INTRODUCTION

What has a greater impact on one's decision to become an engineer, gender or the ability to assemble an automotive part? From current research on occupational choices in areas such as science, technology, engineering and mathematics, it seems that social statuses such as gender have a substantive influence. Sex-based job segregation in these areas exists in most industrialized societies, where men have a greater representation than women. Though some may argue this is a natural type of sorting, due to biology (see Blickenstaff 2005); another force is actually present. Pervasive social constructions of math and technical abilities, aptitudes, and interests by gender could influence how men and women perceive and choose their careers, so that gendered social status may have a larger impact than the genders' differences in ability levels themselves.

This study explores gender segregation in the labor market in fields such as science, technology, engineering and mathematics (STEM). The goal is to understand how gender, as well as other ascribed social statuses such as race, ethnicity and social class, influence individuals' decisions to enter these specific occupational areas that historically in the United States have been dominated by white men. Jobs such as these typically have higher salaries, greater prestige and more opportunities for growth than other occupations (U.S. Department of Labor, Women's Bureau 2009). Though the benefits of such jobs are many, women are consistently not entering them at the same rates as men. Women's presence in engineering has almost doubled between 1983 and 2007, from 6% to 11%, but they are still very much underrepresented. In professions such as computer science, the proportion of females has actually decreased, from 31% to 25% in the same period (National Science Foundation Division of Science Resources Statistics

2007). Research is needed to understand why women are not entering these fields in greater numbers and particularly how much of an impact ability makes in affecting occupational choices in these areas.

Studies investigating gender segregation in the labor market have often focused on how math aptitude influences career decisions, both in perception of this ability and in actual differences in skill level. Research has shown that having a high level of ability in math facilitates attaining more prestigious jobs, such as those in the STEM areas (Shapka et al. 2006). However, individuals' perceptions of their skill level are crucial. Correll (2001) examined how young men and women assess their mathematical abilities and whether perception of their math skill affects their decisions to enroll in advanced math courses and major in science, technology, engineering and mathematics fields. She found that when viewing their math aptitude, men perceive themselves as more skilled than women, even when they have similar or even lower math scores than females. This suggests that some social influence must be affecting men's and women's assessment of their math abilities, which encourages men to exaggerate their skill levels and women to underestimate theirs. Previous research also shows that little gender difference actually exists in math skill, and that small variations in abilities are often exaggerated by society to further shape and differentiate men and women's perceptions of their own aptitudes, which influences career choices in STEM areas (Hyde and Linn 2006); thus the masculine image of these fields is maintained.

While most studies of gender and STEM careers focus on the importance of math skills, the study reported here also includes technical ability in addition to math aptitude, to explore how this skill may affect vocational choices. Technical ability is seldom researched, but could have an important impact on occupational decisions. Correll's study (2001) suggests that perception of technical skill might be as artificially gendered as math ability, if not more. Since assessment of technical aptitude may also affect career selection, specifically in the male-dominated realms of STEM, the present study will examine whether there are significant differences between men and women's technical skills as well as between their math abilities, a topic that has received little attention so far. If no divergences are found, gendered constructions of these skills could be argued to affect career choice, more than the actual abilities themselves.

While the primary focus of the study is on gender, similarities and differences across racial and ethnic groups as well as social class are also investigated, since the intersection of these factors with gender can contribute to even more unequal representation of certain groups. For instance, black women made up only 6% of all female scientists and engineers in 2006, while white women constituted 70% of that population. Hispanic women's numbers are even less, making up 5% of all female scientists and engineers, compared to that of Asian women, who represented 17% of females in these professions (National Science Foundation Division of Science Resources Statistics 2007). According to 2000 Census results, whites represent 75.1% of the population while blacks constituted 12.3% and Asians represented 3.6% of Americans. Hispanics represented 12.5% of the population in 2000, while non-Hispanic whites made up 69.1% of U.S. residents (U.S. Census Bureau 2010). Obviously, both black and Hispanic women are not being proportionately represented in STEM careers, though white women are. Previous studies found that parents' education and household income both significantly affect the number of math and science courses children take, the grades they earn, and the perceptions they have of their math and science abilities (Simpkins et al. 2006). To address these findings, this exploratory study examines the extent to which young men and women in different racial and ethnic groups and socioeconomic levels that are highly skilled in math and technical abilities in high school will work in these well-rewarded and traditionally male careers.

Previous research, such as Shapka et al. (2006), measures the impact of skill and assessment of skill on career aspirations. However, it is also important to know how actual career decisions are affected by skill and gendered perceptions of skill. The National Longitudinal Survey of Youth, the data set used in this study, permits an investigation of actual outcomes through an analysis of what careers young people eventually pursue, some years after their ability levels have been measured. Examination of this data set could further our understanding of why women may have similar aims for high-prestige careers but do not attain them at the same rates as males. If they have a high ability in STEM areas, why are they not choosing them as occupations?

The overall research question for this exploratory study is: What are the impacts of sex, household income, race/ethnicity, math ability and technical ability on occupational choice in STEM areas? Results from the National Longitudinal Survey of Youth will be analyzed to test the overall hypothesis that ascribed social statuses, especially gender but also race and ethnicity and social class, affect STEM career choice apart from math or technical ability.

LITERATURE REVIEW

If there are overwhelming benefits in STEM careers, why are women not entering them in larger numbers, and why has underrepresentation persisted over time? To address this perplexing issue, one must examine how gendered socialization rather than factors such as innate differences between the sexes is more likely to affect men's and women's decisions to enter into a gendered-segregated area such as STEM. In particular, the role played by the gendered construction of technical and mathematical competencies needs to be understood. Attention should be given to how the masculine image of these skills might lead men and women to perceive their abilities differently, which in turn may affect their math and technical course selection and eventually their decisions to enter this field. To better understand how these skills are socially categorized and the impact they make in individuals' career decision process, one must begin by examining how society exaggerates gender differences in STEM-related skills.

Gender and Skill in STEM Areas

The issue of whether men and women are innately different in terms of learning abilities in STEM has been researched extensively. Hyde and Linn's (2006) meta-analysis of over 5000 individual studies focusing on psychological differences between boys and girls in relation to mathematical and scientific abilities and personality traits found that few, if any, differences were present between sex groups. Using the Gender Similarities Hypothesis that women and men are more alike than dissimilar, they conclude that researchers and policy makers should emphasize parallels between men and women in science and math instead of their differences, noting that many policy reports focus on small skill differences between genders, which are statistically significant but practically irrelevant.

One example used in their analysis comes from the 2005 National Assessment of Educational Progress (NAEP) in science, which reported that boys outperformed girls at all three grade levels. However, when one analyzes these data by looking at the magnitude of the effect of gender difference, it is actually quite small. For fourth graders, the average science score for girls was about 149 with a standard deviation of 30 while the boys' average score was about 153 with a standard deviation of 32. On a scale that ranges from 0 to 300, this variation is obviously quite small, less than four points. The NAEP further claims the difference between the sexes easily qualified as being statistically significant since the sample size was quite large, with about 100,000 students in each grade. However, Hyde and Linn (2006) argue that the effect size for gender difference is really small. They conclude that this data set provides more evidence for similarities between boys and girls in science achievement than it does for gender variations; moreover, methodological issues occur with large samples since rather small differences can easily be found to be statistically significant. If the overall effect is not taken into account, then these minor divergences will be argued to be more important than they really are.

Hyde and Linn's criticisms can be applied to recent math scores where socioeconomic status had more of an impact than gender. In the same type of report for 2009, the gender gap in average mathematics scores for both 4^{th} and 8^{th} grade students was only 2 points out of a possible 500 (4^{th} grade: boys' mean was 241 and girls' mean was 239; 8^{th} grade: the mean for boys was 284 and for girls it was 282). While gender made little impact, the results showed that students from higher income levels in 4th and 8th grade had significantly better math scores than those in lower income levels, and that this difference was large, with an average of a 27-point gap. Measuring household income by students' eligibility for reduced-price school lunch, in 4th grade, the average score for high-income was 250, while the average for lower income was 226. For 8th grade, those with more income averaged 294, while the average for students from lower-income backgrounds was 265 (U.S. Department of Education, National Center for Education Statistics 2009). While gender differences in abilities tend to be emphasized in society and reinforced through social beliefs about these divergences, Hyde and Linn's study shows that differences by sex are much smaller than other status differences, such as those for social class.

Examining the consequences of this overemphasis on small gaps between girls and boys in STEM-related abilities is vital to understanding why women continue to be underrepresented in these areas. On a societal level, it can lead to perceptions that men are inherently more adroit than women in these STEM-related skills, which would contribute to the underrepresentation of women in these areas since only negligible gender differences exist. Some other factor must be affecting how these skills are viewed, which leads to gender-differentiated career decisions. Thus, the perception of an association between maleness and these skills, especially in math and technical areas, leads to gender segregation of the workplace.

Gender-Biased Assessment of Math and Technical Ability

Though math and technical subjects are different areas of study, they are both considered masculine, thus creating a stereotype of males in careers that utilize these skills (Correll 2001; Faulkner 2000). Eccles' (1994) expectancy-value model of behavior choices has been applied to understand how this occurs through elementary and secondary school. In this context, boys and girls develop different beliefs about their competencies because of the social environment in which they interact. This gendered socialization continues throughout the career choice process. In an experimental study, Correll (2004) found that when college-aged respondents were informed that males were more proficient in the skill of contrast sensitivity, the men rated their own abilities more favorably and were more likely to name career objectives in quantitative fields than women did. These findings contrast to the control group, where subjects were told that both sexes performed equally at this skill, so that men did not rate themselves as better in ability. Computer-administered sensitivity tests were then implemented, where subjects were given five seconds to judge whether black or white predominate in a series of rectangles. Respondents could not have right or wrong answers because none existed, with the proportions of white and black areas about equal. Though individuals in both groups were assigned artificially equal scores for completing the test, men in the experimental group still rated themselves as better than the women, compared to the group who were told that no sex difference was found. Applying these findings to reality, men might evaluate their mathematical competence more highly and be more likely to pursue STEM careers than women are.

