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Beta Drift: Forecasting the Manifold Relationships between Students and their Pursuit of STEM Careers

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DEDICATION

I am dedicating this dissertation to my loving family, an unwavering constant of happiness, inspiration, laughter, and support. To my children, Shane and Sophia, and my wife Kathy, thank you for the joy you give me every day. Although I can never fully repay you for enduring my late nights away, your commitment to me is the most thoughtful gift I could have imagined. To my parents, Doug and Mary, you have been my most ardent supporters. I successfully made it through the STEM pipeline, and subsequently “leaked” out, because of your sage guidance. Our shared love of science, space, education, politics, and humanity drives my research interests today. Finally, to my late father-in-law Phil, thank you for sharing in my educational journey. I wish you were here to see it through.

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ABSTRACT

Beta Drift: Forecasting the Manifold Relationships between Students and their Pursuit of STEM Careers

by Douglas D. Havard

The purpose of this study was to examine the extent to which motivational and persistence factors predict the occupational career choices of underrepresented students in their pursuit of a STEM career. Data selected from the High School Longitudinal Study beginning with the base year through the fourth wave were employed in a large-scale multinomial regression analysis. Anticipated *STEM occupation at the age of 30* was examined across six years of complex survey data using multiple taxonometric definitions. Social Cognitive Career Theory provided the theoretical framework for defining relevant factors affecting this STEM pursuit construct. The findings from the study suggest that by varying student perspectives on their expected STEM careers, the resulting pathway of pursuit is affected by a different set of predictors. Typographic models developed through fitting multinomial logistic regression models also suggest that female students are propelled into specific STEM careers through early mathematics identity, mid-study science utility, and an evolving dynamic between parent and student expectations. The results additionally highlight race and ethnicity differences which more closely, though less significantly, mirror those of female students. The overall results of these findings raise questions about the continued use of a STEM pipeline metaphor in describing student pursuit. Moreover, adjacent policies, theoretical frameworks, and research methods aligned to this construct should be reviewed on how they portray an inaccurate picture of pursuit amongst underrepresented students seeking STEM careers.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AAAS	American Association for the Advancement of Science
ACT	American College Testing
AP	Advanced Placement
AT	Attribution Theory
BLS	Bureau of Labor Statistics
BRR	Balanced Repeated Replication
CEO	Corporate Executive Officer
CI	Confidence Interval
CIP	Classification for Instructional Programs
CP	College Prepatory
DHS	Department of Homeland Security
EVT	Expectancy-Value Theory
GOT	Goal Orientation Theory
H	Honors
HS&B	High School & Beyond
HSLS	High School Longitudinal Study
ICPSR	Inter-university Consortium for Political and Social Research
IRT	Item Response Theory

IT	Information Technology
MESA	Mathematics Engineering Science Achievement
MET	Mathematics Engineering Technology
MNLM	Multinomial Logistic Model
MNLR	Multinomial Logistic Regression
NAEP	National Assessment of Educational Progress
NAICS	North American Industry Classification System
NASA	North American Space Agency
NCES	National Center for Educational Statistics
NDEA	National Defense Education Act
NELS	National Education Longitudinal Study
NLS	National Longitudinal Study
NRC	National Research Council
NSB	National Science Board
NSF	National Science Federation
NSLDS	National Student Loan Data System
O*NET	The Occupational Network
OECD	Organisation for Economic Co-operation and Development
OMD	Office of Management and Budget
OR	Odds Ratio
PET	Punctuated Equilibrium Theory
PhD	Doctor of Philosophy
PISA	Program for International Student Assessment

