THE RELATIONSHIP BETWEEN GENDER AND IMPLICIT AND EXPLICIT BALANCED STEM IDENTITY PROFILES

A Thesis

by

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ABSTRACT

Persistent gender stereotypes, often reinforced by numerical dominance, have been shown to negatively influence sense of belonging and personal-professional identity development, attributing to the disproportional rate of attrition of women from the fields science, technology, engineering, and mathematics (STEM) when compared to their male peers. This study sought to identify potential relationships between the central personal-professional identities (i.e. Self-Gender, Self-STEM, and STEM-Gender associations), measured both explicitly (i.e. survey scales) and implicitly (i.e. Implicit Association Tests), using the Balance Identity Theory framework. More specifically, the study aimed to understand how the implicit measures of associations might correspond with their explicit counterparts, and if this relationship was different for women in STEM compared to their male peers. The cross-sectional data for this study is situated within a longitudinal study of identity balance among ethnically diverse undergraduate STEM majors in their junior and senior years. Participants completed three randomly displayed, online Implicit Association Tests and answered explicit survey questions measuring perceived gender identity, STEM identity, and STEM-Gender stereotype endorsements, from which implicit and explicit balanced identity scores were calculated.

A series of multiple regression analyses revealed that individual implicit association components did not significantly correlate with their explicit counterparts and this relationship did not vary by gender. However, a moderation analysis found that women exhibited a positive relationship between implicit and explicit balance scores, while the relationship was non-significant among men. Exploratory analyses showed that there were significant differences in implicit balance scores depending on participant's major (Biological/Life Sciences or Engineering/Computer Science), but no significant differences by major for explicit balance scores. Overall, consistent with previous literature, results reaffirm the importance of both implicit and explicit measure of identity and emphasize the potential of gender-specific nuances of balanced identities within the context of STEM fields.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Efforts to confront complex and persistent societal problems are hampered by the lack of diversity in the science, technology, engineering, and mathematics (STEM) enterprises. Researchers have shown that diverse teams will often outperform those composed solely for their cognitive abilities (Hong & Page, 2004). Accordingly, diversity leads to more equitable and productive science and engineering (Medin & Leed, 2012). Consider the design of the seatbelt: Automakers in the 1960’s, overwhelmingly male at the time, insisted on using a single crash test dummy resembling the average sized man to outfit the standard seatbelt. As a result, female drivers were 47% more likely to be severely injured in a car crash. This remained unchanged for nearly 50 years until Anna Carlsson, a Swedish female researcher, designed the world’s first 50th percentile female crash test dummy, marking a significant milestone in vehicle safety (Starr, 2012). The lack of a female perspective in the auto industry jeopardized the safety of nearly 50% of the population. Avoiding the mistakes of the past and confronting the current societal challenges requires adequate representation of diverse perspectives and backgrounds.

As the demand for a diverse, skilled workforce in the STEM disciplines increases, so does the need to recruit and retain highly qualified students from all backgrounds (Litzler et al., 2014). Although 52% of the college educated workforce is female (National Science Board NSF, 2020), women represent only 28% of practicing scientists and engineers (NGC, 2020). Similar disparities are observed at the undergraduate level. Engineering and computer science are more culpable with degrees being conferred to men at a rate approximately four times higher than to their female peers, while biological and life sciences are near parity (Trapani & Hale, 2019). The identification of these gender gaps in male-dominated STEM fields is not novel, however, recent efforts have been made to further the understanding of underlying contributors to these disparities amongst women's academic journeys and shed light on effective interventions that could increase their persistence (Dennehy & Dasgupta, 2017; Diekman et al., 2010).

Gender gaps in science and math *performance* have been closing, but gaps in STEM *self-concept* (i.e., confidence and identification with their STEM field) and *aspirations* (i.e., career intentions and alignment with personal-professional goals) remain large (Cech et al., 2011; Dasgupta, 2004). Research indicates that exposure to persistent gender stereotypes lowers women's sense of belonging, which in turn leads to greater attrition of women from engineering and other male-dominated STEM fields (Dasgupta & Stout, 2014; Jones et al., 2013). Further understanding of the influence of stereotype endorsement in congruence with the development of personal-professional identities is necessary in order to continue the work in changing the culture and conceptions of STEM fields to further support those often ostracized by it. The present study seeks to understand how men and women in their junior and senior year of undergraduate STEM programs hold varying identities and endorsements/rejections of persistent gender stereotypes in the field, measured through both implicit and explicit associations, and how the balance or imbalance of these identities might vary amongst men and women. Results of this research will better inform future studies of personal-professional identities on the potential need to utilize both implicit and explicit measures in order to tease out the gender-specific nuances of these identities.

1.1. Literature Review

1.1.1. Barriers to Identity Development

A sense of belonging and fit play significant roles in the development of a personal-professional STEM identity and are attributed to the attrition rate of those who are underrepresented in male-dominated fields (Rainey et al., 2018). Self-identity is malleable and subject to contextual factors that can either facilitate or constrain development (Markus & Kunda, 1986). For example, research indicates that women and racial/ethnic minorities can have their professional STEM identity thwarted by stereotype threats and preexisting (mis)conceptions about who can be successful in STEM fields (Boston & Cimpian, 2018). Prevailing cultural stereotypes subtly cue what *type* of person can be successful in the workplace or classroom, typically defined as a male of European or Asian descent. Recent efforts have been put forth by researchers, educators, and career specialists to attempt to change the perceptions of and culture within male-dominated STEM fields. For example, an 18-month study conducted by the National Academy of Engineering (NAE) studied teachers', parents', students', and career specialists' perceptions of the nature of engineering (2008). The results revealed the public's fundamental misconceptions about the nature of engineering and highlighted deleterious societal stereotypes that contribute to the lack of belonging and identification amongst women.

1.1.1.1. Developmental Emergence of Barriers to STEM Identity

Researchers have specifically identified the developmental ages at which these stereotypes begin to be internalized, noting that childhood and adolescence are crucial times for development of a STEM identity (Dasgupta & Stout, 2014; see also Christensen & Knezek, 2017; Kim et al., 2018). During childhood, gender stereotypes about math and science are ascribed to children by parents, primarily by mothers (Bhanot et al., 2005; Leaper et al., 2012) and peers (Dasgupta & Stout, 2014; Diekman et al., 2010; Fantz et al., 2011). These stereotypes can influence girls' (mis)perceptions that STEM is primarily for boys and is too challenging to be able to succeed, which together reinforce a perceived lack of belonging within the field (Stout et al., 2013). For example, recent research found that average or high-achieving high school boys and girls have similar intentions to pursue a STEM degree, yet lower-achieving boys intend to pursue at a greater rate than similar young women (Cimpian et al., 2020). The disparity between the STEM aspirations of lower achieving high school students reveals that women receive that message that only the highly capable individuals can succeed in STEM, a message that is not being received by young men (Cimpian et al., 2020). If a young woman *is* able to break through the barriers of these impending stereotypes in adolescence and continue to pursue further education in STEM, she will, unfortunately, more than likely be faced with a resurging dissonance between her developing STEM identity and her chosen career path as she enters the stereotype-laden, male-dominated STEM program.

Similar to the subtle cues that existed in adolescence, women in higher education STEM programs continue to face persistent gendered stereotypes about the people, work, and values in male-dominated environments (Cheryan, 2009; Clark Blickenstaff, 2005). The lack of representation amongst faculty in science and engineering disciplines contributes to these persistent stereotypes endorsed by many students during their academic journey (Nelson, 2017). For example, a recent study among college students showed a significant correlation between perceived number of women in STEM with a sense of imposterism (i.e., feelings of inadequacies, particularly among women) despite students' having proven success throughout their academic journey (Tao & Gloria, 2019).

Contextual cues, such as the visibility of in-group (e.g., same-gender) experts and peers are increasingly recognized as levers that can either reinforce stereotypes or promote inclusion. Recent advancements in theory and evidence point to the importance of positive female role models and mentors in college, in part, because they act as "social vaccines" to such stereotype threats and support women as they navigate the compatibility of their identities and their professional interests (Dasgupta, 2011; see also Dennehy et al., 2018; Dennehy & Dasgupta, 2017; Hernandez et al., 2020; Van Camp et al., 2019). As the development of a strong STEM identity is critical to persistence and success in STEM (Graham et al., 2013; Perez et al., 2014; Woodcock et al., 2012), it is crucial to better understand the influence of the various identities that are held in the midst of environments that pose a challenge to underrepresented groups, in this case, women in male-dominated STEM majors.

1.1.2. Measuring Identity

Research on self-perceptions and social cognition has established an understanding of the dual cognitive processes under which mental faculties operate. The dual-system theory of cognition suggests that there are two ways in which information is processed: (*a*) explicit processes, which can be consciously controlled, intentional, and made aware, and (*b*) implicit processes, which are automatic and unconscious or not under conscious control (Deutsch & Strack, 2006; Evans, 2008; Strack & Deutsch, 2004).

Researchers utilize explicit surveys to measure both the emergence of and the association between career and personal identities for students in STEM fields (Chemers et al., 2011; Darling et al., 2008; Dou et al., 2018). Self-reported survey methods ask participants to respond to questions, usually on a Likert scale, to represent their belief or attitude towards a statement. Recent studies in STEM education have further analyzed the predictive nature of explicit measures of identity for career/degree choices and the variation in this predictive nature for women and men (Godwin et al., 2016; Merolla & Serpe, 2013; Vincent-Ruz & Schunn, 2018).

By contrast, implicit measures of identity and associations with prevailing stereotypes utilize Implicit Association Tests (IAT), developed by Greenwald et al., to capture the strength of association between pairs of terms (2002). The IAT is a computer test that seeks to capture reaction times between pairs of concepts, such as “flowers” and “beautiful” or, in the case of gender-math stereotypes, “male” and “math”. An IAT D-score is calculated from the latency of reaction from the person between the pairs to determine the strength of association.

Implicit Association Tests have been widely used to measure implicit bias or stereotype association with groups, as initially seen in the study “Math = Male…” (Dasgupta, 2004; Greenwald, 2002). These implicit associations have been further adapted to utilize Heider’s Balance Theory as a framework for measuring individualized implicit identity balance (Heider, 1958; Woodcock, Schultz, Hernandez, In Preparation). This Individualized Balanced Identity Design (IBID) framework utilizes individual-level metrics to capture implicit balance between one’s gender identity (Me = My Gender), STEM identity (Me = STEM), and their STEM-Gender association (STEM = My Gender), as depicted in Figure 1 (Appendix A). For a woman with positive associations between self and STEM, self and gender, and STEM and gender, we would classify her identity profile as “balanced.” Additionally, one would be classified as “balanced” if two negative associations existed (ex: positive Self-Gender, negative Self-STEM, negative STEM-Gender), yet the implications of this profile might suggest that persistence in the STEM field may not be as likely as identification with the field has been shown to be a predictor of persistence. Classification and quantification of these balanced (or rather imbalanced) profiles further allows researchers to understand the tension that exists between the predominant identities of an individual in the midst of prevalent stereotypes and potential influencers of this balance.