The consequences of these self-assessments can be damaging for women. Math has consistently been shown as an important gateway to high-paying and prestigious careers, with advanced math knowledge and course-taking related to decisions to choose STEM careers (Shapka et al. 2006). The higher students rate their mathematical ability, the more likely they are to choose careers in quantitative areas (Correll 2001). Called a "critical filter" into careers of high prestige, (Shapka et al. 2006), mathematical task assessment continues to be colored by the assumption of male superiority (Eccles, Alder, and Meece 1984; Blickenstaff 2005). Research has investigated how individuals relate to mathematics and how they assess their own competence in math, which in turn tends to affect their career choice in quantitative fields. Simpkins et al. (2006) found that fifth graders who had high marks in math and participated in math-related extracurricular activities were increasingly likely to be interested in and place a great importance on math. As a result, in tenth grade, they were increasingly likely to have high math grades, take a large number of math courses and perceive themselves as skilled in these areas (Simpkins et al. 2006: 72).

The association of perception of skill and career aspirations can continue through high school to higher education and into the workforce. Through the use of longitudinal data from Grade 9 to three years after high school, Shapka et al. (2006) found that both male and female high school students who perform well in mathematics eventually aspire to more prestigious careers than those who have lower achievement scores. Though no strong gender differences in abilities are evident, the sad reality is that women are still largely underrepresented in these prestigious careers. To understand this issue, skill and career outcomes, not just aspirations, need to be examined.

Though math ability is important for career choice, other areas, such as technical skill, should also be addressed. The perception of a strong connection between maleness and technical areas was found in the Cory and Rezaie's (2008) study, where college students believed that the jobs of engineers and computer and information systems specialists, both highly technical fields, involve masculine personality traits more than other professions such as accountants, insurance broker/agents, lawyers, and physicians.

It is possible that technical adroitness and mathematical ability might affect occupational choice differently, especially when it concerns STEM careers. For example, the academic area of engineering largely focuses more on mathematical and conceptual coursework and less on practical, concrete applications (Faulkner 2000). However, many competent engineers perform only average in mathematics, while possessing high hands-on, technical ability (Hacker 1989). In her recounting of experiences as an engineering student, Hacker (1989) discusses how the first two years of engineering seemed like a hazing experience, where students are put through rigorous mathematical coursework; however, once they enter the field of engineering, individuals' concrete technical aptitude is needed more than math. Robinson and McIlwee (1991) describe how this technical skill corresponds to the workplace in their study of engineers and engineering ideology, demonstrating that technical ability and engineering were always perceived as male specialties:

> Technical emphasis includes not just the abstract and innovative, but also basic hands-on activities. Engineers display a fascination with tools, machinery, and gadgets that is more than just a means to an end. The 'good engineer' is more than competent at hands-on skills; 'he' is obsessed (1991: 405).

The authors claim that there is a "culture of engineering," whereby individuals in this field perpetuate the male gender norm by the emphasis on utilization and presentation of technical ability. They argue that this focus on hands-on skill is strongly connected to masculinity stating: "few things are more closely tied to the male gender role than mechanical activities" (Robinson and McIlwee 1991: 406). As a result, engineers continuously discuss and display their interest in various types of technical skills such as taking apart machinery, constructing materials and using gadgets. By emphasizing the male aptitude for technology, engineers are perpetuating the image of maleness within this and many other careers dominated by men that are seen as technically-based. Robinson and McIlwee conclude that though women and men have equal amounts of mechanical ability, their presentation of this ability is different: "Men are not better engineers, but they are better at *appearing* to be better engineers in a *male defined* way" (1991: 417). As a result, men develop a craft ethic where they can control production through technological skill.

Not only is technical ability perceived to be strongly linked to the male norms within this workplace culture, so also is organizational power. Since engineers are often managers, they are seen as competitive, aggressive and most importantly, skilled at technology – all attributes popularly linked to masculinity. To "fit in" with this type of engineering culture, individuals must present themselves as looking, talking and acting within this masculine role; thus, women who do not identify with these characteristics of aggressiveness and hands-on skill are deterred from entering engineering, perpetuating gender segregation.

From this perspective, women who are skilled in technical crafts and math skill are not evaluating their abilities highly and are not choosing careers in male areas such as engineering or computer technology because of the gendered construction of both math and technical skill. As mentioned previously, women and men have little difference in ability in these areas. However, gender segregation continues in STEM. To better understand the role social interaction plays here, several arguments from social science concerning gender and STEM occupations can be applied.

Sociological Explanations for Gender Differences in STEM Occupations

Women's underrepresentation in these well-paid non-traditional occupations in the areas of science, technology, engineering and mathematics (STEM) is not a new issue. Scholars, policymakers and activists have devoted countless hours, money and energy to understanding this phenomenon. From their research, various theoretical arguments have been developed to explain gender segregation in the workplace through socialization.

Social scientists interested in understanding women's low representation in male-dominated careers have paid particular attention to "demand-side" factors (Correll 2001), such as the structure of labor markets and institutional discrimination (Reskin and Roos 1990). However, only a small amount of sociological research has examined the "supply-side" aspects, those shaping men and women to choose courses, activities and interests that are connected to masculine or feminine careers (Correll 2001). Studying these supply-side factors is important. Demand-side challenges are less consistent and can change depending on the situation. For example, one engineering program may have more female faculty than another or one firm may have better family policies than another. In contrast, the supply-side factors are more universal, pervasive and detrimental, since they affect whole categories of individuals when they are forming assessments of their abilities and deciding what types of careers would be a good fit for them.

One of these supply-side aspects which is of crucial concern is the societal view of these careers and the masculine characterizations of the skills associated with them (Correll 2001). Depictions of an occupation as masculine or feminine can affect whether individuals become attracted to a career (Kimmel 2004). Examining what happens in these areas is significant, since common representations of men or women in a specific job affect how the career is perceived. When specific types of employment become strongly associated with one gender, this affects how individuals view these areas and who enters them in future. As a result, the image of these jobs will further perpetuate gender segregation, since groups will continue to choose careers in which their sex dominates. The status, wealth, and power associated with a given type of career will tend to rise or fall, depending on how heavily men or women, respectively, dominate in the field (Kimmel 2004).

Though this sociological perspective of supply-side factors regarding skill is important, many arguments commonly focus on the demand-side impacts. One popular theory addresses the “leaky pipeline,” in which young women individually abandon an interest in STEM careers at different stages to a greater extent than young men. Much of the literature paints a picture of a tangle of challenges young women experience, causing them to “drop” from this pipeline at several possible points, from elementary through postsecondary education and into the workforce. Reasons cited for their leaving include sex bias within career guidance, ignorance among educators and parents about a women’s ability to enter the field, alienating classroom climates, lack of role models, little encouragement to enter science, technology, engineering and mathematics fields, and few role models of women in these areas (Bastalich et al. 2007; DeWelde et al. 2007).

In addition to identifying factors that might lead women to leave a STEM field, it is also important to clarify what keeps them from developing an interest in this area in the first place. The masculine image of these fields presents a problem, since society perceives STEM areas as being incompatible with femininity; thus young women may find it difficult to balance an interest in these fields and with an interest in maintaining their feminine image. As a result of gendered images of STEM careers, a young woman may meet resistance from those around her, if she decides to pursue a career in a STEM field. Because of all of these challenges, young women may decide that there is little reward in majoring in traditional masculine careers, even if they have high math and/or technical abilities (Bastalich et al. 2007; DeWelde et. al 2007; Giurleo 1997; Hartman and Hartman 2009; Simpkins, Davis-Kean, and Eccles 2006; Sonnert, Fox, and Adkins 2007).

Psychologists have paid considerable attention to women and STEM, following this model of the leaky pipeline to understand how external factors affect internal attitudes in career development (Eccles 1994; Farmer et al. 1995; Porfeli, Hartung, and Vondracek 2008; Simpkins et al. 2006). Using longitudinal data, they look at eventual outcomes and add to the understanding of this issue by addressing gender, math skill and perception. However, their research focuses more on personality traits and individual perceptions than on collective images of skills and careers that are constructed by society. It addresses divergences in self-perceptions but does not investigate their origins. Thus, more sociological examination is needed, since it can provide an understanding of how social images of these careers shape beliefs about which groups possess the skills needed for those particular jobs. Instead of simply noting differences, sociological research would attempt to understand the social construction of perceptions and choices of careers.

Using a sociological perspective can enhance understanding of how men and women perceive their competence in certain tasks differently, leading them to choose fields where their gender already dominates. Further, a focus on societal structure can reveal the impact of social interaction on gendered constructions of skill and career choice. Gender is socially reinforced through the three interrelated levels of institutional structure, interpersonal practice and individual identities (Aulette, Wittner, and Blakely 2009). Through macro-scale policies, everyday interactions and internalization of certain beliefs, men and women are socialized differently to believe and act in certain masculine or feminine ways, affecting how they perceive their abilities. This is especially emphasized in the school and workplace, where the three reinforcing levels affect girls' and boys' perceptions of what is "women's work" and "men's work" (Aulette et al. 2009). Ridgeway and Correll (2004) address this issue, arguing that social interaction is incredibly important in continuing gender roles because women and men interact repeatedly. Following this line of reasoning, Correll (2004) claims that men and women choose different careers because they are culturally conditioned to have gendered perceptions of what tasks they can accomplish, such as women being proficient at care-giving jobs like nursing. As a result, individuals will choose careers that correspond with the traits and skills associated with their sex, which are divided between traditionally male and female areas of employment.

