instructor will treat students with respect
9. The instructor will treat students fairly
10. The instructor will motivate students to succeed in the class
11. The instructor is interested in student success
12. The instructor will encourage students to ask questions and participate in class
13. This person will be an excellent instructor for this course
14. I want to be in this instructor's class

Figure 3 Black Female Professor

Figure 4 Black Male Professor

Figure 5 White Female Professor

Figure 6 White Male Professor

Appendix C

Institutional Review Board Exemption Letter

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	March 2, 2018
TO:	Stephanie Clampitt, Undergraduate
FROM:	University of Delaware IRB
STUDY TITLE:	[1164053-1] Female Faculty in STEM fields' effect on students' implicit bias
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	March 2, 2018
REVIEW CATEGORY:	Exemption category # *(2)*

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Nicole Farnese-McFarlane at (302) 831-1119 or nicolefm@udel.edu. Please include your study title and reference number in all correspondence with this office.

cc:

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