1.1.3. Addressing the Gaps

The question remains: how do implicit associations relate to their explicit counterparts? Research has previously shown evidence for an advantage of implicit associations over their explicit counterparts in predicting outcomes relevant to retention (Dunlap & Barth, 2019; Zitelny et al., 2017), although further research is still required to determine the extent of this superiority. Further studies have examined differences of these STEM identities and their relationships to stereotypes predicted by implicit and explicit associations and have found that such relationships exist for implicit but not for explicit associations (Nosek & Smyth, 2011; Cvencek et al., 2020). Additionally, studies suggest the presence of varying strengths of relationship between the implicit and explicit attitudes, suggesting this relationship can exist while each method can contribute individually to the analysis of these associations (Cunningham et al., 2001; Smyth & Nosek, 2015).

Less well understood is how these relationships between implicit and explicit associations might vary amongst the majority (males) and minority (females) in the midst of prevailing stereotype contexts. The current study seeks to understand the individual-level implicit associations with self and STEM, gender, as well as the gender-stereotype associations and how these implicit measures might correspond to their explicit counterparts; more specifically, if this relationship looks different for women in STEM than it does for men.

1.2. Current Study

The current study is situated within a longitudinal study for the proposed methodology of individual balanced identity design on the basis of ethnicity and gender in STEM undergraduate fields. This particular study utilizes the data regarding gender, both implicit and explicit identity measures, to address the relationships between the three components of gender-STEM identity profiles and potential moderating effects of participant gender. The standardized identity balance (IBID) methodology will also be used as a foundation for an explicit standardized identity balance score, and the study will explore subsequent relationships between the two, specifically if there are differences in these relationships for men and women. The following research questions are addressed in this study.

1.2.1. Research Questions and Hypotheses

1. To what extent do the components of implicit identity balance (self/STEM/gender) correlate with their explicit counterparts? Based on prior research, I hypothesize that there will be a small to moderate positive correlation between each of the implicit identity balance components with their explicit counterparts.
2. To what degree does this correlation vary as a function of participant gender? I hypothesize that this positive relationship will be stronger for women, whereas men will have a non-significant relationship between their implicit and explicit components.

3. To what extent is implicit balanced identity correlated with explicit balanced identity? I hypothesize that there will be a small to moderate but significant positive correlation between implicit balance scores and explicit balance scores.
4. To what degree does this correlation vary as a function of participant gender? Specifically, this relationship will be moderated by participant gender, with there being a stronger, more positive relationship between implicit and explicit balance for females compared to males.

2. METHODS

2.1. Participants

This longitudinal study included 275 total participants from three California State University schools over five semesters beginning in the Fall of 2017. The complete sample of 275 participants is composed of 51% females, 43.1% White and 52.6% Hispanic/Latinx, and all within various STEM majors (Biological & Life Sciences: 69.7%, Engineering: 19.7%, and Computer Science: 10.6%). Due to missing data across from the explicit survey and IAT measures, the analytic sample size for this study includes 146 participants. Similar to the overall sample, the analytic sample was 59% Hispanic and 58% female. Participants were declared STEM majors within Biological and Life Sciences (73%), Engineering (18%), and Computer Science (9%).

2.2. Procedures

An initial screening questionnaire was emailed to potential participants to ensure they were currently enrolled in a STEM field, considered junior or senior status, and of either White or Hispanic/Latinx ethnicity. Eligible participants were invited to the *MyCollegePathways* study in the Spring of 2017 and were provided with a $20 gift card, either Starbucks or Amazon, at the beginning of each of the five survey waves. In addition to providing demographic information, participants were asked to complete a series of explicit measures of identity with their STEM field, their race/ethnicity (asked during waves 0, 2, and 4), their gender (asked during waves 1 and 3), and stereotype endorsement with their race/ethnic or gender. After completing questionnaire items, participants completed a series of three randomly displayed, personalized online Implicit Association Tests (IAT; Greenwald et al., 1998). Data for the current study came from Wave 3 of data collection during the Fall of 2018.

2.3. Measures

2.3.1. Explicit Computer Science/Engineering/Science Identity

To measure explicit STEM identity, a shortened scale of the Science Career Identity (Chemers et al., 2011) and an adapted scientific belonging measure, constructed by Estrada utilizing theoretical methods from Kelman (2006), Darling et al. (2008), Nguyen & Benet-Martinez (2007), and Benet-Martinez & Haritatos (2005) were used. The explicit STEM identity scale measures participants' perceptions of how their personal identity aligns with their selected major, specifically as a professional who might participate in research activities within their area of study. The 11-question scale was adapted for each of the 3 STEM categories in the study (science, engineering, computer science). Scale items were measured on a scale of 1 (strongly disagree) to 5 (strongly agree) and asked questions about belonging (eg. "I have a strong sense of belonging to the community of scientists") and career identity (eg. "Being a scientist is an important reflection of who I am"). The 11 scale items were then averaged to produce one field specific identity score. A STEM identity score was generated by using the individual score (science, engineering, or computer science) and placing that score into a new STEM Identity variable. Historically, the Science Career Identity scale has a high internal consistency (α=.89 and .90) for undergraduates and graduates, respectively (Chemers et al., 2011). The current sample yielded an adequate average alpha value of

.88, with each domain having high internal consistency, as shown in Table 1 (Appendix B).

2.3.2. Explicit Gender Identity

To measure the degree to which the participant identifies with their gender, a four-item scale adapted from Luhtanen and Crocker's (1992) self-esteem subscale was used according to the participant's previously identified gender (e.g. "Being a woman is an important part of my self-image" or "Being a man is an important reflection of who I am"). Scale items were rated on a scale of 1 (strongly disagree) to 7 (strongly agree) and a composite score was developed averaging the item responses. Cronbach's alpha values of reliability historically range from .83 to .88 indicating sufficient levels of internal consistency (Luhtanen & Crocker, 1992). Internal consistency was sufficient for the current sample with a Cronbach alpha average of .81 across males and females (Table 1; Appendix B).

2.3.3. Explicit Computer Science/Engineering/Science Stereotype Endorsement

To measure the extent to which the participant endorses various stereotypes associated with their gender and their STEM domain, the STEM Stereotype Endorsement scale (Schmader et al., 2004) was used (e.g. "In general, men may be better than women at Engineering"). This 3-item scale was measured from 1 (strongly disagree) to 7 (strongly agree) and each scale item was catered towards the participant's STEM domain (engineering, science, or computer science). A composite score was calculated in which higher scores indicated a greater endorsement for gender-STEM stereotypes. The scale has a high internal consistency with a Cronbach alpha value of reliability of .88.

2.3.4. Implicit Identity Balance

To capture the strength of associations between various identities and stereotype endorsements, the Implicit Association Tests (IAT) were used (Greenwald et al., 1998). Scores of the reaction-based game are calculated at the individual level, wherein scores from the “practice” block (D1) followed by a test block (D2) are averaged to create the overall D score (DT). The three constructs utilized in this study as previously outlined include STEM identity (Me=STEM), Gender identity (Me=My Gender), and Gender-Stereotype Endorsement (STEM=My Gender). Because of the nature of the implicit association measures, reliability analysis is only feasible through test and repeat measures, however this is outside the scope of this particular study.

Utilizing the Individualized Balanced Identity Design score (IBID), an individual-level classification of identity balance allows for the quantification of an individual’s personal identities situated within existing stereotypes (Woodcock, Schultz, Hernandez, In Preparation). The IBID method calculates standardized identity balance scores by dividing the product of each of the three IAT D-scores (ibr (1); individual balance numerator) by the absolute value of the ibr plus the ibr multiplied by the standard deviation of the ibr, as represented in (2) below.

$$\boldsymbol{ibr_{implicit} = D_{Gender\ ID} * D_{STEM\ ID} * D_{Stereotype\ Endorsement}} \quad \textbf{(1)}$$

$$\boldsymbol{IBID_{implicit} = ibr_{implicit}/(|ibr_{implicit}| + (|ibr_{implicit} * sd(ibr_{implicit})|)} \quad \textbf{(2)}$$

Implicit IBID scores range from -1 to 1, with negative scores representing imbalance profiles and 1 representing optimally balanced profiles.

2.3.5. Explicit Identity Balance

Similar to that of the implicit IBID, explicit classification of identity balance is utilized in the study. Using the same Balanced Identity framework, explicit measures were used to capture STEM identity, Gender identity, and Gender-Stereotype Endorsement (scales previously outlined above). Prior to creating the explicit balance scores, all measures were converted to proportion of maximum scores (POMS; Little, 2013), a method which transforms scale scores to all be on a standard metric of 0 to 1. Then, the POMS were linearly transformed to adjust the scale from -.50 to .50, with a meaningful zero to represent neutrality. The explicit balance scores were then calculated similarly to implicit balance, but using the transformed POMS (cPOMS), the process of which can be seen in (3) and (4).

$$\boldsymbol{ibr_{explicit} = cPOMS_{Gender\ ID} * cPOMS_{STEM\ ID} * cPOMS_{Stereotype\ Endorsement}} \quad \textbf{(3)}$$

$$\boldsymbol{IBID_{explicit} = ibr_{explicit}/(|ibr_{explicit}| + (|ibr_{explicit} * sd(ibr_{explicit})|)} \quad \textbf{(4)}$$

Explicit IBID scores range from -1 (imbalanced) to 1 (optimally balanced), similar to that of implicit scores.

2.4. Plan of Analysis

2.4.1. Data Preparation

Prior to substantive analyses, the data was screened and cleaned in STATA version 16.1 (STATCorp, 2019). The categorical gender variable was recoded so that males are utilized as the reference group (male = 0, female = 1). The Gender-STEM Stereotype Endorsement scale composite score was reverse coded for females so that scores indicated greater stereotype endorsement for each gender (Men: STEM = males; Women: STEM = women). Next, IAT scores were screened. Acceptable IAT scores typically utilize the DT scores (average of the practice [D1] and test [D2] blocks), when the difference between the D1 and D2 scores is relatively small (i.e., the difference between D1 and D2 is less than |1|). However, data screening revealed significant outliers in the practice blocks (D1), which skewed the DT scores. Removing cases with extreme differences between D1 and D2 would have resulted in substantial loss of cases (i.e., n = 55 cases dropped). Therefore, in order to preserve sample size and avoid using the problems associated with the practice block (D1), only test block scores (D2), instead of DT.