Because of this cultural conditioning, women are more likely to choose traditionally women-dominated fields and have lower social prestige. Once a gender begins occupying a certain career in large numbers, the vocation itself begins to take on feminine or masculine characteristics. For instance, many traditional female jobs involve some aspect of care-giving, which is congruent with their nurturant role at home as mothers and wives, (Lorber 2005). However, the gendering of occupations is socially constructed. Reskin and Roos (1990) argue that almost any career can come to be seen as more appropriate for one sex or another because they contain both stereotypical male and female aspects. For example, the field of engineering involves personal communication and teamwork, attributes that would seem to favor women, but it is still a male-dominated occupation because masculine areas of technology and mathematics are emphasized in the field. Most importantly, gendering affects social attitudes by reinforcing stereotypes about how girls are not as astute in these areas, such as math and technical skill, leading women to not enter STEM careers and thus continuing gender segregation.

This sex segregation in turn reinforces gender stereotypes, affecting how various tasks are categorized as male or female and associated with specific jobs. In an experimental study, college students were asked to identify the occupations of accountant, elementary school teacher and engineer with either male or female names on a computer as quickly as possible. White and White (2006) found that respondents were able to more quickly match women's names with elementary school teachers and men's names with the occupation of engineer than if the two sexes were switched, so that only male names were present for elementary school teachers and female names were present for engineers. They argued that these vocations are significantly gender-stereotyped. This study shows that people are socialized to believe certain careers are male or female, based on these societal views.

Though men and women feel they are “freely choosing” their vocation, social and institutional factors are actually influencing their decisions, relegating them to specific areas (Reskin and Padavic 2002). Thus, women and men are adapting their aspirations and abilities to “fit” within these constructed gendered categories. These actions are socially constrained, but are considered individual choices by men and women who continue to reproduce the structural gender segregation of male-dominated areas, such as STEM (Hanson 2009). As a result, women may not acknowledge their abilities in science, technology, engineering and mathematics fields, seeing them as masculine and not identifying with these occupations, whereas boys associate with them and feel more capable of pursuing a career in STEM (Aulette et al. 2009).

Career choice is made more complex with the intersection of socioeconomic status and race/ethnicity, whereby certain groups of men and women choose separate areas of employment. Applying Aulette et al.’s (2009) intersectional theoretical analysis to this study, gender as well as other “oppressed” (5) social categories of race/ethnicity and class will be investigated to understand how these interact to further create inequality. The authors claim that all women do not experience discrimination in the same way; further, men are not always the recipients of masculine privilege. They state: “Being a white, well-born man opens doors, offers privileges, and produces rewards. Being a poor black woman increases the difficulties and barriers a woman faces in her life” (5). Though this concept of intersectionality is important, Aulette et al. do not specifically detail throughout their analysis of whether real interaction occurs or whether an accumulation of disadvantaged statuses simply exists. Further, the authors do not specifically address STEM career choice or measure it through statistically significant interaction effects. Though these limitations are crucial, the overall theoretical argument of intersectionality can be applied so that these other social statuses compound the effect of gender on who benefits from the rewards of a STEM career. This intersectionality argument can be applied to current patterns within STEM. Blacks, Hispanics, American Indians/Alaska Natives, and Native Hawaiians/other Pacific Islanders represent only ten percent of science and engineering professions in 2006 (National Science Foundation Division of Science Resources Statistics 2007). This compares with about a 25% share of the U.S. population (U.S. Census Bureau 2010). This type of intersection further impacts those who actually enter STEM. In a study of the American Chemical Society survey, black women made less money than black and white men and white women. Black women also earned significantly less income when in positions of authority as well (Adler, Koelewijn-Strattner and Lengermann 1995).

Socioeconomic status can also reproduce itself through young people's career choices, where youth from more affluent families are more likely to enter high-status occupations such as those in STEM (Court and Moralee 1995). Simpkins et al. (2006) found that both parents' education and income significantly affect the number of math and science courses children take, the grades they earn and the self-concept they have of their math and science abilities. As noted previously, the differences in math scores were larger between high- and low-income students compared to the differences between girls and boys (U.S. Department of Education, National Center for Education Statistics 2009). As a result, racial and ethnic minority groups and those having a lower socioeconomic status are less likely to enter these areas than those who are more privileged or white.

These potential intersections of gender, race and ethnicity and socioeconomic status need to be analyzed to understand if they occur in STEM career choice, so that poor or minority women are even more disadvantaged than one would expect from the additive effects of their group memberships. Intersectional analysis will be applied to this study to investigate if a significant interaction effect exists and how certain social groups are affected. Few studies before have looked at this interaction effect in STEM areas, so this research will provide further insight into this type of theoretical analysis.

As the literature demonstrates, males and females are inherently similar in their math and science aptitudes and related psychological attributes. However, they are being socialized to choose different careers based on their conceptions of the masculine or feminine images of these careers (White and White 2006). Young men are more likely to choose the high-paying and valued careers in STEM occupations, while women are deciding to enter fields that are not as prestigious or financially rewarding, apparently because they are associated with an image of femininity. The aspect of individual choice is emphasized in this vocational process, while participants remain unaware of the substantial impact of gendered social relations at all three levels. They do not acknowledge how gendered stereotypes operate to affect institutional-level practices, social expectations, and their own perceptions of their vocational skills. Instead, they tend to attribute their decisions to their innate talents or inclinations towards certain careers. As a result, gender inequality continues to reproduce itself, as shown through the Department of Labor’s (2009) recent results of the paucity of women in these areas in 2008, where women occupy less than a quarter of many of the jobs in STEM.

An examination of perceptions of career-related skill can provide a better understanding of why women continue to be underrepresented in male-dominated fields such as STEM. Correll's (2001) longitudinal study of this life-course process, which includes the development of biased self-assessments, comes closest to clarifying the impact of gender on how individuals make their career decisions. By analyzing math and verbal aptitudes, skill assessments and course-taking, as well as college majors of students as they progress from 8th grade to two years into their postsecondary education, she finds that males assess their mathematical abilities higher than females, though they may have similar test scores, leading them to choose employment in quantitative areas more often than females. She argues, "Boys do not pursue mathematical activities at a higher rate than girls do because they are better at mathematics. They do so, at least partially, because they *think* they are better" (Correll 2001: 1724).

This study addresses a reframing of questions normally investigated in the context of women in nontraditional areas. Rather than ask why women are excluded and falling from this leaky pipeline after their decision to enter it, it attempts to understand the role of social statuses and skill levels in young men's and women's initial decisions to enter STEM careers. It looks at who is entering STEM careers and what affects their choice of such an occupation. Social statuses, especially gender, are expected to play a key role in determining who chooses occupations within these areas, not because certain groups have substantially more aptitude in math and technology but because socially constructed notions about math skill, rather than the ability itself, influence these choices. Unlike most other research on this topic, this study will examine technical skill as well as math skill to determine if aptitude in these areas has a significant impact in vocational decisions in STEM fields.

While the primary focus of this research is to explore factors associated with women's decisions to enter non-traditional fields, it is important to keep in mind that women are not a monolithic group. Drawing from Aulette et al.'s (2009) argument for intersectional analysis in gender, this study will also explore whether or not there are any significant interaction effects on STEM career choice from particular combinations of gender and race statuses and between gender and household income groups. Since Aulette et al. did not specifically measure intersectionality or detail whether a real interaction effect occurs among gender, race/ethnicity and income, it is not known whether real interaction occurs in STEM career choice. This study will look for real interaction in the form of a significant interaction effect, controlling for other variables.

SPECIFIC AIMS

This study uses longitudinal data to look at how career choices regarding STEM fields are affected by ability in math and technical areas and the social statuses of race/ethnicity, household income and especially gender. Building upon the literature, the following hypotheses explore the associations between these variables.

Past research has argued that gender greatly influences the image of STEM careers as being masculine, with men more likely to choose them.

Hypothesis1: Men are more likely than women to choose STEM careers.

Previous studies have shown that math skill has a significant effect on STEM career choice, with those who have higher math scores choosing STEM fields.

Hypothesis 2: Individuals with higher math scores are more likely to choose STEM careers than those with lower math scores.

Current academic arguments focus on math ability and STEM career choice. The following test will use a new measure of ability to explore the impact of technical skill on STEM career choice.

Hypothesis 3: Individuals with higher technical scores are more likely to choose STEM careers than those with lower technical scores.

Research has shown that those who are minorities and have lower household income are underrepresented in these areas. Because the literature suggests that race/ethnicity and household income affect students' career choices, the following hypotheses will be tested.

Hypothesis 4: Blacks/Hispanics are less likely than whites to choose STEM careers.

Hypothesis 5: Individuals from higher income households are more likely to choose STEM careers than those from lower income households.

The literature discusses the significant influence of math ability on career decisions, and argues how gendered constructions of this skill cause men and women to have different outcomes. To clarify the association of this variable with career choice, the following hypothesis will be examined:

Hypothesis 6: Math ability will have a significant effect on career choice, independent of technical ability and social status variables (gender, race/ethnicity, and household income).

The following hypothesis builds upon the previous one. Though the literature usually focuses on math skill, use of technical skill will enable a further examination into the impact of this ability on STEM career choice. Previous research has hinted at how technical skill can have an impact on occupational decisions in STEM.

Hypothesis 7: Technical ability will have a significant effect on career choice independent of math ability and the social status variables.

The literature pays particular attention to the impact of gender on STEM career choice, and how perceptions of math and technical abilities are gendered. To investigate the specific impact of gender, the following hypothesis will be examined:

Hypothesis 8: Gender will have a significant effect on career choice independent of math and technical ability and the other two social status variables (race/ethnicity and household income).

Though gender is important, the other two social statuses of race and ethnicity as well as household income are also expected to affect how gender operates in society

(Aulette et. al 2009). To analyze the effects of race/ethnicity and household income separately, the following hypothesis will be tested:

Hypothesis 9: Race/ethnicity will have a significant effect on career choice independent of math and technical ability and of the other the other two social status variables (gender and household income).