PSU	Primary Sampling Unit
R&D	Research & Development
ROC	Receiver Operating Curve
RT	Retention Theory
S&E	Science & Engineering
SCCT	Social Cognitive Career Theory
SCT	Social Cognitive Theory
SDT	Self-Determination Theory
SES	Socioeconomic Status
SET	Science Engineering Technology
SLS	Secondary Longitudinal Studies
SME&T	Science Mathematics Engineering & Technology
SMET	Science Mathematics Engineering Technology
SOC	Standard Occupational Classification
STEAM	Science Technology Engineering Arts Mathematics
STEM	Science Technology Engineering Mathematics
TIMSS	Trends in International Mathematics and Scientific Study
US	United States
USSR	United Socialist Soviet Republic
VIF	Variance Inflation Factors

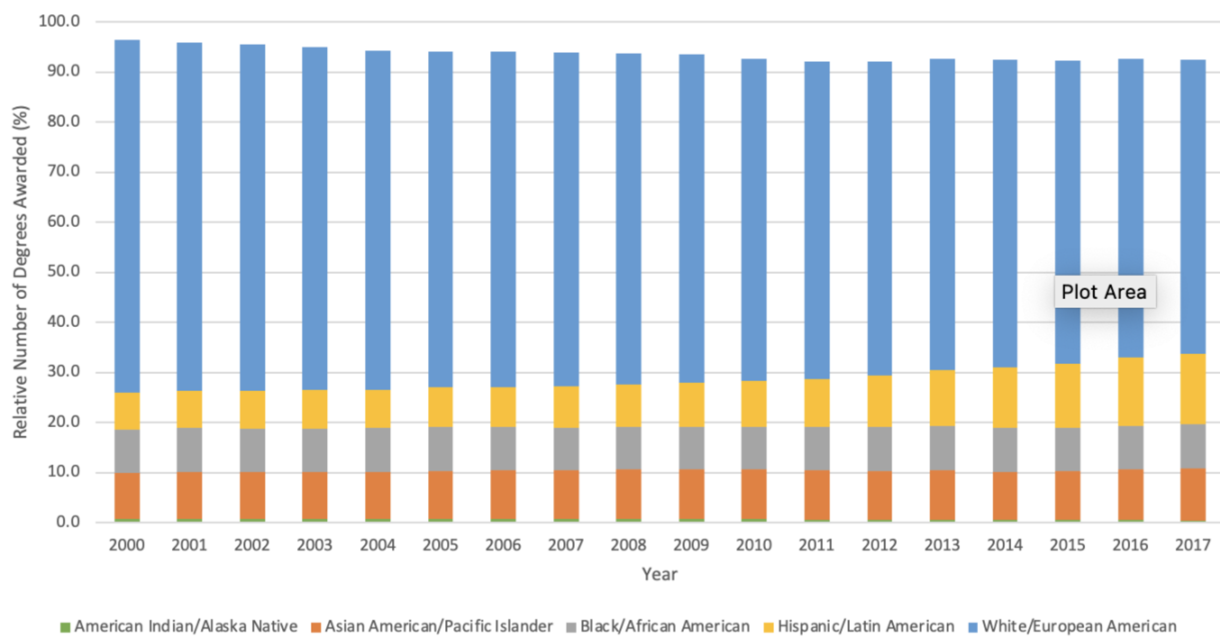
LIST OF SYMBOLS

Symbol	Meaning
β	Logit model coefficient
Ω	Log odds of a particular outcome
n	Sample Size
N	Population size
b	Base outcome (reference category or control)
m	Comparison outcome
J	Total number of alternative categories
OR	Odds Ratio
$\Delta\beta$	Cook's distance
ΔD	Deviance
h	Leverage
ΔX^2	Change in Pearson chi-square
Δn	Change in sample size
df1	Degrees of freedom as the number of treatment levels - 1
df2	Degrees of freedom as the number of observations – number of groups
F	F-statistic
p	p-value
t	t-statistic