2.4.2. Tests for Outliers and Statistical Assumptions

Next, several tests were conducted to determine if there were any violations of regression assumptions. First, missing data were examined to determine if the assumption of data missing complete at random (MCAR) was tenable. Little's MCAR revealed that the data were consistent with missing completely at random ($\chi^2_{df=4} = 7.55$, $p = .11$) . Next, outliers were addressed using a holistic approach across four different methods. Added variable plots had no specific patterns or fan shapes amongst the residuals (Figures 6-10; Appendix C), there were no predicted leverage values above the maximum leverage ([2k+2]/n), all values of Studentized residuals were within a range of

-3 to 3, and no predicted Cook's D values were equal to or larger than (Judd et al., 2009). These results imply there are no outliers of concern.

Next, assumptions of normality, linearity, and homoscedasticity were checked, again with a holistic approach, by analyzing plots of the residuals and the results of the Shapiro-Wilks test (Appendix C). Although the Shapiro-Wilks test was significant ($z_{n=146}$= 2.56, *p*<.05), suggesting the data are not normally distributed, the Kernel density plots and QQ-plots suggest normality, with residuals falling linearly and only slight deviation at the tails of the QQ-plot. Additionally, the means of the Studentized and standardized residuals were centered around zero and their standard deviations close to one. Holistically, the data does not show cause for concern regarding normality. The Cook-Weisberg test for heteroskedasticity was not significant (χ^2=.03, p=.87), as well as the Cameron & Trivedi's decomposition for heteroskedasticity (χ^2=4.09, p=.54), both suggesting the model is homoscedastic. The results also suggest the data is not significantly skewed (χ^2=5.06, p=.17) nor is it significantly kurtotic (χ^2=1.49, p=.22).

Lastly, the IAT data were analyzed to test the balance congruity assumption using the four-step tests, per Greenwald and colleagues (2002; Appendix C). That is, using a series of sequential regression models, each edge of a triadic profile (e.g., Me=STEM or STEM Identity) is first regressed on the multiplicative term of the other two edges of a triadic profile (e.g., Me=My Gender × STEM = My Gender; or Gender Identity × Gender-STEM Stereotype) and second regressed on the two components of the multiplicative term (e.g., Gender Identity and Gender-STEM Stereotype). The four-step test hypotheses that (a) the beta coefficient of the multiplicative term will be positive and explain significant variance in the outcome, (b) the combination of the two components will not explain significant variance in the outcome, (c) the multiplicative term will remain positive when the two components are entered, and (d) the beta coefficients of each component will be non-significant. The results of the analyses imply no major concerns for both implicit and explicit assumptions of balance congruity, with implicit analyses holding balance congruent patterns more so than explicit congruencies, similar to expectations outlined by Cvencek and colleagues (2020).

3. RESULTS

3.1. Relationship Between Implicit and Explicit Associations

Prior to the formal regression analyses, I examined the descriptive statistics and bivariate correlations between the implicit and explicit measures (Table 2; Appendix B). On average, women explicitly endorsed the STEM = My Gender association more so than men. Women also explicitly had slightly higher scores for both STEM identity and Gender identity compared to males. Both men and women, on average, held positively balanced profiles for both explicit and implicit measures, however men had a higher implicit balance score than women, while women had a higher explicit balance score than men on average. Men and women both had strong implicit associations with their gender identities, with men having stronger implicit associations than women on average. Additionally, men and women both had strong implicit associations with their STEM disciplines.

The bivariate correlation analysis shown in Table 3 (Appendix B) suggests that explicit gender identity scores had a small correlation with explicit stereotype endorsement (i.e., r=.20), while explicit stereotype endorsement scores had a positive correlation with explicit STEM identity scores. The three implicit STEM identity, Gender identity, and stereotype endorsement scores were positively correlated. Interestingly and consistent with hypotheses, when the correlations were grouped by gender (Tables 4 and 5; Appendix B), only the females had significant correlations amongst their IAT scores, as well as the explicit STEM identity and explicit Stereotype endorsement scales. Males had no statistically significant correlations amongst any of the variables.

3.1.1. Research Questions 1 and 2

A bivariate correlational analysis was conducted to examine the extent do the components of implicit identity balance (self/STEM/gender) correlate with their explicit counterparts (Question 1). Inconsistent with expectations, the overall results indicate that implicit measures were not significantly correlated with their explicit counterparts (Table 3, e.g., $r_{Implicit\text{-}Gender,\ Explicit\text{-}Gender} = .04$; Appendix B). When the correlation analyses were conducted separately by gender, the pattern was similar for males (Table 4; Appendix B), but females showed a significant moderate positive correlation between implicit and explicit gender stereotype endorsement (Table 5; Appendix B).

Next, a series of two-step sequential multiple regression analyses were conducted to determine if relationship between the implicit measures and their explicit varied as a function of participant gender (Question 2). For example, explicit gender identity scores were regressed on participant gender and implicit gender identity scores in step-1 and a gender × implicit gender identity multiplicative term in step-2. The analysis revealed that explicit gender identity was uniquely predicted by participant gender (Table 6, Gender Identity; Appendix B), such that women reported strong gender identity than men (Table 7, Gender, $b_1 = 0.15$; Appendix B). However, consistent with expectations the implicit gender identity and implicit gender identity by gender interaction effects were not statistically significant (Tables 6 and 7; Appendix B). Although the interaction effect non-significant, a simple slopes plots were produced for the sake of completeness

(Figure 2; Appendix A). The plot further confirms that the relationship between implicit gender identity and explicit identity was equivalent among men and women (i.e., parallel lines).

Identical analyses were performed for the explicit stereotype gender-STEM stereotype endorsement and STEM identity. As above, the analyses showed that only gender predicted stereotype endorsement, such that women reported higher STEM=Female stereotypes (Table 6, Table 8, and Figure 3; Appendix A & B). In addition, explicit STEM identity was not predicted by gender, implicit gender identity, or the multiplicative term (Table 6, Table 9, and Figure 4; Appendix A & B). Thus, the series of tests were inconsistent with the expectation that gender may moderate the relationship between implicit and explicit components of identity balance.

3.1.2. Research Questions 3 and 4

A bivariate correlation analysis was conducted to examine the overall relationship between implicit and explicit balanced identity scores. Inconsistent with expectations, the results indicated a positive but non-significant overall relationship between implicit and explicit balance scores (Table 3, r = .05; Appendix B). When the analysis was conducted separately by gender, males showed a similar pattern (Table 4; Appendix B), but the positive association approached conventional level of statistical significance among females (Table 5; Appendix B).

As above, a two-step sequential multiple regression analysis was conducted to determine if relationship between implicit and explicit balance identity scores varied as a function of participant gender (Question 4). Consistent with expectations, the results indicated that gender moderated the relationship between implicit and explicit identity (Table 6, Balance Scores – Step 2; Appendix B). That is, implicit balance identity scores positively predicted explicit balance identity scores among women, but the relationship was non-significant among men (Table 10 and Figure 5; Appendix A & B).

3.2. Supplemental Exploratory Analyses

Additional analyses were conducted to determine if there were statistically significant differences in the means of predictors and outcome variables due to participant major, seeing as the majority of participants were in the Biological and Life Science majors. Prior research suggests the influence of sense of belonging for women in fields where numeric representation of women is low (i.e. Engineering and Computer Science) when compared to groups with higher representation of women, such as Biological and Life Sciences (Rainey et al., 2018). Preliminary t-tests suggested no significant differences in the means of explicit balance scores between those in Biological/Life Sciences (code=1) when compared to those in Engineering and Computer Science (code=0) (Mean difference = -.18, $t_{df=144}$=-1.29, p=.20). However, significant differences in means were found for implicit balance scores between groups (Mean difference= -.32, $t_{df=144}$=-2.81, p<.01). Bivariate correlations suggest a moderate positive correlation between implicit balance and major group (r=.23, p<.01), while there was no significant relationship between major group and explicit balance scores (r=.11, p=.20). Since there was not a significant relationship between being in Biological/Life Sciences and the outcome of interest (explicit balance), a decision was made to exclude the categorical Major variable from the analyses and proceed as originally planned.

4. DISCUSSION

Prior literature suggests that explicit measures alone do not hold the same predictive validity as implicit measures when considering the effects of persistent stereotypes on identity profiles for those in STEM fields (Greenwald et al., 2019). Results of these relationships between implicit and explicit measures have been found to often be conflicting, as more recent studies suggest the possibilities of an existing relationship between the two. When considering identity balance and balance congruity, previous literature suggests that balance congruity often holds implicitly, while less evidence is present to suggest this for explicit balance congruity (Cvencek et al., 2020). This study sought to add to the body of literature surrounding the relationships between implicit and explicit measures of identity associations and balance congruity and further investigate if differences in these relationships exist between male and female undergraduates in STEM disciplines.

Results of the study indicate that, overall within the data, no significant correlations exist between implicit and explicit legs of the triangle. When considered separately, women had a significant positive correlation between implicit and explicit stereotype endorsement measures. However, when considered formally via moderation analysis, the association between implicit and explicit stereotype endorsement came close to expected levels of statistical significance, with limitations concerning power to find a significant effect. Furthermore, the non-significance of the implicit measures predicting the explicit measures in the individual legs of the balance profile still has important theoretical implications. Findings may not have supported the original hypotheses (i.e. a small to moderate, positive correlation would exist), however they do reflect results of some previous literature on the inconsistencies between participants' implicit and explicit attitudes (Greenwald et al., 2019). For researchers, it is important to understand the implications of implicit measures when used in studies, as explicit measures themselves do not fully reflect various aspects of identity. This further suggests the importance of utilizing implicit measures when conducting studies involving stereotypes in STEM fields.

In regard to differences in the relationships between implicit and explicit balance scores, no statistically significant differences were found overall. When considered separately, women had a significant positive correlation between implicit and explicit balance. Consistent with this correlation, the formal moderation analysis showed that the association between implicit and explicit balance was only significant for women. This finding further supports the idea that both implicit and explicit measures (as well as balance calculations) are important in order to capture differences between males and females.

4.1. Limitations

Although results of the study, in part, support various aspects of prior literature, it is important to keep in mind potential limitations of the results. First, the study was underpowered in all cases, thus reducing the ability to find the hypothesized effects and increasing Type II error rates. A larger sample size would not only increase power, but might reduce the standard errors of the parameters, which were relatively large, thus reducing the amount of noise within these predictors in predicting the various explicit measures. This would be particularly true for the analysis of the relationship between implicit and explicit balance, as the moderation term was statistically significant even though the parameters that made up the interaction were not. Additionally, adding other potential covariates to the model might have explained more of the variance in the outcome measures and reduced the standard error in the parameter estimates.