Hypothesis 10: Household income will have a significant effect on career choice independent of math and technical ability and the other two social status variables (gender and race/ethnicity).

Some scholars argue that an interaction effect exists between gender, race/ethnicity and income so that minority and/or low-income females are more likely to face inequality in society (Aulette et al. 2009). Applying intersectional analysis to this study, the following hypothesis will be tested to explore potential interaction effects:

Hypothesis 11: An interaction effect will exist between gender and race/ethnicity and gender and household income so that black/Hispanic/mixed race women or low-income women are less likely to choose STEM careers than predicted from the component variables of the interaction terms.

METHODOLOGY

Design and Study Population

Data for this project come from the National Longitudinal Survey of Youth, cohort of 1997 (NLSY97), a study implemented by the United States Department of Labor, Bureau of Labor Statistics. The purpose of this research was to detail young men's and women's experiences from adolescence into adulthood, from the roles of students to workforce members. Eligible respondents were those born between the years of 1980 and 1984 who had been identified as residents of selected households through the screening interviews, where 75,291 of 96,512 households were represented (for a 78% response rate). The first round of interviews was conducted in 1997-1998. Probabilities of selection are based on total housing units in a geographic area. Multi-stage cluster-sampling methods that involved the master probability sample for national surveys of the NORC (National Opinion Research Center) were utilized in the sampling. Counties were first selected, then census enumeration districts, blocks, and housing units, utilizing simple random samples. The last stage could include more than one youth per household being interviewed. Among the 9,806 youths known to be of the right age in the selected households, 8,984 or 91.6% participated in the Round 1 survey. Eleven following rounds have been annually conducted and provide a wide range of variables associated with each youth (U.S. Bureau of Labor Statistics National Longitudinal Survey Program of Youth 1997, 2009).

Round 1 of the NLSY included individuals who participated in the Armed Services Vocational Aptitude Battery (ASVAB), a military enlistment test that was under development by the U.S. Department of Defense. Also termed as the Profile of American

Youth 1997, the purpose of this test was for the U.S. Department of Defense to formulate new standards for the ASVAB (Center for Human Resource Research, The Ohio State University 2009). Among those in the Round 1 sample who were deemed eligible for the ASVAB, 79% (7,127) completed this test.

The sample used for the present study, (N=1,885) includes individuals in the cross-sectional sample[1] of students in grades 9-12 in 1997[2] who took the ASVAB, gave valid responses about their occupation for Round 10 and were in the labor force (in 2006)[3], in the most recent year where data were collected regarding respondents' occupations. More specifically, they were in one of the following categories: employed at work, employed absent from work, unemployed on layoff, unemployed looking for work or in the Active Armed Forces. For those in the cross-sectional sample, the response rates were 92.1% participation in Round 1 (6,748/7,327) and 83.3% in Round 10 (5,624/6,748). Excluding those who died later by Round 10, the number increased to 92.8% in Round 1 (6,748/7,268) and 84.1% in Round 10 (6,748/6,689). The participation rate for the cross-sectional sample is 94.3% for the screening interviews, out of 54,253 that were screened.

If the Round 1 interviews and ability tests were done at different times, then some of the apparent non-response may be due to ineligibility. Drop-outs after Round 1 would presumably not have been tested on ability, since the ASVAB was given only to those in school or intending to enroll after summer. Additionally, for Round 10, even more responses were coded by NLSY as invalid, thus a large amount of attrition occurred. Further, a notable amount of the respondents were not in the labor force (29.3%) or did not have valid responses (25.0%) in 2006, leading to 6,030/8,984 (67.1%) response rate.

The majority of the sample was non-Black/non-Hispanic (72.0%), with smaller percentages of Black, non-Hispanic (15.1%) and Hispanic (11.7%). Regarding sex, 957 females (50.8%) and 928 males (49.2%) were present in the sample. The median for household income was $56,252.24 in 1996. The sample's characteristics correspond fairly closely with the Census 2000 data, where 49.1% of the population is male and 50.9% is female. Whites represented 75.1% of the population in the Census, and blacks represented 12.3%. Hispanics constituted 12.9% with non-Hispanic whites representing 69.1%. The sample's average household income does appear to be much higher than the median household income in 1999, which was $41,994 (U.S. Census Bureau 2010). One reason for the income discrepancy is that households with teen-age children have adults who have been in the labor force longer and had more time to find good-paying jobs, and these households seem more likely to have more than one earner

Measurements

The five main independent variables examined in this study are: gender (sex), race/ethnicity, household income[4], math ability and technical ability. The codes for sex, race/ethnicity, and household income used by NLSY researchers are kept in this analysis for descriptive statistics, but recoded for other types of analyses. Sex was recoded to indicate whether the respondent was female (Yes = 1, No = 0). Race/ethnicity was originally coded by the Bureau into four categories: black, Hispanic, mixed race and non-Black/non-Hispanic[5]. For this study, blacks, Hispanics and mixed race respondents were grouped together, to create a BlackHispanicMixedRace variable (Yes = 1, No = 0). Household income was the gross household income of the previous calendar year (1996). This variable can include negative values [6] and was originally top-coded by the NLSY researchers at the two percent level. This indicates that the mean of the top two percent of cases (with very high-incomes) is used as the value for these. Additionally, the mean of this variable was used for cases with missing data[7].

The variables of ability and career choice were recoded for the purposes of this study. To measure skill in math and technical areas, scores from the ASVAB are used[8]. This multiple-choice test is administered by the military to high school students for enlistment purposes. It also is designed to reveal for which areas of the armed forces a person is best suited; thus, it is a type of a vocational test which focuses on the very abilities this study aims to examine.

The ASVAB was administered using computer-adaptive testing, so that the difficulty of the questions changed with how the respondent answered. Scoring is based on an Item Response Theory (IRT) model, where all test questions and examinee abilities are placed on the same scale (U.S. Military 2009). The year that NLSY respondents took the ASVAB, it included twelve subtests. Nine of the twelve subtests were used in this study: arithmetic reasoning, mathematical knowledge, numerical operations, coding speed, assembling objects, auto information, electronics information, mechanical comprehension and shop information. Three subtests were not used because they did not directly relate to math or technical ability. These were general science, paragraph comprehension and word knowledge. Each subtest had a range of 20 to 30 multiple-choice questions. To measure auto information, students were asked questions such as "All of the following are types of screwdrivers, EXCEPT..." To measure electronics information, students were asked questions such as, "Increasing the voltage applied to a circuit will cause…?" (U.S. Military 2009).

The NLSY created ASVAB final ability estimates to summarize each youth's performance in each of these subtests. These variables were created because of the adaptive testing procedure where the respondents' raw scores cannot be directly compared because they are not all asked the same questions. These final ability estimates may be positive or negative scores because of the type of calibration that the researchers used in creating the variables. The scoring was analogous to standardization, as the mean was 0 and the standard deviation was set at 1. However, each subtest estimate originally had two variables, one for positive scores and one for negative scores, though each respondent will have a valid score for only one of the indicators. The NLSY researchers instruct that these scores should be combined when undertaking analyses[9] (Center for Human Resource Research, The Ohio State University 2009). For the present study, the final ability estimate scores from each of the relevant subtests (of arithmetic reasoning, mathematical knowledge, numerical operations, coding speed, assembling objects, auto information, electronics information, mechanical comprehension, and shop information) were recoded[10]

A factor analysis was performed to determine which of nine subtests that measured ability could be grouped into reliable scales, for math or technical ability. Two independent components were extracted using the Principal Components method, with the Varimax Rotation method. Arithmetic reasoning, mathematical knowledge, numerical operations, and coding speed loaded high on one component in the rotated factor matrix (above .721),while assembling objects, auto information, electronics information, mechanical comprehension, and shop information loaded relatively high on another component (above .416). Any items with loadings under .300 would have been excluded in the scale-building process. These subtests were then used to develop two different scales.

The scores within the areas of arithmetic reasoning, mathematical knowledge, coding speed and numerical operations were added together to form the Math Ability Scale, which was found to be modestly reliable (Cronbach's alpha=.618). The scores for assembling objects, auto information, electronics information, mechanical comprehension and shop information were summed to form the Technical Ability Scale, which was found to be highly reliable (Cronbach's alpha=.834).

The dependent variable was career choice, which was measured by the respondents' occupation in 2006, nine years after they took the ability tests. These responses were coded by the NLS agency using the four-digit 2002 Census Occupational Codes (see Appendix A). The respondent could list all occupations that they presently had; in this study, only the first job listed was analyzed, since this is assumed to be the most important type of employment of the respondent. From the Census Occupational Code descriptions, the employment categories that were coded as STEM included those within the areas of computer and mathematical occupations, architecture and engineering occupations, and life, physical and other science occupations.[11] Within the management occupational category, those who were coded as computer and information systems managers and engineering managers were also included in the STEM category. Jobs were coded as being either STEM occupations or all other occupations (Yes = 1, No = 0), see Appendix A.

Data Analysis

SPSS16 software was used to analyze the data. Data were cleaned for missing responses and the missing and invalid entries were recoded accordingly. Additionally, data were double-checked to ensure no obvious coding errors remained.

Since this is an exploratory study, several statistical methods are used to investigate different types of significant relationships. To test each hypothesis separately, a variety of statistical techniques that make the fewest assumptions about the degree of precision in the measurements or the patterns in the population are used. More advanced techniques that involve more assumptions and other complications are used later in the data analysis, allowing for the introduction of other variables simultaneously. The goal of this type of data analysis is to attain a broad understanding of the associations between variables, proceeding to more in-depth analyses to investigate simultaneously how different variables affect STEM career choice.