Chapter 1. Introduction

Science, Technology, Engineering, and Mathematics (STEM) has grown from its public policy origins to headline debates over labor market trends, pipeline models, and educational initiatives (Funk & Parker, 2018; Lucena, 2005; Maltese & Tai, 2011; Teitelbaum, 2003; Xie & Killewald, 2012). Tangent to the economic and educational policy discussions from the early 2000s (National Academy of Sciences et al., 2007; National Governors Association, 2007; National Research Council, 2002), research today is reflecting a renewed focus on identifying intersectional barriers to, supports of, and models predicting STEM pursuit amongst the most marginalized. This shifting research priority has come in response to historic degree attainment data revealing that "many groups of Americans remain underrepresented among Science and Engineering [S&E] degree recipients" (National Science Board [NSB] & National Science Foundation [NSF], 2020). In-group comparisons between gender, race, ethnicity, and socio-economic status (see Figure 1) are spotlighting these differences on a national scale. While the total number of degrees conferred by female students across the nation has reached 58%, the quantity of STEM degrees (36%) compared to the national average (45%; NSB & NSF, 2019; National Center for Educational Statistics [NCES], 2016) is unveiling a significantly different image. Underlying this difference in STEM degrees attained (-9%), is an overall lack of parity in the "pipeline" to pursuit. These trends have become even more concerning when examining the STEM subfields of engineering, computer science, and mathematics and statistics (see Figure 2; NSB & NSF, 2019). Considering the degree composition by race within these disciplines, Black people remain underrepresented "at all degree levels" and Hispanic people are represented singularly at the associate's level (NSB & NSF, 2020). Figures 1 and 2 illustrate these gaps in STEM pursuit between 2000 and 2017 at the bachelor's degree level based on race and ethnicity and by STEM sub-discipline. Ascribing these differences to longitudinal pursuit factors such as lower high school completion rates, progression to advanced coursework, college enrollment, and degree attainment (NSB & NSF, 2020), the one-dimensional pipeline models employed to explain them present a rigid form of empiricism when defining and organizing the policy-problem space. Belied by the lack of an accepted operationalized definition of STEM, federal policies developed over the last fifteen years utilizing pipeline theories have been further limited by a depth of understanding of STEM pursuit and its application. The result is an affirmation to this increasingly subjective endeavor and to a *drifting* set of indicators which provide limited power in predicating career attainment.