Specifically speaking on the generalizability of the study, the current sample is made up of juniors and seniors and may not be generalizable to all students in undergraduate programs. Prior literature suggests that stereotype threat is particularly present within the first two years of college, thus influencing self-efficacy and sense of belonging. It is possible that the relationships between the predictors and outcome variables, more specifically the likelihood of a participant having a balanced profile (either implicit or explicit), may have been a result of persisting past their sophomore year. At this point in their academic journey, women may be more familiar with existing stereotypes and are more likely to hold balanced identity profiles.

Lastly, construct validity of the stereotype endorsement explicit measure may be of concern due to the wording of the scale, which was presented in the same way to both males and females (i.e. "It may be possible that men are better at Engineering than women." By reverse coding the composite score for females, we believe we are appropriately measuring the explicit association of STEM = Female for women, however future studies would need to present specific phrasing to females to ensure the meaning of the scale holds true for both genders.

4.2. Future Research

Findings from the study suggest that, if adequately powered to find the effect, there may be a potential relationship between some of the implicit and explicit measures, specifically for balance scores, for females. As the current sample consists of juniors and seniors, it would be interesting to find out how this pattern might change for women in their first or second year of their undergraduate program, when stereotype threat is often at its highest. At Texas A&M, engineering students in their first year do not select a specific engineering major until after they have finished their freshman year. A longitudinal study could examine the changes in implicit and explicit balance (and individual constructs) across the first two years of their undergraduate program, during a particularly dynamic time for identity development.

Additionally, there are notable differences in representation amongst different majors within STEM fields, specifically within engineering disciplines. For example, Biological and Environmental Engineering majors often have similar parity between numerical gender representation as the Biological Sciences, while disciplines like Electrical and Mechanical Engineering still struggle to recruit and retain women. A future study could examine the differences, not only between implicit scores as outcomes, but to examine the relationship between implicit and explicit measures for women within these different engineering disciplines. Based on prior literature, we might expect that females in engineering fields with particularly low representation would have less of a relationship between their implicit and explicit measures, including balance, when compared to their female peers in fields that are adequately numerically represented (Biological and Life Sciences).

Additional studies might also seek to see if similar patterns exist amongst other minority groups within the STEM fields. The larger study this report comes from additionally involves IAT and explicit measures surrounding ethnic (White/Hispanic) personal-professional profiles and could be utilized to see if moderations of the relationship between implicit and explicit measures exist between ethnic groups. Further understanding of the literature surrounding representation of ethnic groups within different STEM fields would be important in order to determine if the participant's major would need to be considered as a covariate in the models. Ultimately, this research would serve to add to the existing literature of various stereotypes that exist in the fields of science, technology, mathematics, and engineering, including how stakeholders can best serve students to dampen the effects of stereotype threat during crucial periods of identity development.

5. CONCLUSION

As researchers continue to investigate the nature of identity development throughout one's academic journey surrounding prevailing stereotype threats in the STEM fields, the importance of multiple measures of associations of academic domains and the endorsements of these persistent stereotypes at the center of personal-professional congruence prevails. Analyses support prior literature that implicit measures do not always correlate with their explicit counterparts as explicit measures are often subject to deliberate cognitive processes. This further suggests the need for multiple methods of assessment, especially when utilizing the measures for predictive means of important outcomes such as persistence and academic success in STEM. Additionally, results suggest the need for further investigation into the gendered differences amongst the implicit and explicit relationships; more specifically, if the relationship between implicit and explicit balance congruity is in fact different for women in STEM than it is for men.