Chi-square tests were performed to test for significant group differences in the propensity for a STEM career choice. These were used for Hypotheses 1 and 4.

To test for significant effects of math ability, technical ability, household income, gender, and race/ethnicity separately on STEM career choice, one-tailed Pearson zero-order correlations were calculated. These analyses would test Hypotheses 1-5.

T-tests for two independent sub-samples were used to determine significant differences in means. The means for STEM area career choices in low and high-scoring groups in math ability were compared, using the median for math skill to distinguish the two groups. The means for STEM career choice in low and high-scoring groups in technical skill, using the median of technical ability. They were also calculated for STEM career choice in low and high household income groups, again using the median. These were used to test Hypotheses 2, 3 and 5.

Logistic multiple regression tests were performed to analyze whether significant differences in the propensity for a STEM career choice occur by math ability, technical ability, gender, race/ethnicity, and household income, when all the other independent variables are controlled. New variables were created for math and technical ability to find meaningful results since these three measures have large ranges. The scores in each variable were divided by 100 to examine how the odds ratio changes for every 100 points on these original indicators. These were used for Hypotheses 6-10.

A test of logistic regression using the forward stepwise selection (likelihood ratio) was used to determine whether gender had the most significant influence on career choice, independent of all other variables. This was used for Hypothesis 8.

Analyses of Covariance were calculated to look at the interaction effects of gender with race/ethnicity and gender with household income, with household income recoded into high and low, using the mean (0=high-income, 1=low-income). If a significant interaction effect is found, a new variable will be calculated which is the product of the two measures that have a significant interaction effect. Controls of math and technical ability will be introduced, to ensure that there is a genuine interaction, not just an artifact of the component variables. This approach was used to test Hypothesis 11.[13]

RESULTS

The sample characteristics of the respondents overall, as well as the frequencies of those who choose STEM careers, are presented in Table 1. Men and women are about equally represented. A much larger proportion of non-black/non-Hispanics exist (72.0%) than the Black, Hispanic, or Mixed Race categories, but this reflects the disparate population shares of these groups.

Looking at career decisions in Table 1, almost 95% of respondents choose careers in some other field besides STEM. Since over 900 occupational categories existed, respondents' job codes could range widely. Only 53 of these were coded as STEM, which is only a small fraction of the myriad of occupational categories.

Tests of Hypotheses

Hypothesis 1: This hypothesis was supported.). Over two-thirds of the group choosing STEM careers was male (73.6%). For the chi-square goodness of fit test, the results also indicate that gender does have a significant association with career choice (X^2 with 1 degree of freedom = 27.839, $p = .000$) (Table 1). Female gender has a significant negative correlation with STEM career choice (r= -.122, $p < .01$), so that males are more likely to go into STEM careers. The association is, however, modest (see Table 2

Hypothesis 2: This hypothesis was supported. Math ability correlates significantly with STEM career choice, (r=.126, $p < .01$), so that those with higher math ability scores were more likely to go into STEM careers. Though the association is modest, it still shows a statistically significant positive relationship between the two variables (Table 2). For those going into STEM careers, a greater proportion of individuals had average math scores that were at or above the median. The t-test on two independent sub-samples also shows a statistically significant relationship, with those going into STEM careers scoring better in math ability (t=4.126, p=.000). Respondents who have higher math scores are statistically significantly more likely to go into STEM careers (.08 vs. .04) (see Table 3).

Hypothesis 3: Interestingly, this hypothesis has stronger support than the previous one, as Table 2 shows. Technical ability correlates significantly with STEM career choice (r=.186, $p < .01$), so those with higher technical ability scores were more likely to go into STEM careers. This positive association is modest, but greater than that for the math ability variable, where r = .126 (Table 2). The t-test on two independent sub-samples shows a statistically significant association for those going into STEM careers who are better scoring individuals in technical ability (t=5.538, p=.000). Respondents who have higher technical scores are statistically significantly more likely to go into STEM careers (.09 vs. .03). Significant differences are larger for technical ability than math ability as well, with larger t-values (Technical: 5.538 vs. Math: 4.126) (Table 3).

Hypothesis 4: This hypothesis was supported as well. For the chi-square goodness of fit test, the results also show that race/ethnicity does have a significant association with career choice (X^2 with 1 degree of freedom = 7.859, p = .005) (Table 1). As shown in Table 1 for STEM career choice, slightly more non-black/non-Hispanics than the overall sample chose these areas (83.6% vs. 72.0%). Consequently, fewer blacks, Hispanics and mixed race individuals choose STEM careers compared to their representation in the overall sample (blacks: 11.8% vs. 15.1%; Hispanics: 3.6% vs. 11.7%; mixed race: 0.9% vs. 1.2%). The change is especially large for Hispanics, with about an eight percent decrease. Additionally, Race/ethnicity correlates significantly with STEM career choice. The Black/Hispanic/Mixed group is significantly less likely to go into STEM careers (r=-

.065, $p < .01$). However, the association is weaker than all the others reported so far (Table 2), and could be seen as just an artifact of the large sample size.

Hypothesis 5: This hypothesis was somewhat supported, in that one of the tests showed that young people from higher income backgrounds are more likely to choose STEM careers. Household income does not correlate significantly with STEM career choice (see Table 2). However, the t-test on two independent sub-samples showed a statistically significant difference, with those having household incomes that were at or above the median being more likely to choose a STEM career (t=2.332, p=.02). Respondents from higher income households are statistically significantly more likely to go into STEM careers (.07 vs. .05). The group difference here is smaller than for the other comparisons made (Table 3). In fact, it is so small (7% vs. 5% STEM careers for the High and Low Income categories) that this result illustrates the kind of statistically significant but substantively trivial result that a very large sample can produce.

Hypothesis 6: This hypothesis was supported. A binary logistical regression analysis was done to predict STEM career choice from math ability, controlling for all other variables in the model. Math ability remained as a statistically significant predictor in STEM career choice, controlling for all other variables in the study (p=.000). For every 100-point increase in math ability (on the scale that ranges from -5,011.00 to 60,143.00), the odds of choosing a STEM career versus all other careers increased slightly by a factor of 1.004 (or 0.4%), when controlling for every other variable in the model (Table 4).

Hypothesis 7: This hypothesis was also supported. A binary logistical regression was calculated to predict STEM career choice from technical ability, controlling for all other variables in the model. Technical ability remained as a statistically significant predictor in STEM career choice, controlling for all other variables in the study (*p*=.000). For every 100 point increase in technical ability (on the scale that ranges from -11,368.00 to 7,653.00), the odds of choosing a STEM career versus all other careers increased by a factor of 1.020 (or 2%) when controlling for every other variable in the model (Table 4) Even though the ranges are different, these results suggest that STEM career choice is more sensitive to differences in technical ability than math. Thus, this variable might be more important to address when understanding ability and STEM career choice.

Hypothesis 8: This hypothesis was mostly supported. A binary logistical regression was calculated to predict STEM career choice from sex (Female), controlling for all other variables in the study (*p*=.001). A significant effect on STEM career choice remained when race/ethnicity, household income, math ability, and technical ability were held constant. The odds of a female choosing a STEM career are .442 times less than the odds that a male would choose a STEM career, when controlling for all other variables in the model (Table 4). This equates respectively to a .253:1 (.0247:.9753) probability for females vs. .0569:1 (.0538:9462) for males, at the average values for the control variables

When a forward selection stepwise logistic regression test was run, technical ability was chosen first as explaining the most variance in STEM career choice, followed by math ability and then female. When gender was added, it significantly increased the adjusted R^2 from .040 to .046, explaining an additional 0.6% of the variance in STEM career choice (Table 5). Though it was not the first variable selected, being female has a negative linear relationship with STEM career choice, so that men were more likely to decide on these occupations, which supports the hypothesis.[14]

Hypothesis 9: This hypothesis was not supported. A binary logistical regression was calculated to predict STEM career choice from minority-group status (Black/Hispanic/Mixed Race), controlling for all other variables in the model. The odds that a black/Hispanic/mixed race respondent would choose a STEM career are about .984 times less than a non-black/non-Hispanic individual, when controlling for all other variables (see Table 4).

Hypothesis 10: This hypothesis was not supported. A binary logistical regression was calculated to predict STEM career choice from household income, controlling for all other variables in the model. Household income was not a statistically significant predictor of STEM career choice, when other factors were controlled for (p=.839), see Table 4.

Hypothesis 11: This hypothesis was supported only for race/ethnicity. An Analysis of Covariance test was done to find if interaction effects existed for sex and race/ethnicity as well as sex and household income. In preparation for this analysis, an investigation was undertaken to see if the statistical prerequisites for doing the test correctly were met. ANOVA assumes the groups being compared have the same variances or standard deviations in the population. To investigate this, the Levene Test of Homogeneity of Variances was applied, and the result was unfortunately significant, indicating there might be a significant amount of heterogeneity. A second test, recommended by Pett (1997:54) was conducted to explore this further, which involves comparing the standard deviations for all groups, looking for any that is at least twice as large as another. The standard deviations for all of the groups were less than twice as high as another, permitting further analyses with ANOVA. Thus, the significant result from Levene's test does not seem to be so serious as to preclude application of ANOVA here, and the initially troublesome result of Levene's test might just be due to the large size of the sample.

A significant interaction exists between race/ethnicity and sex (*p*=.090), which meant that at least one combination of gender and race/ethnicity seems to have a different population mean for STEM career choice than other combinations, when controlling for the component variables, see Table 6. For the Estimated Marginal Means, the results show that STEM career choice is predicted to be higher for males than females, even for black/Hispanic/mixed race males and females. A notable gender difference exists in both racial/ethnic groups. Non-black/non-Hispanic males have the highest estimated marginal mean, followed by black/Hispanic/mixed race males, then non-black/non-Hispanic females and finally black/Hispanic/mixed race females. The gender gap was larger for nonblack/non-Hispanic group than for the black/Hispanic mixed group (.056 vs. .015), which suggests an interaction of race/ethnicity and gender. There was no significant interaction effect for household income and sex (*p*=.125). For the Estimated Marginal Means, the results show that STEM career choice is predicted to be higher for males than females, even for low-income males and females. High-income males have the greatest estimated marginal mean, followed by low-income males, then low-income females and finally high-income females (see Table 6).