Figure 1*. Share of STEM Bachelor's Degrees Awarded from 2000-2017*

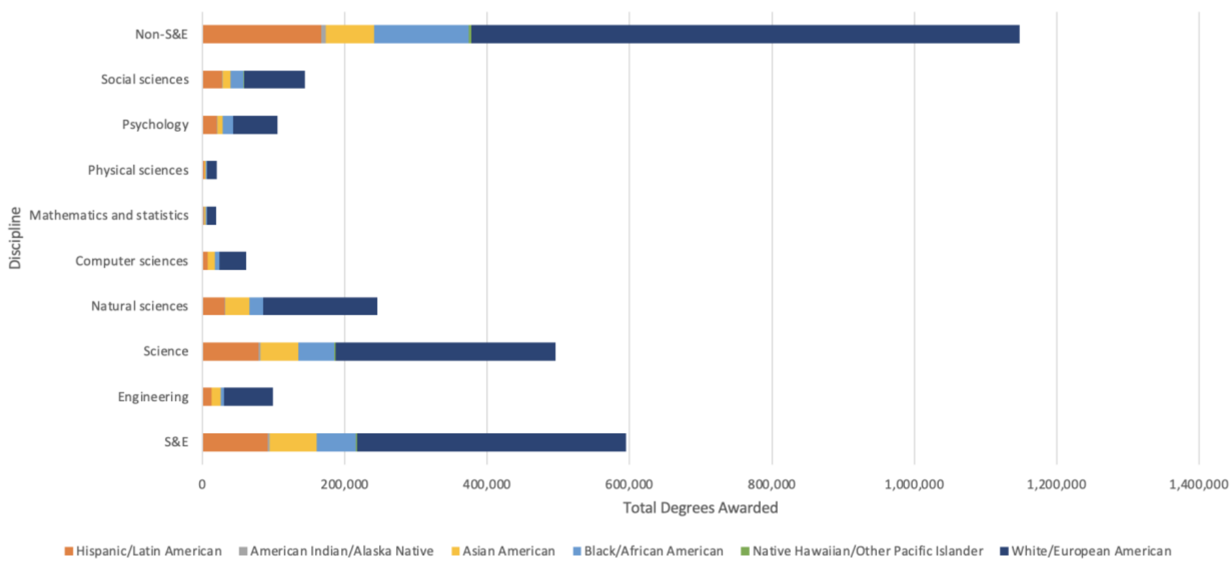


Note. Data were compiled from the *Science and Engineering Indicators 2020* (National Science Board et al., 2020) showing a percentage decrease in respondent reporting from 2000 to 2017.

Amidst these challenges, contemporary quantitative research has begun to employ analysis methods that consider intersectional relationships in identifying model factors that support the development of gap-reducing policies. Typological (Engberg & Gilbert, 2014; James et al., 2019; Wang et al., 2017), factor analysis (Yang & Barth, 2017), hierarchical models (Andersen & Ward, 2014; Ibrahim & Johnson, 2020; Jackson & Laanan; 2015; Robnett & Leaper, 2013; Woo et al., 2021; Xu, 2008), and multinomial regression techniques (Gottlieb, 2018; Kremer, 2020) have shown promise in evaluating these intersections as well as their application to longitudinal data. The High School Longitudinal Study (HSLS:09; Ingels et al., 2018) is the most recent NCES dataset capturing longitudinal panel data on S&E pursuit factors, extending from secondary to postsecondary educational environments and STEM careers, aligning to traditional pursuit models and research-supported motivational and persistence constructs of pursuit. With the goal to "further understand the correlates of educational success in the United States", *HSLS:09* aligns to the modern approaches of STEM pursuit research including many contextual, environmental, and demographic components that have been shown to affect students pursuing S&E careers.

However, without clarity in the factors supporting the pursuit of a well-defined, modern definition of STEM, the U.S. has yet to acknowledge the positive impacts of a changing demographic of citizenry, and the resulting economic bearing – the corollary to a stance it has long supported in promoting individual and national growth (Piketty & Goldhammer, 2014, pp. 416-420) – on stimulating innovation in science and engineering. Investing in high-quality STEM education and providing access to undergraduate STEM programs, are not only the "building blocks of the American innovation ecosystem" (National Economic Council et al., 2015) but, more importantly, a critical component for developing student agency in STEM. *Agency* is the human ability of students to make decisions about how they engage in a particular learning setting (Giddens, 1984). Although many students are building STEM agency outside the formal educational system (Levinson, 2014), motivation to continue to pursue difficult STEM career outcomes relies on the building of a formal and informal learner agency designed around student interests and real-world relevancy (Levinson, 2014; Murphy et al., 2019; Rosenzweig, 2016). While innovation has undoubtedly been a driver of the post-modern economy (Carnevale, Smith, & Strohl, 2010), future STEM graduates will rely on their agency to develop innovative solutions that transcend economic means and lead to cultural, scientific, and engineering discoveries. The impacts of these new discoveries may have the capability to evolve the human condition.

Figure 2. *STEM Bachelor's Degrees Awarded in 2017 by Race and Ethnicity*



Note. Data were compiled from the *Science and Engineering Indicators 2020* (National Science Board et al., 2020).