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APPENDIX A

FIGURES

Figure 1. Components of Balanced Identity Framework

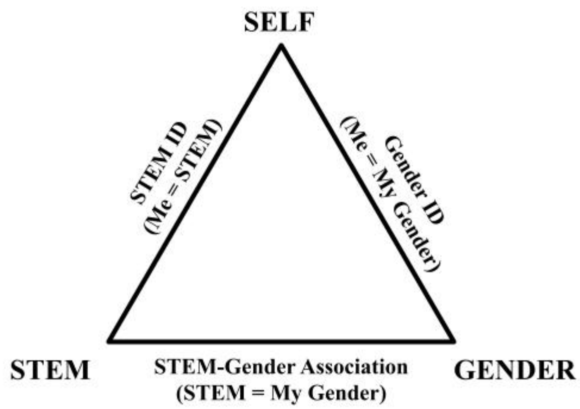


Figure 2. Simples Slopes Analysis of Gender Identity Moderated by Gender

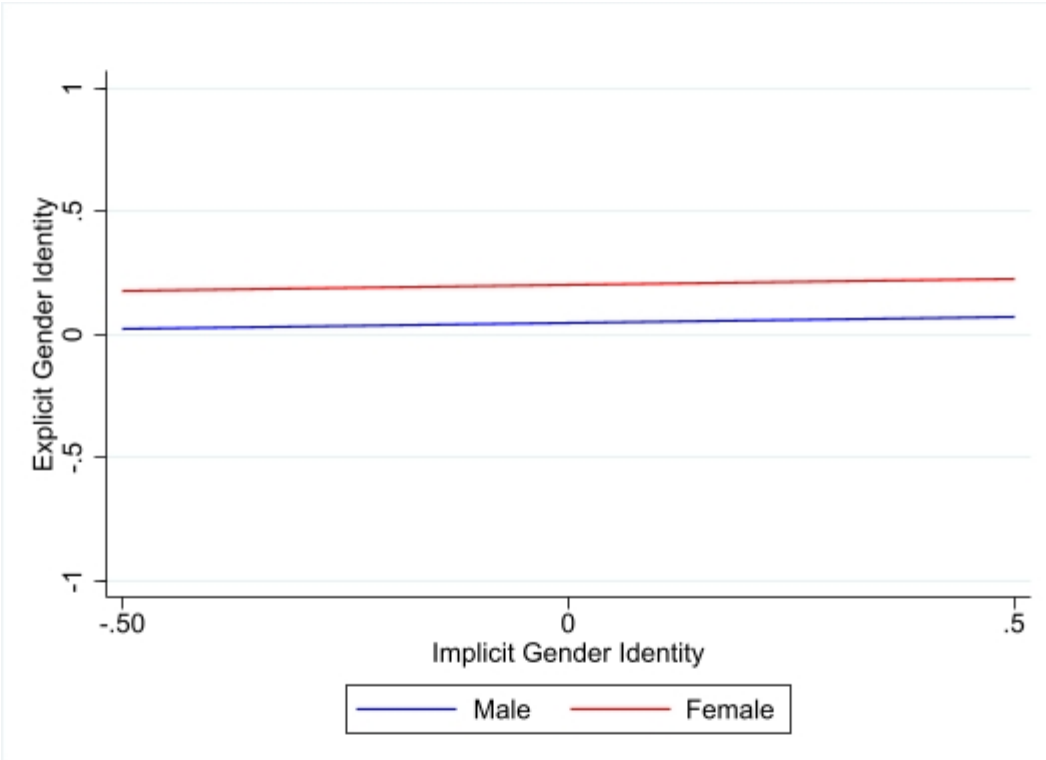


Figure 3. Simples Slopes Analysis of Stereotype Endorsement Moderated by Gender

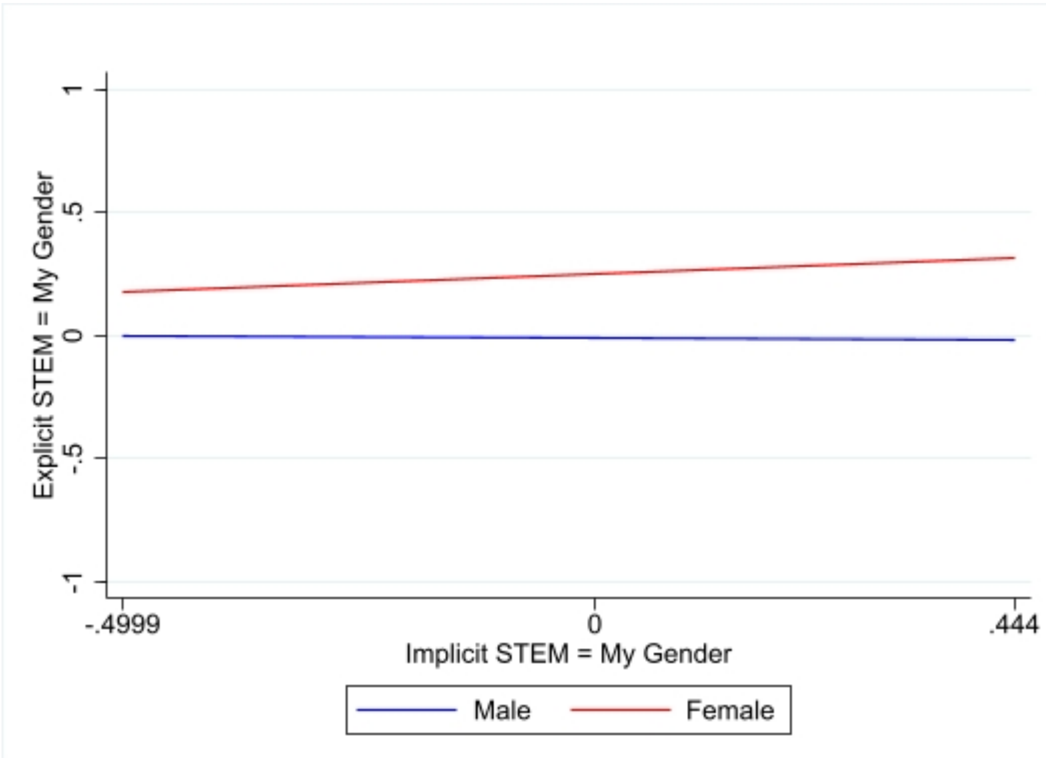


Figure 4. Simples Slopes Analysis of STEM Identity Moderated by Gender

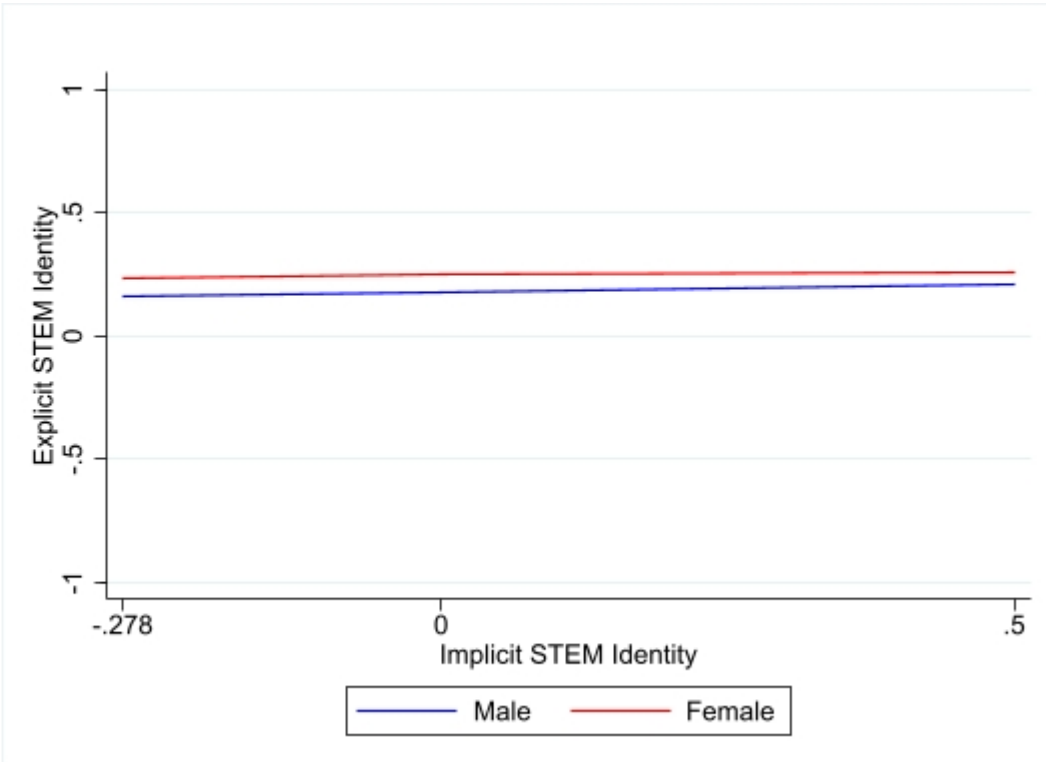
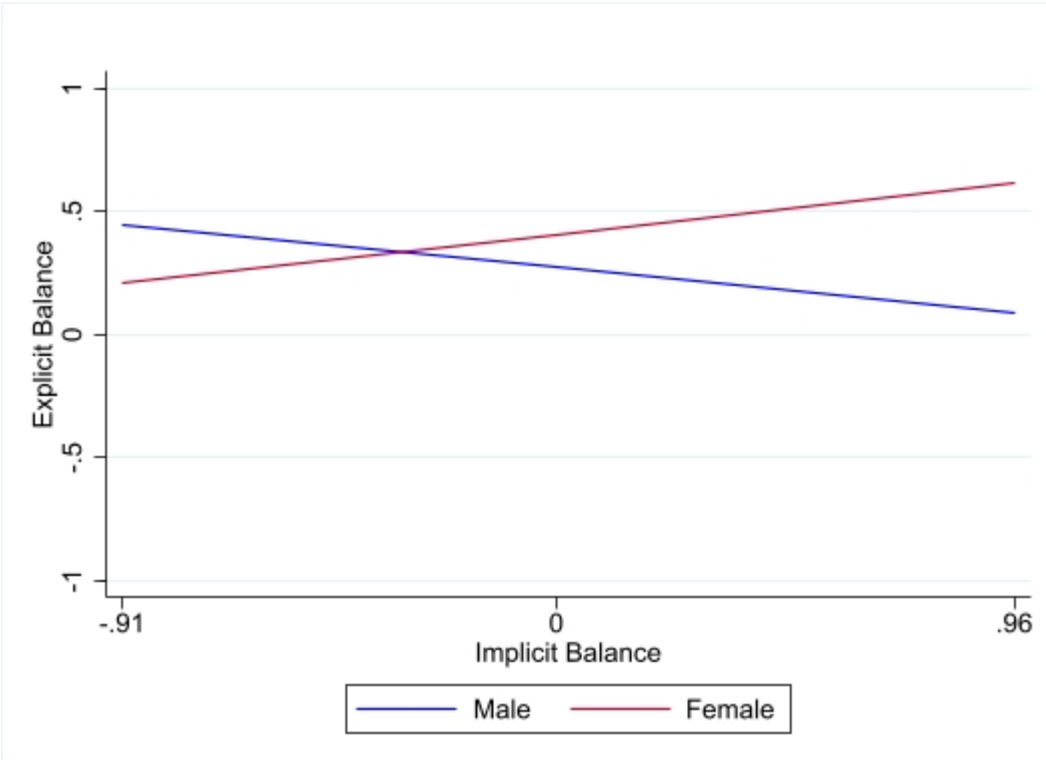


Figure 5. Simples Slopes Analysis of Balance Scores Moderated by Gender



APPENDIX B

TABLES

Table 1. Reliability of Explicit Measures

Measure		*a*
Gender Identity		.81
	Male	.82
	Female	.80
STEM Identity		.88
	Science	.90
	Engineering	.85
	Computer Science	.89
Stereotype Endorsement		.79
	Science	.72
	Engineering	.90
	Computer Science	.75

Table 2. Summary of Descriptive Statistics for Implicit and Explicit Measures

	Males (*n=60*)		*Females* (*n=86*)	
Variable	*M*	*SD*	*M*	*SD*
Explicit				
Gender Identity	3.34	1.03	3.91	1.03
Stereotype Endorsement	3.87	2.26	5.82	1.68
STEM Identity	3.84	.70	4.06	.72
Standardized Balance	.19	.79	.48	.71
Implicit				
Gender Identity IAT	.80	.52	.57	.55
Stereotype Endorsement IAT	.52	.55	.34	.56
STEM Identity IAT	.57	.56	.56	.55
Standardized Balance	.42	.58	.32	.67

Note. Sample includes those who have all 3 explicit scale scores and all 3 IAT D2 scores. Stereotype endorsement (STEM = My Gender) on a scale of 1 (strongly disagree) to 7 (strongly agree). Gender Identity and STEM Identity variables on a scale of 1 (strongly disagree) to 5 (strongly agree).

Table 3. Overall Summary of Correlations Among Predictors and Outcomes (*N*=146)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Gender ID Explicit	--							
2. Stereotype Endorsement Explicit	.20*	--						
3. STEM ID Explicit	.09	.28***	--					
4. Gender ID IAT	.04	-.09	-.10	--				
5. Stereotype Endorsement IAT	.09	.06	.12	.32***	--			
6. STEM ID IAT	.06	.00	.12	.29***	.18*	--		
7. Explicit Balance	.27**	.42***	.22**	-.11	.17*	.06	--	
8. Implicit Balance	-.11	.01	.15†	.19*	.54***	.29***	.05	--

†$p<.10$, *$p<.05$, **$p<0.01$, ***$p< 0.001$

Table 4. Summary of Correlations Among Predictors and Outcomes for Males (*n*=60)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Gender ID Explicit	--							
2. Stereotype Endorsement	.18	--						
Explicit (STEM = My Gender)								
3. STEM ID Explicit	-.10	.17	--					
4. Gender ID IAT	.09	-.02	-.16	--				
5. Stereotype Endorsement	.06	-.03	.04	.20	--			