Since a significant interaction effect for race/ethnicity and sex existed, a new variable was created, which is the product of race/ethnicity and sex. A Yes=1 code on this variable represents minority (Black/Hispanic/Mixed Race) females; no=0 represents the rest of the sample. This variable was utilized for a second logistic regression analysis (see Table 7). In this test, sex and both abilities separately had significant impacts on STEM career choice, when controlling for the other variables. Race/ethnicity and household income were not significantly impacting career choice, which is similar to the previous logistic regression analysis. The interaction variable of Female Gender and Black/Hispanic/Mixed Race also did not show any significant effect on STEM career choice *(p*=.469)[12] though black/Hispanic/mixed race females are 1.499 times more likely than nonblack/non-Hispanic males to choose a STEM career.

A micro-level analysis was performed on the few women who chose STEM careers (n=29) to study more closely at individual patterns for future research, see Table 8. Looking further at those women who did pursue STEM careers, most had high math scores, with the average math skill score for this group higher than the overall mean (33,963.06 vs. 26,291.57). For technical scores, the mean was higher than the overall average as well (-1,436.14 vs. -2,400.22). Seven out of the 29 women were black, with no Hispanic or mixed race women choosing STEM careers. Interestingly, this group came from households with higher-than-average incomes in 1996, (Women in STEM Mean: $ 60,117.97; Entire Sample Mean: $56,252.24). Women who did not choose STEM areas had lower household incomes and math and technical scores than women in STEM (income: $56,455.19 vs. $60,117.97; math: 27,033.29 vs. 33,963.06; technical: -3,267.86 vs. -1,436.14), though Hispanic and mixed race females were actually represented because of the larger sample size, compared to zero Hispanics and mixed race women in STEM areas, see Table 8. Men who chose STEM careers had slightly higher household incomes than women in STEM ($60,824.99 vs. $60,117.97). For abilities, this group of men had lower math ability scores but much higher technical scores (math: 30,387.96 vs.

33,963.06; technical: 252.1 vs. -1,436.14). Nonblack/non-Hispanics were a much larger group for men in STEM than for women in STEM (86.4% vs. 75.9%), see Table 8.

For those women who were going into STEM occupations (Table 9), professions included computer and information systems managers, computer scientists and systems analysts, computer programmers, computer support specialists, database administrators, network systems and data communications analysts, statisticians, chemical engineers, environmental engineers, industrial engineers, including health and safety, drafters, surveying and mapping technicians, biological scientists, medical scientists, chemists and materials scientists, market and survey researchers, psychologists, agricultural and food science technicians, biological technicians, and other life, physical, and social science technicians.

DISCUSSION

Overall, the results followed what the literature had led one to expect, but some surprising results emerged. Most notable of these is the finding that these five variables of sex, race and ethnicity, household income, math and technical abilities only explained about 5.0% of the variance in STEM career choice (Table 5), so other indicators must have a larger effect on the respondents' decisions. The literature had focused on how sex, race and ethnicity, income and abilities would affect STEM career choice. However, these variables only explained a small amount within the model. Thus, variables such as classroom environment, parent occupation, perception of abilities or other types of social indictors predict STEM career choice apart from ability alone.

The findings did provide support for the overall argument within the literature. Sex was found to have a significant effect on STEM career choice for every single test, supporting Hypotheses 1 and 8. This can be seen from the significant correlations, chi-square tests, logistic regression and stepwise linear regression findings. Though sex was not the first factor chosen in explaining STEM career choice in the linear regression, it still was the second most important explanatory variable in accounting for decisions to enter these fields. Additionally, this test confirmed previous analyses in that men were significantly more likely to decide on STEM careers than women.

For race and ethnicity, Blacks and Hispanics were almost as likely to be represented in STEM careers as others (Table 1). Being nonblack/non-Hispanic did affect STEM career choice (Table 2), with statistically significant effects in predicting STEM career choice. A greater significance might have been found if the coding of race and ethnicity had been different. The fact that the non-black/non-Hispanic group included every other ethnicity and race besides black, Hispanic and mixed race may help explain why no significant impact was found for the logistic analysis (Table 4). If the results were further specified to include other races and ethnicities or if a white category was present, more notable results might have been found. On the other hand, this non-black/non-Hispanic grouping includes Asians, who do constitute the next largest group of employed scientists and engineers (in 2006, they represented 17% of scientists and engineers, compared to 6% of Blacks, 5% of Hispanics and 2% all other races/ethnicities, with whites representing 70%) (National Science Foundation Division of Science Resources Statistics 2007). Asians' share of the population was 3.6% in the 2000 Census (U.S. Census Bureau 2010).

Interestingly, race/ethnicity and sex were found to have a significant interaction effect, so that being a woman who is black/Hispanic or mixed race are especially unlikely to choose STEM careers, compared to the other groups—more so than gender or race/ethnicity by themselves can account for (Table 6). This further supports the literature that found minority women increasingly underrepresented in these professions, much more than white women, with black and Hispanic women totally only 11% of all female scientists and engineers (National Science Foundation Division of Science Resources Statistics 2007). Though little previous research was performed on interaction effects in STEM, these results do support the intersectional analysis that Aulette et al. (2009) had discussed, where low-income, minority women are more disadvantaged than higher income, white women.

Only one of the three tests provided evidence for the hypothesis that those with higher parents' incomes were found to be more likely to choose STEM careers. However, the higher income group was also significantly more likely to have higher math and technical ability scores (see Table 2). Since both math and technical ability scores also correlated significantly with STEM career choice, it can be argued that household income affects both ability levels, which can affect how individuals choose these careers. This is supported by educational reports which conclude that differences in math scores are greater for income groups than those between girls and boys (U.S. Department of Education, National Center for Education Statistics 2009).

Those who went into STEM careers had high math scores, which were found to be statistically significant. Overall, this sub-sample had a high average math ability score, among both men and women (Tables 1 and 2). When controlling for all other variables, math ability alone did have a significant effect on STEM career choice (Table 4). These results might be explained by the literature's main argument that men are socialized to believe they are better at math than women, even if they have equal ability levels (Correll 2001).

Interestingly, technical ability scores correlated more strongly than math did with STEM career choice, and those who went into STEM careers had higher technical scores (Table 2). When controlling for all other variables, technical ability alone had a significant effect on STEM career choice (Table 4). This demonstrates the importance of studying technical skills as potential determinants of STEM career choice. Though those going into STEM occupations had lower technical abilities than math, the effect of this variable on STEM career decisions was statistically significant, much more so than math ability. Thus, to recruit more individuals into STEM, technical skill should be addressed.

Looking at the stepwise regression, technical ability was the most significant factor in explaining STEM career choice, though math ability was important as well (Table 5).

Besides the overall hypothesis testing, other interesting results were found. For the correlations, it was interesting to find such a strong positive correlation between sex and math ability, so that women were performing better in math than men. This result supports the literature arguing that small differences do exist between men and women regarding math (Hyde and Linn 2006). Though usually males perform slightly better (U.S. Department of Education, National Center for Education Statistics 2009), women are actually the group in this sample who have higher math ability levels.

When looking at the small group of women who choose STEM areas, more support for the hypotheses is shown. The women came from households with higher incomes and had higher math and technical ability scores than the sample and also for women who did not choose STEM, However, women in STEM did have lower technical scores than the males who pursued STEM careers, but higher math ability scores than men in this area. Having parents who have a larger household income as well as higher-than-average math and technical abilities might be the right formula for getting women to choose STEM careers over other occupations.

These findings overall show that the social status variables of race/ethnicity and sex have a significant effect in predicting STEM career choice, with non-black/non-Hispanic men being most likely to choose these careers. However, it seems that technical ability has the largest effect on STEM career choice, so that those with higher technical abilities pursue these areas whether social status variables were included in the test or not, with math ability following this variable as being the second strongest indicator. Sex was found to be a significant predictor, but not the strongest since it was the third variable chosen as predicting STEM career choice. From this analysis, both abilities and sex most strongly determine STEM occupational decisions among the variables included in this analysis.

CONCLUSION

This exploratory analysis is aimed at looking the influence of social status on STEM career choice to understand if sex, race/ethnicity and household income had larger effects on STEM employment choice than did technical and math ability levels. Significant associations were found with all the variables. The strongest relationships were between technical skill and STEM career choice, but significant, strong associations were also found between math ability and STEM choice as well as gender and STEM career decisions.

This study adds to the existing literature in several ways. First, technical skill needs to be incorporated into research on STEM career choices, in addition to math ability. Future studies should look at technical ability in understanding STEM as well as other male-dominated careers. Blue-collar jobs such as construction workers and automotive technicians might rely on this skill more than STEM careers do. Additionally, future studies should also look at the impact of other abilities, such as science skill in understanding its impact on STEM occupational decisions. Gender was also shown to be the most important social status variable; thus research should continue to investigate the effects of this factor on STEM career choice.

Additionally, the use of longitudinal data to look at career choices adds to existing literature on STEM career choices. Many studies focus on the individual’s aspirations (Shapka et al. 2006) or their college major (Correll 2001). This study focused on the actual outcomes by using respondents’ career choices nine years later. Those in the sample would have been between the ages of 23-27, years where they can often report a career choice instead of their intention of choosing one.