IAT (STEM = My Gender)								
6. STEM ID IAT	-.04	-.14	.17	.20	.10	--		
7. Explicit Balance	.09	.37**	.17	-.19	.02	.01	--	
8. Implicit Balance	-.23†	-.22†	.24†	.14	.50***	.45***	-.14	--

$^{\dagger}p<.10$, $^{*}p<.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 5. Summary of Correlations Among Predictors and Outcomes for Females (*n*=86)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Gender ID Explicit	--							
2. Stereotype Endorsement Explicit (STEM = My Gender)	.04	--						
3. STEM ID Explicit	.15	.32**	--					
4. Gender ID IAT	.10	.02	-.01	--				
5. Stereotype Endorsement IAT (STEM = My Gender)	.20†	.30**	.21*	.37***	--			
6. STEM ID IAT	.15	.17	.08	.37***	.24*	--		
7. Explicit Balance	.35***	.39***	.22*	.02	.35**	.12	--	
8. Implicit Balance	-.004	.27**	.12	.20†	.56***	.19†	.20†	--

$^{\dagger}p<.10$, $*p<.05$, $**p<0.01$, $***p< 0.001$

Table 6. Summary of F-Tests for the Direct and Moderated Effect of Gender on Implicit and Explicit Relationships (*N*=146)

Step	*SS*	*df*	*MS*	*F*	R^2	ΔF	Δdf	ΔR^2
				Gender Identity				
1	.80	2	.40	6.04**	.08			
2	.80	3	.27	4.00**	.08	.00	1	.00
				Stereotype Endorsement				
1	4.03	2	2.01	19.53***	.21			
2	4.33	3	1.44	14.21***	.23	3.03†	1	.02
				STEM Identity				
1	.17	2	.09	2.74†	.04			
2	.18	3	.06	1.87	.04	.16	1	.001
				Balance Scores				
1	3.20	2	1.60	2.89†	.04			
2	5.35	3	1.78	3.28*	.06	3.94*	1	.03

Notes: Variables entered in Step 1 include: Gender and Implicit IAT score. Variables entered in Step 2 include: Gender X Implicit IAT score moderation terms.
$^{\dagger}p$<.10, *p<.05, **p<0.01, ***p< 0.001

Table 7. Summary of Parameter Estimates for the Gender Identity Sequential Regression (*N*=146)

	b	*S.E.*	*95% CI [LL, UL]*	*β*
Step 1				
Gender, b_1	.15	.04	[.06, .24]	.28
Gender IAT, b_2	.05	.04	[-.03, .12]	.09
Intercept, b_0	.05	.05	[3.61, 3.97]	.
Step 2				
Gender, b_1	.15	.07	[.01, .30]	.28
Gender IAT, b_2	.05	.06	[-.08, .17]	.09
Gender by Gender IAT Interaction, b_3	.00	.08	[-.16, .16]	.00
Intercept, b_0	.05	.06	[-.07, .17]	.

Notes: Gender coded 0 = male, 1 = female.

Table 8. Summary of Parameter Estimates for the Stereotype Endorsement Sequential Regression (*N*=146)

	b	*S.E.*	*95% CI [LL, UL]*	*β*
Step 1				
Gender, b_1	.34	.05	[.23, .45]	.47
Stereotype Endorsement IAT, b_2	.08	.05	[-.01, .18]	.13
Intercept, b_0	-.06	.05	[-.16, .03]	.
Step 2				
Gender, b_1	.26	.07	[.13, .40]	.36
Stereotype Endorsement IAT, b_2	-.02	.08	[-.17, .13]	-.03
Gender by Stereotype Endorsement IAT Interaction, b_3	.17	.08	[-.02, .36]	.22
Intercept, b_0	-.01	.06	[-.12, .10]	.

Notes: Gender coded 0 = male, 1 = female.

Table 9. Summary of Parameter Estimates for the STEM Identity Sequential Regression (*N*=146)

	b	*S.E.*	*95% CI [LL, UL]*	*β*
Step 1				
Gender, b_1	.05	.03	[-.004, .11]	.15
STEM ID IAT, b_2	.04	.03	[-.01, .10]	.12
Intercept, b_0	.19	.03	[.13, .24]	.
Step 2				
Gender, b_1	.07	.04	[-.02, .15]	.19
STEM ID IAT, b_2	.05	.04	[-.03, .14]	.16
Gender by STEM ID IAT Interaction, b_3	-.02	.06	[-.14, .09]	-.06
Intercept, b_0	.18	.03	[.12, .24]	.

Notes: Gender coded 0 = male, 1 = female.

Table 10. Summary of Parameter Estimates for the Balance Scores Sequential Regression (*N*=146)

	b	*S.E.*	*95% CI [LL, UL]*	*β*
Step 1				
Gender, b_1	.29	.13	[.04, .54]	.19
Implicit Balance, b_2	.08	.10	[-.12, .27]	.06
Intercept, b_0	.16	.10	[-.05, .37]	.
Step 2				
Gender, b_1	.13	.15	[-.16, .43]	.09
Implicit Balance, b_2	-.19	.17	[-.52, .14]	-.16
Gender by Implicit Balance Interaction, b_3	.41	.20	[.002, .81]	.29
Intercept, b_0	.27	.12	[.04, .51]	.

Notes: Gender coded 0 = male, 1 = female.

APPENDIX C

SUPPLEMENTAL MATERIALS

Greenwald et al., (2002) 4-Test for Balance Congruity STATA Output

```
Greenwald 4-Test of Assumptions  Saturday February 13 16:23:33 2021   Page 1

                                                                    ___  ____  ____  ____  ____(R)
                                                                   /__    /   ____/   /   ____/
                                                                  ___/   /   /___/   /   /___/
                                                                    Statistics/Data analysis

                                                                      User: Rachelle Pedersen
                                                                   Project: Master's Thesis
------------------------------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\Greenwald 4-Test of Assumptions.smcl
  log type:  smcl
 opened on:  13 Feb 2021, 16:22:17

1 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

2 . /* Greenwald's Assumptions of Balance */
3 . /* Implicit Balance Assumption 4-Test Method */
4 .
  end of do-file

5 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

6 . /* Gender and STEM product predicting STEM Stereotype */
7 . /* Step-1 should be significant and positive, Step-2 should be non-significant and individual terms should be non-
8 . nestreg : regress D2_STEMST_3 (D2GenderXD2STEM) (D2_GENDER_3 D2_STEM_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

  Block  1: D2GenderXD2STEM

        Source |       SS           df       MS      Number of obs   =       146
  -------------+----------------------------------   F(1, 144)       =      0.83
         Model |  .398969682         1  .398969682   Prob > F        =    0.3651
      Residual |  69.5906584       144  .483268461   R-squared       =    0.0057
  -------------+----------------------------------   Adj R-squared   =   -0.0012
         Total |  69.9896281       145   .48268709   Root MSE        =    .69518

  ----------------------------------------------------------------------------
      D2_STEMST_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
  ----------------+-----------------------------------------------------------
  D2GenderXD2STEM |  -.0911285   .1002949    -0.91   0.365    -.2893689    .1071118
            _cons |    .055427   .0735684     0.75   0.452    -.0899864    .2008404
  ----------------------------------------------------------------------------

  Block  2: D2_GENDER_3 D2_STEM_3

        Source |       SS           df       MS      Number of obs   =       146
  -------------+----------------------------------   F(3, 142)       =      0.62
         Model |  .900194921         3  .300064974   Prob > F        =    0.6053
      Residual |  69.0894332       142  .486545304   R-squared       =    0.0129
  -------------+----------------------------------   Adj R-squared   =   -0.0080
         Total |  69.9896281       145   .48268709   Root MSE        =    .69753

  ----------------------------------------------------------------------------
      D2_STEMST_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
  ----------------+-----------------------------------------------------------
  D2GenderXD2STEM |  -.2113388    .205812    -1.03   0.306    -.6181902    .1955125
      D2_GENDER_3 |   .1552217   .1572586     0.99   0.325    -.1556489    .4660923
        D2_STEM_3 |   .0300476   .1774039     0.17   0.866    -.3206465    .3807417
            _cons |  -.0100862   .1157317    -0.09   0.931    -.2388659    .2186935
  ----------------------------------------------------------------------------


    +-------------------------------------------------------------+
    |       |          Block  Residual                     Change |
    | Block |       F     df        df   Pr > F       R2    in R2 |
    |-------+-----------------------------------------------------|
    |     1 |    0.83      1       144   0.3651   0.0057          |
    |     2 |    0.52      2       142   0.5986   0.0129   0.0072 |
    +-------------------------------------------------------------+
```

```
 9 . /* Gender and STEM Stereotype product predicting STEM */
10 . nestreg : regress D2_STEM_3 (D2GenderXD2STEMSTr) (D2_GENDER_3 D2_STEMSTr_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

Block  1: D2GenderXD2STEMSTr

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(1, 144)       =      4.72
       Model |  1.19536073         1  1.19536073   Prob > F        =    0.0314
    Residual |  36.4362338       144  .253029401   R-squared       =    0.0318
-------------+----------------------------------   Adj R-squared   =    0.0250
       Total |  37.6315945       145  .259528238   Root MSE        =    .50302

------------------------------------------------------------------------------------
         D2_STEM_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
D2GenderXD2STEMSTr |   .1720001   .0791343     2.17   0.031     .0155852     .328415
             _cons |   .5003145   .0510096     9.81   0.000     .3994902    .6011387
------------------------------------------------------------------------------------

Block  2: D2_GENDER_3 D2_STEMSTr_3

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(3, 142)       =      4.88
       Model |  3.51761329         3  1.17253776   Prob > F        =    0.0029
    Residual |  34.1139812       142  .240239304   R-squared       =    0.0935
-------------+----------------------------------   Adj R-squared   =    0.0743
       Total |  37.6315945       145  .259528238   Root MSE        =    .49014

------------------------------------------------------------------------------------
         D2_STEM_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
D2GenderXD2STEMSTr |  -.0558714   .1299822    -0.43   0.668    -.3128216    .2010788
       D2_GENDER_3 |   .2572705   .0855591     3.01   0.003     .0881364    .4264046
      D2_STEMSTr_3 |   .1191434   .1127966     1.06   0.293    -.1038341     .342121
             _cons |   .3647777    .066123     5.52   0.000      .234065    .4954905
------------------------------------------------------------------------------------


  +-------------------------------------------------------------+
  |       |          Block  Residual                     Change |
  | Block |       F     df        df   Pr > F       R2    in R2 |
  |-------+-----------------------------------------------------|
  |     1 |    4.72      1       144   0.0314   0.0318          |
  |     2 |    4.83      2       142   0.0093   0.0935   0.0617 |
  +-------------------------------------------------------------+

11 . /* STEM and STEM Stereotype product predicting Gender */
12 . nestreg : regress D2_GENDER_3 (D2STEMXD2STEMSTr) (D2_STEM_3 D2_STEMSTr_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

Block  1: D2STEMXD2STEMSTr

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(1, 144)       =     10.12
       Model |  2.86659417         1  2.86659417   Prob > F        =    0.0018
    Residual |  40.7737565       144  .283151087   R-squared       =    0.0657
-------------+----------------------------------   Adj R-squared   =    0.0592
       Total |  43.6403507       145  .300967936   Root MSE        =    .53212

----------------------------------------------------------------------------------
     D2_GENDER_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
D2STEMXD2STEMSTr |   .2800719   .0880229     3.18   0.002     .1060881    .4540557
           _cons |   .5880054   .0505314    11.64   0.000     .4881264    .6878845
----------------------------------------------------------------------------------
```

```
Greenwald 4-Test of Assumptions  Saturday February 13 16:23:33 2021   Page 3

Block  2: D2_STEM_3 D2_STEMSTr_3

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(3, 142)       =     11.40
       Model |  8.46955328         3  2.82318443   Prob > F        =    0.0000
    Residual |  35.1707974       142  .247681672   R-squared       =    0.1941
-------------+----------------------------------   Adj R-squared   =    0.1770
       Total |  43.6403507       145  .300967936   Root MSE        =    .49768

------------------------------------------------------------------------------
   D2_GENDER_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
D2STEMXD2STEMSTr |  -.3933992   .1648636    -2.39   0.018    -.7193034   -.0674949
      D2_STEM_3 |   .4276197    .108354     3.95   0.000     .2134242    .6418152
   D2_STEMSTr_3 |     .51534   .1251474     4.12   0.000     .2679473    .7627327
          _cons |   .3249301   .0740382     4.39   0.000     .1785706    .4712895
------------------------------------------------------------------------------


  +-------------------------------------------------------------+
  |       |          Block  Residual                     Change |
  | Block |       F     df        df   Pr > F       R2    in R2 |
  |-------+-----------------------------------------------------|
  |     1 |   10.12      1       144   0.0018   0.0657          |
  |     2 |   11.31      2       142   0.0000   0.1941   0.1284 |
  +-------------------------------------------------------------+

13 .
   end of do-file

14 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

15 . /* Explicit Balance Assumption 4-Test Method */
16 .
   end of do-file

17 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

18 . /* Gender and STEM product predicting STEM Stereotype */
19 . /* Step-1 should be significant and positive, Step-2 should be non-significant and individual terms should be non-
20 . nestreg : regress cpsQ286_3 (EGenderXESTEM) (cpsQ133f_3 cpsQ91_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

   Block  1: EGenderXESTEM

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(1, 144)       =     14.28
       Model |  1.69296781         1  1.69296781   Prob > F        =    0.0002
    Residual |  17.0772843       144  .118592252   R-squared       =    0.0902
-------------+----------------------------------   Adj R-squared   =    0.0839
       Total |  18.7702521       145  .129450015   Root MSE        =    .34437

------------------------------------------------------------------------------
    cpsQ286_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
EGenderXESTEM |   1.165125   .3083731     3.78   0.000     .5556028    1.774648
        _cons |   .1175854   .0316651     3.71   0.000     .0549969    .1801738
------------------------------------------------------------------------------

   Block  2: cpsQ133f_3 cpsQ91_3
```

```
      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(3, 142)       =      6.64
       Model |  2.30930156         3  .769767187   Prob > F        =    0.0003
    Residual |  16.4609506       142  .115922187   R-squared       =    0.1230
-------------+----------------------------------   Adj R-squared   =    0.1045
       Total |  18.7702521       145  .129450015   Root MSE        =    .34047

------------------------------------------------------------------------------
    cpsQ286_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
EGenderXESTEM |   .7193339   .5992583     1.20   0.232    -.4652864    1.903954
   cpsQ133f_3 |   .0556209    .192266     0.29   0.773    -.3244526    .4356943
     cpsQ91_3 |   .4165746   .1891394     2.20   0.029     .0426817    .7904675
        _cons |   .0272134   .0556972     0.49   0.626    -.0828895    .1373162
-------------------------------------------------------------------------------


  +-------------------------------------------------------------+
  |       |          Block  Residual                     Change |
  | Block |       F     df        df   Pr > F       R2    in R2 |
  |-------+-----------------------------------------------------|
  |     1 |   14.28      1       144   0.0002   0.0902          |
  |     2 |    2.66      2       142   0.0735   0.1230   0.0328 |
  +-------------------------------------------------------------+

21 . /* Gender and STEM Stereotype product predicting STEM */
22 . nestreg : regress cpsQ91_3 (EGenderXESTEMSTr) (cpsQ133f_3 cpsQ286_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

Block  1: EGenderXESTEMSTr

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(1, 144)       =     11.78
       Model |  .350924742         1  .350924742   Prob > F        =    0.0008
    Residual |  4.28835776       144  .029780262   R-squared       =    0.0756
-------------+----------------------------------   Adj R-squared   =    0.0692
       Total |   4.6392825       145  .031995052   Root MSE        =    .17257

---------------------------------------------------------------------------------
        cpsQ91_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+---------------------------------------------------------------
EGenderXESTEMSTr |   .4087877   .1190845     3.43   0.001     .1734083    .6441671
           _cons |   .2227243   .0153892    14.47   0.000     .1923065    .2531422
---------------------------------------------------------------------------------

Block  2: cpsQ133f_3 cpsQ286_3

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(3, 142)       =      5.74
       Model |  .501864727         3  .167288242   Prob > F        =    0.0010
    Residual |  4.13741777       142  .029136745   R-squared       =    0.1082
-------------+----------------------------------   Adj R-squared   =    0.0893
       Total |   4.6392825       145  .031995052   Root MSE        =    .17069

---------------------------------------------------------------------------------
        cpsQ91_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+---------------------------------------------------------------
EGenderXESTEMSTr |    .291075   .1412357     2.06   0.041     .0118788    .5702713
      cpsQ133f_3 |  -.0224405   .0579472    -0.39   0.699    -.1369911    .0921101
       cpsQ286_3 |   .1000046   .0443719     2.25   0.026     .0122897    .1877195
           _cons |   .2151862   .0174379    12.34   0.000     .1807147    .2496577
---------------------------------------------------------------------------------
```

```
Block  |          F    Block  Residual                       Change
       |                  df        df   Pr > F        R2     in R2
-------+-----------------------------------------------------------
     1 |      11.78        1       144   0.0008    0.0756
     2 |       2.59        2       142   0.0785    0.1082    0.0325

23 . /* STEM and STEM Stereotype product predicting Gender */
24 . nestreg : regress cpsQ133f_3 (ESTEMXESTEMSTr) (cpsQ91_3 cpsQ286_3) if Good_IATD2_3 ==1 & Good_Exp_3 ==1

  Block  1: ESTEMXESTEMSTr

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(1, 144)       =      9.85
       Model |  .658092678         1  .658092678   Prob > F        =    0.0021
    Residual |  9.62421899       144  .066834854   R-squared       =    0.0640
-------------+----------------------------------   Adj R-squared   =    0.0575
       Total |  10.2823117       145  .070912494   Root MSE        =    .25852

--------------------------------------------------------------------------------
    cpsQ133f_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ESTEMXESTEMSTr |   .5941877   .1893571     3.14   0.002     .2199091    .9684662
         _cons |   .1327232   .0241636     5.49   0.000     .0849621    .1804843
--------------------------------------------------------------------------------

  Block  2: cpsQ91_3 cpsQ286_3

      Source |       SS           df       MS      Number of obs   =       146
-------------+----------------------------------   F(3, 142)       =      3.29
       Model |  .668004825         3  .222668275   Prob > F        =    0.0226
    Residual |  9.61430684       142  .067706386   R-squared       =    0.0650
-------------+----------------------------------   Adj R-squared   =    0.0452
       Total |  10.2823117       145  .070912494   Root MSE        =     .2602

--------------------------------------------------------------------------------
    cpsQ133f_3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ESTEMXESTEMSTr |   .6682903   .3684739     1.81   0.072     -.060113    1.396694
      cpsQ91_3 |   -.051117   .1363002    -0.38   0.708    -.3205567    .2183226
     cpsQ286_3 |  -.0146804     .10875    -0.13   0.893    -.2296586    .2002977
         _cons |   .1432109   .0368661     3.88   0.000     .0703336    .2160882
--------------------------------------------------------------------------------

Block  |          F    Block  Residual                       Change
       |                  df        df   Pr > F        R2     in R2
-------+-----------------------------------------------------------
     1 |       9.85        1       144   0.0021    0.0640
     2 |       0.07        2       142   0.9295    0.0650    0.0010

25 .
  end of do-file

26 . log close
      name:  <unnamed>
       log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\Greenwald 4-Test of Assumptions.smcl
  log type:  smcl
 closed on:  13 Feb 2021, 16:22:51
```