Several limitations existed in this analysis. First, this study could not measure self-perceptions of math or technical ability. Having data on this variable would add to the understanding of the gendered perceptions of these skills. Since the variables used in this study only predicted about 4.0% of the variance, the effect of other variables such as perception could have explained more. A second limitation involves the categorization of race and ethnicity. This variable was coded for only black, Hispanic, mixed race and non-black/non-Hispanic groups in the original data set. If this variable was a little more specific, significant effects could have been found on STEM career choice. Another limitation involves the large amount of missing data or invalid responses. The original sample included over 8,000 respondents, but many of these were excluded because their responses were invalid. Some of these invalid responses could be attributed to individuals who are still pursuing education or possibly housewives. Thus, the final sample include only 1,885 cases, so these findings are not as generalizable as they would have been if more valid responses would have been included. Though these limitations are notable, the use of a large data set such as the NLSY 97 does strengthen the results of this study because it is nationwide, generalizable and performed by a team of distinguished researchers instead of one individual.

Is one's gender a greater predictor of their career choice in STEM than their actual math and technical ability levels? The findings from those analysis show mixed results. Though men are more likely to choose STEM careers than women, other factors are also important. If the male's parents have larger incomes, and if the male is nonblack, non-Hispanic, has a higher technical and math ability level, he is more likely to pursue a STEM career. While confirming many of the previous studies, this analysis sets the stage for future research efforts which focus on the impact of technical skill on careers in STEM, especially since this variable was found to be the strongest impact in STEM occupational choice in these tests. As a result, this exploratory analysis provides a framework for future improvement in women's representation in STEM. Policies can focus on professional networks and can also investigate the informal factors which influence more men to choose STEM areas, such as the culture of engineering that Robinson and McIlwee (1991) detail, where men promote their skill in this craft through social interaction. However, this study does show that all of these variables of household income, technical and math ability, race/ethnicity and gender in one way or another had an influence on career choice in science, technology, engineering and math and were definite technicalities in determining decisions to enter careers in STEM.

APPENDIX A

2002 Census Occupational Code Categories

CODE	OCCUPATIONAL CATEGORY
10 TO 430:	MANAGEMENT
500 TO 950:	BUSINESS AND FINANCIAL OPERATIONS
1000 TO 1240:	COMPUTER AND MATHEMATICAL
1300 TO 1560:	ARCHITECTURE AND ENGINEERING
1600 TO 1960:	LIFE, PHYSICAL AND SOCIAL SCIENCE
2000 TO 2060:	COMMUNITY AND SOCIAL SERVICES
2100 TO 2150:	LEGAL
2200 TO 2550:	EDUCATION, TRAINING AND LIBRARY
2600 TO 2960:	ARTS, DESIGN, ENTERTAINMENT, SPORTS AND MEDIA
3000 TO 3540:	HEALTHCARE PRACTIONER AND TECHNICAL
3600 TO 3650:	HEALTHCARE SUPPORT
3700 TO 3950:	PROTECTIVE SERVICE
4000 TO 4160:	FOOD PREPARATION AND SERVING RELATED
4200 TO 4250:	BUILDING AND GROUNDS CLEANING AND MAINTENANCE
4300 TO 4650:	PERSONAL CARE AND SERVICE
4700 TO 4960:	SALES AND RELATED
5000 TO 5930:	OFFICE AND ADMINISTRATIVE SUPPORT
6000 TO 6130:	FARMING, FISHING, AND FORESTRY
6200 TO 6940:	CONSTRUCTION TRADES AND EXTRACTION
7000 TO 7620:	INSTALLATION, MAINTENANCE, AND REPAIR
7700 TO 8960:	PRODUCTION AND OPERATING
9000 TO 9750:	TRANSPORTATION AND MATERIAL MOVING
9800 TO 9840:	MILITARY SPECIFIC OCCUPATIONS

Specific Occupation Coded as STEM Careers:

Computer and information systems managers
Engineering Managers
Computer scientists and systems analysts
Computer programmers
Computer software engineers
Computer support specialists
Database administrators
Network and computer systems administrators
Network systems and data communications analysts
Actuaries
Mathematicians
Operations research analysts
Statisticians
Miscellaneous mathematical science occupations
Architects, except naval
Surveyors, cartographers, and photogrammetrists
Aerospace engineers
Agricultural engineers
Biomedical engineers
Chemical engineers
Civil engineers
Computer hardware engineers
Electrical and electronics engineers
Environmental engineers
Industrial engineers, including health and safety
Marine engineers and naval architects
Materials engineers
Mechanical engineers
Mining and geological engineers, including mining safety engineers
Nuclear engineers
Petroleum engineers
Engineers, all other
Drafters
Engineering technicians, except drafters
Surveying and mapping technicians
Agricultural and food scientists
Biological scientists
Conservation scientists and foresters
Medical scientists
Astronomers and physicists
Atmospheric and space scientists
Chemists and materials scientists
Environmental scientists and geoscientists
Physical scientists, all other
Economists

Market and survey researchers
Psychologists
Agricultural and food science technicians
Biological technicians
Chemical technicians
Geological and petroleum technicians
Nuclear technicians
Other life, physical, and social science technicians

APPENDIX B

Table 1.
Distribution of Respondents (N=1,885)

Variables	Overall Results		STEM Career Choice			
	N	%	N	%	X^2	*df*
Sex					27.839*	1
Male	928	49.2	81	73.6		
Female	957	50.8	29	26.4		
Race/Ethnicity					7.859*	1
Black, non-Hispanic	285	15.1	13	11.8		
Hispanic	221	11.7	4	3.6		
Mixed Race, (non-Hispanic)	22	1.2	1	0.9		
Non-Black/Non-Hispanic	1,357	72	92	83.6		
STEM Career Choice						
All Other Careers	1,775	94.2	-	-	-	-
STEM Career	110	5.8	-	-	-	-

*p<.01

Table 2.
Correlations and Descriptive Statistics (N=1,885)

Variables	1	2	3	4	5	6
1. Sex [a]	-					
2. Race/ Ethnicity [b]	.042*	-				
3. Household Income	.008	-.209**	-			
4. Math Ability	.097**	-.181**	.182**	-		
5. Technical Ability	-.279**	.398**	.131**	.384**	-	
6. STEM Career Choice [c]	-.122**	-.065**	.027	.126**	.186**	-
M	0.51	0.28	56,252.24	26,291.57	-2,400.22	0.06
SD	0.50	0.45	40,025.97	9,948.47	2,956.98	0.23
Range	0-1	0-1	-48,100.00-246,474.00	-5,011.00-60,143.00	-11,368.00-7,653.00	0-1

Note: One-tailed, Pearson Zero-Order correlation
[a] Sex: 0=Male, 1= Female. [b] Race/Ethnicity: 0= Non-Black/Non-Hispanic 1=Black,Hispanic or Mixed Race (Non-Hispanic). [c] STEM Career Choice: 0= All Other Careers, 1=STEM Career Choice.
**p*<.05. ***p*<.01.

Table 3.
STEM Career Choice and Means of Selected Variables (N=1,885)

	High Grouping	Low Grouping	T-Value	F	Sig. (Lev)
Math Ability [a]	n=944	n=941	4.13*	70.47	.00
STEM Choice Mean of sub-sample	0.08	0.04			
Technical Ability [b]	n=943	n=942	5.54*	130.62	.00
STEM Choice Mean of sub-sample	0.09	0.03			
Household Income [c]	n=963	n=922	2.33*	21.83	.00
STEM Choice Mean of sub-sample	0.07	0.05			

Note: One-tailed test of significance, used median as cut-point for each group
[a] Median=26,728.00. [b] Median=-2,279.00. [c] Median=56,252.24
*p<.01

Table 4.
Summary of Logistic Regression Analysis for Variables Predicting STEM Career Choice, Controlling for Selected Variables (N=1,885)

Predictor	*B*	*SE B*	*Exp(B)*
1. Female [a]	-0.809	0.243	0.442*
2. Black/Hispanic/Mixed Race (non-Hispanic) [b]	-0.016	0.288	0.984
3. Household Income	0.000	0.000	1.000
4. Math Ability [c]	0.040	0.001	1.004*
5. Technical Ability [c]	0.020	0.004	1.020*
Constant	-3.454	0.385	.032*
X^2	89.601*		
df	5		
Cox & Snell R^2	0.046		

Note: One-way tests of significance, Exp(B) represents the change in Odds Ratio per each unit of increase in the Independent Variable
[a] Sex: 0=Male, 1= Female. [b] Race/Ethnicity: 0= Non-Black/Non-Hispanic 1=Black,Hispanic or Mixed Race (Non-Hispanic). [c] Values dived by 100 to find meaningful results for odds ratios.
*p<.01.

Table 5.
Stepwise Forward Selection Logistic Regression (Likelihood Ratio) Predicting STEM Career Choice (N=1,885)

	Step 1: Technical Ability Added		Step 2: Math Ability Added		Step 3: Female Added	
	B	*Exp(B)*	B	*Exp(B)*	B	*Exp(B)*
Technical Ability	.028	1.029*	.025	1.026*	.020	1.020*
Math Ability			.004	1.004*	.004	1.004*
Female					-.807	0.446*
Constant	-2.397	.091*	-3.502	.030*	-3.439	.032*
Cox & Snell R^2	.035		.040		.046	
Model X^2	66.814*		77.848*		89.552*	
df	1		2		3	

Note: 95% Confidence Interval, one-way tests of significance. Excluded variables: Black/Hispanic/Mixed and Household Income. Exp(B) represents the Change in Odds Ratio per each unit of increase in the Independent Variable
[a] Sex: 1=Female, 0= Male. [b] Race/Ethnicity: 0= Non-Black/Non-Hispanic 1=Black,Hispanic or Mixed Race (Non-Hispanic). [c] Values dived by 100 to find meaningful results for odds ratios.
*p<.01

Table 6.
Analysis of Covariance for Sex, Race/Ethnicity, Household Income and STEM Occupation (N=1,885)

Predictor	*B*	*t*	*Sig*	*Mean*	*Est. Marginal Mean*
Sex and Race/Ethnicity					
Math Ability	0.00	3.49	0.00	262.91	-
Technical Ability	0.00	4.51	0.00	-24.00	-
Non-black/Non-Hispanic [b]	0.02	-1.29	0.20	0.07	0.06
Black/Hispanic/Mixed Race	0[a]	-	-	0.03	0.06
Male	0.02	0.78	0.44	0.09	0.08
Female	0[a]	-	-	0.03	0.04
Non-black/Non-Hispanic*Male	0.04	1.70	0.09	0.10	0.09
Non-black/Non-Hispanic *Female	0[a]	-	-	0.03	0.03
Black/Hispanic/Mixed Race*Male	0[a]	-	-	0.05	0.07
Black/Hispanic/Mixed Race*Female	0[a]	-	-	0.02	0.05
Levene's Test F	46.47*				
Sex and Household Income					
Math Ability	0.00	3.30	0.00	262.91	-
Technical Ability	0.00	4.89	0.00	-24.00	-
High-Income [c]	0.00	-0.12	0.91	0.07	0.07
Low-Income	0[a]	-	-	0.05	0.05
Male	0.03	1.74	0.08	0.09	0.08
Female	0[a]	-	-	0.03	0.04
High-Income*Male	0.02	1.54	0.13	0.10	0.10
High-Income*Female	0[a]	-	-	0.04	0.04
Low-Income*Male	0[a]	-	-	0.07	0.07
Low-Income*Female	0[a]	-	-	0.02	0.04
Levene's Test F	40.09*				

Note: Covariates were Math and Technical Ability scores divided by 100
[a] Parameter set to zero because it is redundant. [b] Race/ethnicity recoded for non-black/non-Hispanic = 0, Black/Hispanic/ Mixed Race =1. [c] Household income was recoded into high and low, using the mean to categorize them (0=high-income, 1=low-income).
*$p<.01$

Table 7.
*Summary of Logistic Regression Analysis for Variables Predicting STEM Career Choice, Controlling for Selected Variable sand Interaction of Female*Black/Hispanic/Mixed Race (non-Hispanic) (N=1,885)*

Predictor	*B*	*SE B*	*Exp(B)*
1. Female [a]	-0.892	0.271	.410*
2. Black/Hispanic/Mixed Race (non-Hispanic) [b]	-0.158	0.356	0.854
3. Household Income	0.000	0.000	1.000
4. Math Ability [c]	0.004	0.001	1.004*
5. Technical Ability [c]	0.019	0.004	1.020*
6. Female*Black/Hispanic/Mixed Race (non-Hispanic)	0.405	0.558	1.499
Constant	-3.431	0.386	.032*
X^2	90.116*		
df	6		
Cox & Snell R^2	0.047		

Note: One-way tests of significance, Exp(B) represents the Change in Odds Ratio per each unit of increase in the Independent Variable
[a] Sex: 1=Female, 0= Male. [b] Race/Ethnicity: 0= Non-Black/Non-Hispanic 1=Black,Hispanic or Mixed Race (Non-Hispanic). [c] Values dived by 100 to find meaningful results for odds ratios.
**p*<.01.

Table 8.
Characteristics of Women Who Choose STEM Careers and Comparisons with Other Groups

	STEM Women (n=29)		Non-STEM Women (n=928)		STEM Men (n=81)		Entire Sample (N=1,885)	
Variables	N	%	N	%	N	%	N	%
Race/ Ethnicity								
Black, non-Hispanic	7	24.1	157	16.9	6	7.4	285	15.1
Hispanic	0	0.0	112	12.1	4	4.9	221	11.7
Mixed Race (non-Hispanic)	0	0.0	10	1.1	1	1.2	22	1.2
Non-black/non-Hispanic	22	75.9	649	69.9	70	86.4	1,357	72.0
Mean Household Income	60,117.97	-	56,455.19	-	60,824.99	-	56,252.24	-
Mean Math Ability	33,963.06	-	27,033.29	-	30,387.96	-	26,291.57	-
Mean Technical Ability	-1,436.14	-	-3,267.86	-	252.10	-	-2,400.22	-

Table 9.
Occupations of STEM Women (n=29)

Occupation	N	%
Computer and information systems managers	1	3.4
Computer scientists and systems analysts	2	6.9
Computer programmers	1	3.4
Computer support specialists	4	13.8
Database administrators	1	3.4
Network systems and data communications analysts	5	17.2
Statisticians	1	3.4
Chemical engineers	1	3.4
Environmental engineers	1	3.4
Industrial engineers, including health and safety	1	3.4
Drafters	1	3.4
Surveying and mapping technicians	1	3.4
Biological scientists	1	3.4
Medical scientists	1	3.4
Chemists and materials scientists	1	3.4
Market and survey researchers	1	3.4
Psychologists	1	3.4
Agricultural and food science technicians	1	3.4
Biological technicians	2	6.9
Other life, physical, and social science technicians	1	3.4

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ENDNOTES

1. Cross-sectional was used for simplicity. When cross-sectional and supplementary sample of oversampled blacks/Hispanics and their STEM career choice were tested using independent sample t-tests of means, no great differences were found. I recoded Hispanic/Black/Mixed as 1 and all other as 0. When the data includes both supplement. and cross-sectional, the significance is .000 with mean difference for equal variances not assumed as .041 and a t=4.853.When only the cross-sectional sample is used, the significance is .001 with a mean difference for equal variances not assumed of .034 and a t=3.227. From seeing this, the results are similar, thus the cross-sectional sample is utilized.
2. Only this group was used since other ages were not eligible for the ability tests. Only those in grades 9-11 in Spring and Summer of 1997, those not enrolled in Spring or Summer but expecting to be in grades 10-12 in Fall 1997, or those enrolled in grades 10 12 when interviewed in Fall 1997 were eligible to take the ability tests. Another problem is that younger individuals would typically be 13-14 years old in 1997 and 22-23 years old in 2006. They might just have finished college, if they did not go part-time or take time off along the way, but they would not have had time to get the kinds of advanced degrees that would make it easier to enter a STEM field.
3. Those not in the labor force were excluded from this sample. Since the dependent variable is occupation, those whose careers might be temporarily interrupted by unemployment or some other instance are still included, since it is the chosen field that ultimately is of importance.

4. Parents' education would also have been a good measure of social class and is often shown in other studies to be an important factor in STEM career choice. However, the data set used in this project lacked adequate data on father's and mother's schooling because of the large number of missing cases for these indicators.
5. Several limitations exist in this coding of race and ethnicity, since there are only three groups. Though black/non-Hispanic and Hispanic are somewhat focused, nonblack/non-Hispanic is not. This group not only includes whites, but any other race that is not black or not Hispanic, i.e. whites, Asians, Native Americans, etc. Mixed race was not included because it was a "perfect predictor" for logistical regression, thus the results were not accurate. Only 7 cases total were in this sample. The variable was recoded so that there were only three groups.
6. Negative values were not invalid cases (e.g. "Don't know"). Possibly negative incomes were reported on tax returns in years with big losses for the farm or business. Only three actual cases had negative values in sample.
7. There were 409 cases which were missing which were replaced with the mean. When the tests were re-run without this step, the same results were found.
8. Each subtest has different ranges of scores: Arithmetic Reasoning: -3140 to 2361; Numerical Operations: -2328 to 43346; Auto Information: -2541 to 1769; Shop Information: -2591 to 2046; Math Knowledge: -2796 to 2678; Mechanical Comprehension: -2557 to 2745; Coding Speed: -6497 to 17559; Electronics Information: -2735 to 2914; Assembling Objects: -2378 to 1938.
9. The ASVAB is administered using an adaptive testing procedure, so that the difficulty of the question corresponds to the ability level of the respondent. After the test-taker answers the first item that is of average difficulty for all respondents, the computer adapts the questions to match the ability level of the individual taking it, updating this level for the fixed number of questions in the area. Since this computer-adaptive testing format has respondents answering different questions, the raw scores cannot be compared. To create comparable scores, final ability scores are computed for each area. A lower score indicates weak performance while a higher score shows better performance. In the original coding using Item Response Theory, these final ability estimates yielded both positive and negative results because they are on a scale generated by those who administered the ASVAB, which set the mean of the ability scores to 0 and the standard deviation to 1. Therefore, the final ability estimates are reported in two separate variables, one for positive scores and one for negative scores. However, since negative values are used for missing data in the NLSY97 study, two variables are used, with the final ability estimate being measured in positive scores and negative scores, one for each respondent, though each individual will only have one valid value (Center for Human Resource Research, The Ohio State University 2009).
10. All negative codes in each subtest were recoded with a zero. Since two variables existed for each subtest, one positive and one negative, these values needed to be recoded further and combined so that they are consistent in direction for statistical testing, since it would be too complex to have one variable measuring skill and another measuring lack of skill.

[11] Sociologists and urban planners were omitted from STEM careers per suggestion from thesis committee chair because they were generally more open to females. Not categories for managers of scientific research institutes or projects were recorded in this variable.

[12] Changing the coding to get nonblack/non-Hispanic or and high-income males vs. other instead of black/Hispanic/mixed or low-income females vs. other did not change the insignificant outcome. The coding was such that the interaction term that had the significant interaction effect was for the Low categories of Race and Gender, so Majority Male is the group whose distinctiveness is being detected, since their percent of STEM careers was the outlier, compared to the other Race*Gender combinations.

[13] A two-way ANOVA was performed as well, with a significant gender*race interaction term. However, since there were no math and technical ability controls, it was not used because the interaction term's significance disappeared in the logistic regression when the controls were introduced into the model.

[14] Forward selection (conditional) and forward selection (Wald) tests were performed as well and yielded similar results, with technical ability chosen first, then math ability and finally gender.