Outlier and Statistical Assumptions Plots

Figure 6. Added Variable Plot of Gender/STEM Identity Regression Analysis

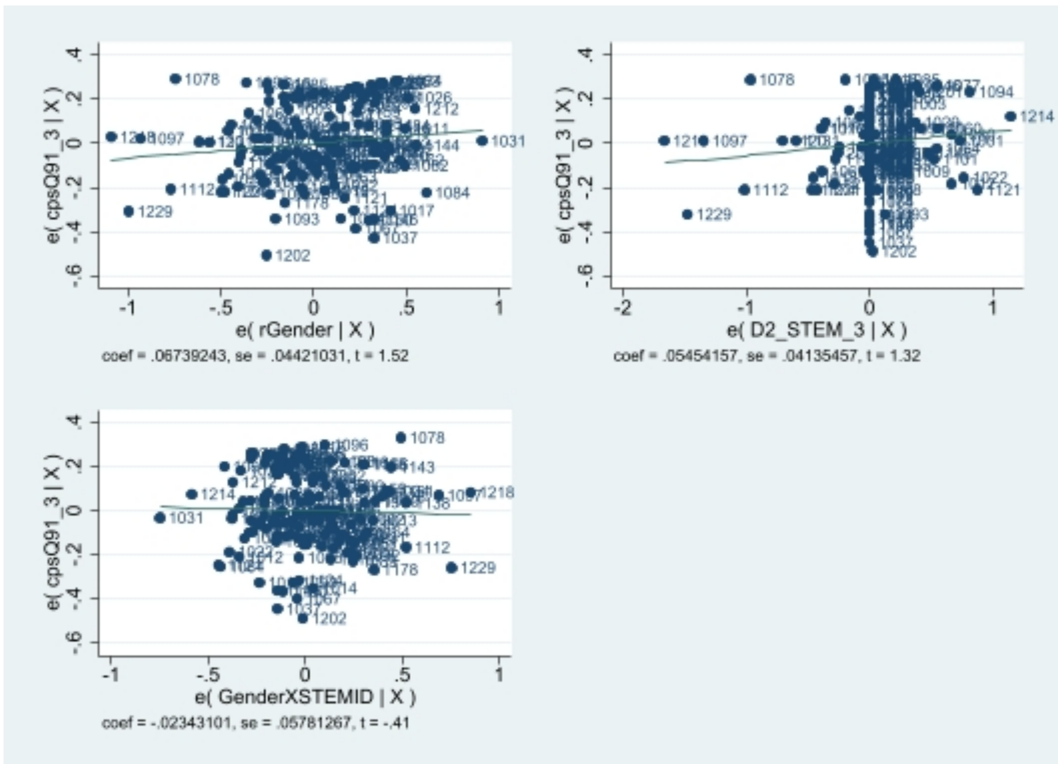


Figure 7. Kernel Density Plot of STEM Identity Regression Residuals

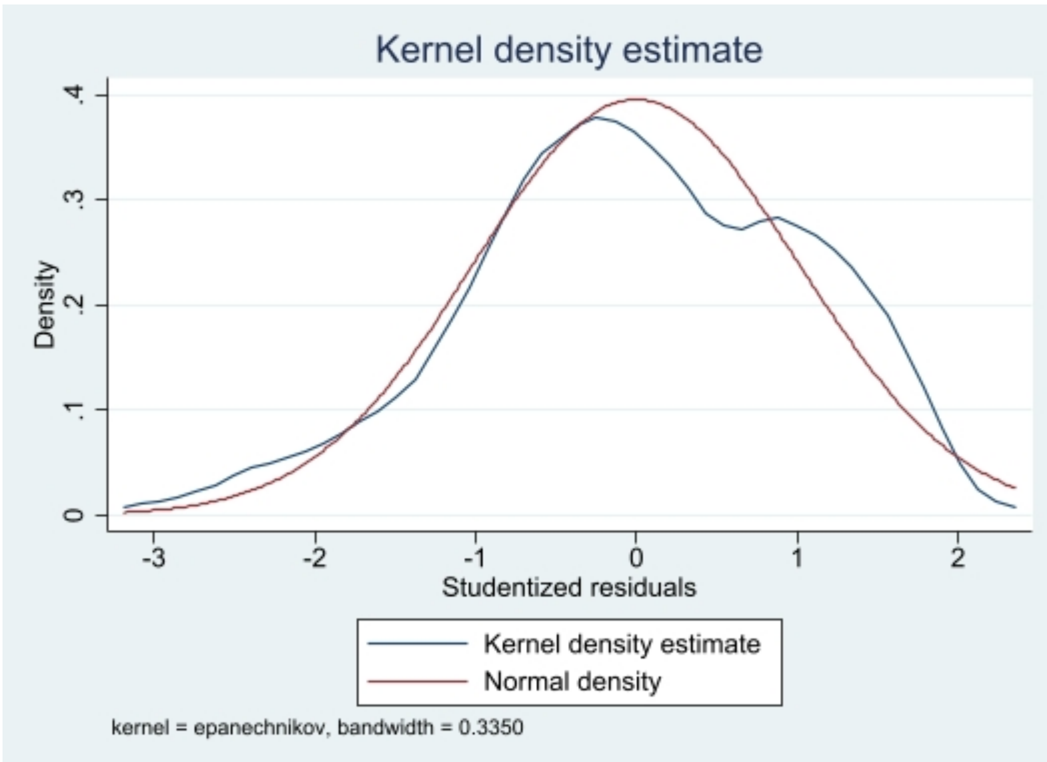


Figure 8. QQ Plot of STEM Identity Regression Residuals

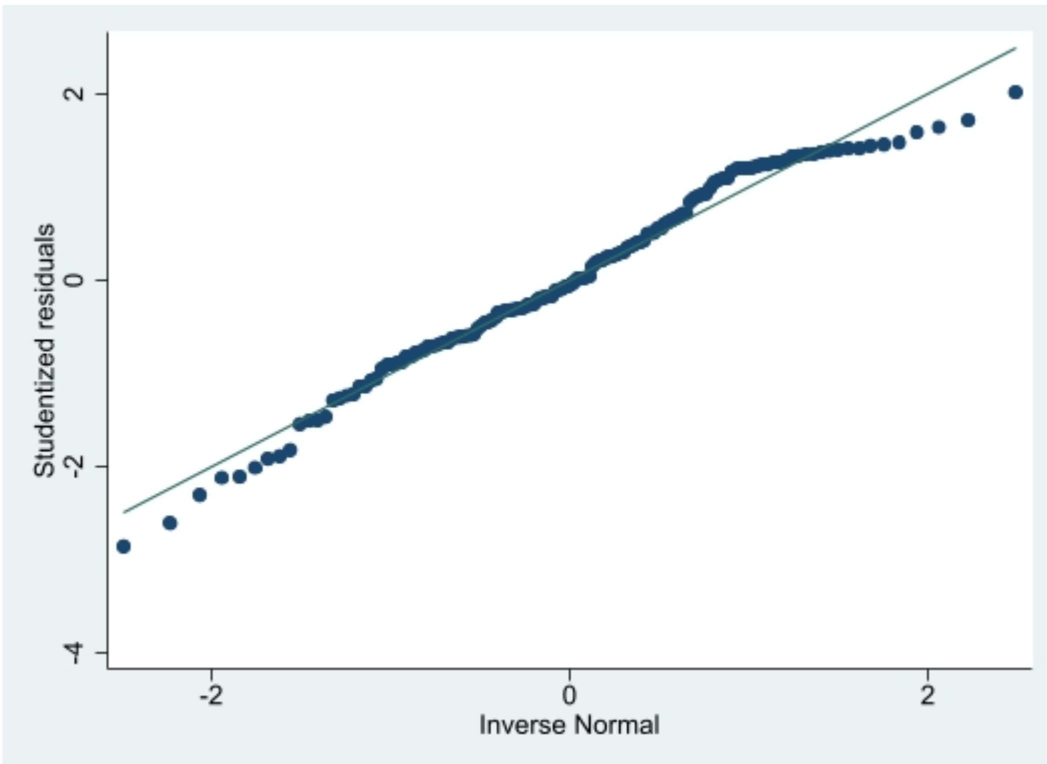
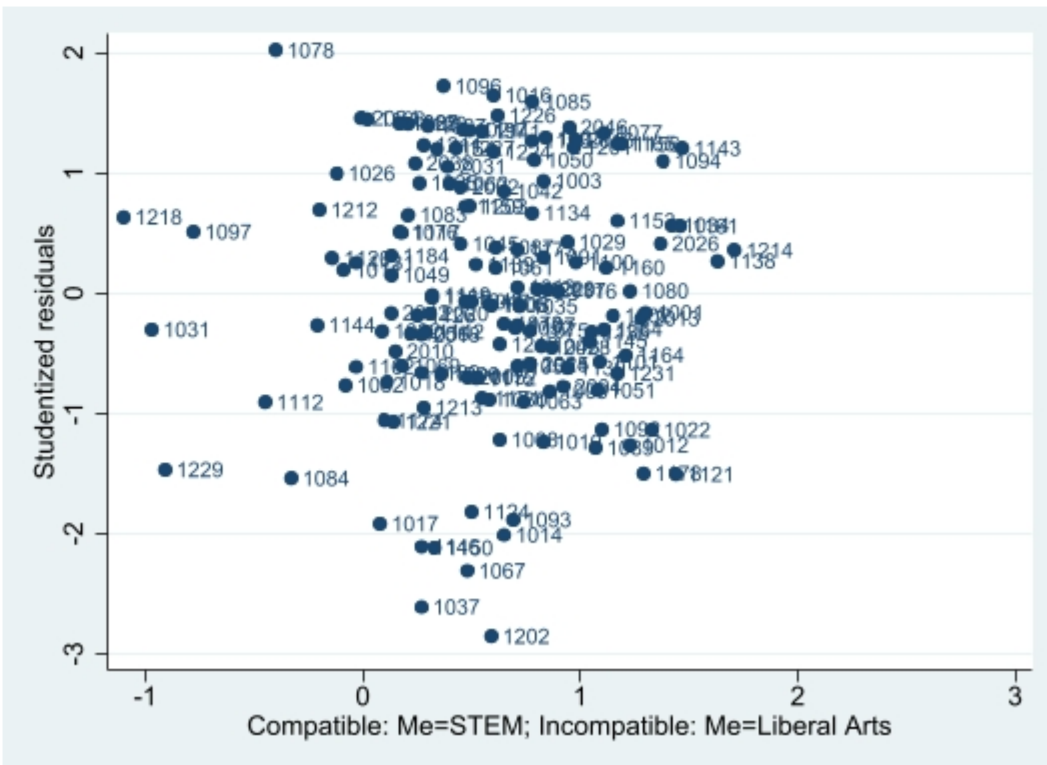


Figure 9. Scatter Plot of Studentized Residuals from STEM Identity Regression



Supplemental Exploratory Analysis Results STATA Output

```
STEM Major Supplemental Exploratory Analysis Results  Saturday February 13 16:34:00 2021   Page 1

                                                                ___  ____  ____  ____  ____(R)
                                                               /__    /   ____/   /   ____/
                                                              ___/   /   /___/   /   /___/
                                                                Statistics/Data analysis

                                                                  User: Rachelle Pedersen
                                                               Project: Master's Thesis
std_Balanc~3 |         39    .1259567    .6728296  -.8458089   .8801754
      name:  <unnamed>
       log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\STEM Major Supplemental Exploratory Analysis Results.s
  log type:  smcl
 opened on:  13 Feb 2021, 16:31:09

1 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

2 . /* Analyses to see if there are differences in majors */
3 .
  end of do-file

4 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

5 . /* Descriptives for new variable */
6 . by Major_Bio, sort : summarize std_ibr_3 std_Balance2_3 if Good_IATD2_3 ==1 & Good_Exp_3 ==1

------------------------------------------------------------------------------------------------
-> Major_Bio = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
   std_ibr_3 |         39    .2270126    .7947299  -.9048423          1
std_Balanc~3 |         39    .1259567    .6728296  -.8458089   .8801754

------------------------------------------------------------------------------------------------
-> Major_Bio = 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
   std_ibr_3 |        107    .4087024    .7367132  -.9028061          1
std_Balanc~3 |        107     .449546    .5946677  -.9129136   .9660726


7 . /* test if explicit balance scores are different between major groups */
8 . ttest std_ibr_3 if Good_IATD2_3 ==1 & Good_Exp_3 ==1, by(Major_Bio)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |      39    .2270126    .1272586    .7947299   -.0306091    .4846342
       1 |     107    .4087024    .0712208    .7367132    .2675003    .5499044
---------+--------------------------------------------------------------------
combined |     146    .3601688    .0624168     .754185    .2368045     .483533
---------+--------------------------------------------------------------------
    diff |           -.1816898    .1407454               -.4598837    .0965041
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -1.2909
Ho: diff = 0                                     degrees of freedom =      144

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0994         Pr(|T| > |t|) = 0.1988          Pr(T > t) = 0.9006
```

```
 9 . /* test if implicit balance scores are different between major groups */
10 . ttest std_Balance2_3 if Good_IATD2_3 ==1 & Good_Exp_3 ==1, by(Major_Bio)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |      39    .1259567     .107739    .6728296   -.0921494    .3440628
       1 |     107     .449546    .0574887    .5946677    .3355691    .5635229
---------+--------------------------------------------------------------------
combined |     146    .3631077    .0521979    .6307094    .2599408    .4662747
---------+--------------------------------------------------------------------
    diff |           -.3235893    .1152695               -.5514281   -.0957505
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -2.8072
Ho: diff = 0                                     degrees of freedom =      144

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0028         Pr(|T| > |t|) = 0.0057          Pr(T > t) = 0.9972

11 . /* correlation */
12 . pwcorr Major_Bio std_Balance2_3 std_ibr_3 if Good_IATD2_3 ==1 & Good_Exp_3 ==1, sig

             | Major_~o std_Ba~3 std_ib~3
-------------+---------------------------
   Major_Bio |   1.0000 
             |
             |
std_Balanc~3 |   0.2278   1.0000 
             |   0.0057
             |
   std_ibr_3 |   0.1070   0.0486   1.0000 
             |   0.1988   0.5599
             |

13 .
end of do-file

14 . log off
      name:  <unnamed>
       log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\STEM Major Supplemental Exploratory Analysis Results.s
  log type:  smcl
 paused on:  13 Feb 2021, 16:31:38
--------------------------------------------------------------------------------------------------------------------
--------------------------------------------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\STEM Major Supplemental Exploratory Analysis Results.s
  log type:  smcl
resumed on:  13 Feb 2021, 16:33:24

15 . do "C:\Users\PEDERS~1\AppData\Local\Temp\STD43ec_000000.tmp"

16 . by rGender, sort: pwcorr Major_Bio std_Balance2_3 std_ibr_3 if Good_IATD2_3 ==1 & Good_Exp_3 ==1, sig

--------------------------------------------------------------------------------------------------------------------
-> rGender = Male
```

```
             | Major_~o std_Ba~3 std_ib~3
-------------+---------------------------
   Major_Bio |   1.0000 
             |
             |
std_Balanc~3 |   0.2489   1.0000 
             |   0.0551
             |
   std_ibr_3 |  -0.2868  -0.1402   1.0000 
             |   0.0263   0.2853
             |

--------------------------------------------------------------------------------------------------------------

-> rGender = Female

             | Major_~o std_Ba~3 std_ib~3
-------------+---------------------------
   Major_Bio |   1.0000 
             |
             |
std_Balanc~3 |   0.3090   1.0000 
             |   0.0038
             |
   std_ibr_3 |   0.4153   0.2020   1.0000 
             |   0.0001   0.0622
             |

17 .
   end of do-file

18 . log close
        name:  <unnamed>
         log:  C:\Users\pedersenr\Desktop\EAGER\Master's Thesis\STEM Major Supplemental Exploratory Analysis Results.s
    log type:  smcl
   closed on:  13 Feb 2021, 16:33:32
--------------------------------------------------------------------------------------------------------------
```