Background, Context, and Theoretical Framework

A defining spirit of innovation has underscored a national identity long before STEM was phrased into the educational policy landscape. Before 2000, "SME&T" represented the "collective" disciplines of Science, Mathematics, Engineering, and Technology. However, by 2008 and after some reimagining of the acronym at the National Science Foundation, "STEM" was beginning to be used extensively throughout educational research, policy, postsecondary education, and the disciplines themselves. What is commonly believed to have generated a fervent proliferation of STEM is the convergence of three seminal reports released in 2005 – comprised of unique coalitions of non-profit organizations and corporate, academic, and educational leaders (Breiner et al., 2012; Koehler et al., 2012; Lantz, 2009; Teitelbaum, 2014). Each report had similar goals: (1) bringing to light a shared belief that the United States was failing to produce a quality science and engineering workforce, (2) that the U.S. was quickly being surpassed by rising foreign nations, and (3) to provide policy recommendations for addressing these forecasted challenges. As a basis for their calculations, the authors employed generalized economic models based around interpretations of the STEM occupations, each showing a similar crisis on the horizon.

Of these three historicizing reports, *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future* (2005), developed out of an ad hoc committee from the National Research Council (NRC), impelled the use of National Science Foundation (NSF)-supported economic and pipeline models to the forefront of STEM education policy. By playing to the competitive fears of the public, the NRC report considered how the U.S. would become technologically competitive on an international stage as a perceived shortage of adequately trained STEM professionals furthered a lack of U.S. preparation into the new globalized economy. Historically, student national achievement levels in math and science have ebbed and flowed over the last three decades (Desilver, 2017). Within the last few years any gains shown in National Assessment of Educational Progress (NAEP) scores have stalled (Desilver, 2017). Recent 2015 PEW research surveyed a representative sample of American Association for the Advancement of Science (AAAS) members and the public about their perceptions of the country's STEM status in relation to the rest of the world. Only 29% of the public and 16% of

AAAS members surveyed believed the U.S. remained at or above other developed countries (Pew Research Center, 2015, p. 5). These positions are becoming increasingly supported by 2015 and 2018 Program for International Student Assessment (PISA) scores showing the United States lagging behind other Organisation for Economic Co-operation and Development (OECD) nations (such as Canada, Japan, United Kingdom, Singapore, Hong Kong, Germany, and South Korea) and either at or below the OECD average (Desilver, 2017). Creating high quality jobs and responding for the need for clean energy were two challenges deemed by the committee as being closely tied to the future of S&E success. Therefore, the report pushed for reforms that increased training efforts, furthered a development plan to expand the supply-side STEM talent pool, and supported overall improvements to K-12 education. However, with the coupling of one-dimensional human-capital economic models with a non-operationalized definition of STEM, predictive models for determining factors of pursuit for underrepresented S&E graduates has proven elusive – resulting in a workforce variance between 5 - 20% of the U.S. economy (Lowell & Salzman, 2007; Teitelbaum, 2014; Xie & Killewald, 2012; Xue & Larson, 2015). Nevertheless, the STEM pipeline model of supply-side inputs and demand-pulling outputs remains the most widely employed method for explaining and assessing the "state of STEM" compared to other industrialized nations.

Modern research has revealed a growing role of typologies – a competing perspective to the one-dimensional pipeline approaches – in predicting STEM career pursuit for underrepresented groups of students. Results from these studies are challenging historical views which have relied on STEM pipeline models to examine factors associated with motivation and persistence. These models, conversely, do not address a changing demographic of citizenry and untapped workforce potential through: (1) a reliance on supply-side economics that have led to flawed measurements and the “leaky path” analogy, (2) a single dimensionality (or linearity) of career pursuit milestones with a single career entry point that does not fully explain contemporary educational pathways, and (3) the homogenization of people and fields.

Statement of the Problem

The research herein considers the barriers to, and supports of, STEM pursuit for underrepresented students across their secondary and postsecondary schooling. Results from a typological, student-focused approach across the longitudinal pursuit span of traditional pipeline models may illuminate critical barriers and supports for underrepresented groups of students interested in pursuing careers in critical STEM fields.

Purpose of the Study

The purpose of this study is to examine the extent to which motivational and persistence factors predict U.S. secondary and postsecondary students’ occupational career choice and how their arrangement fit positive typologies of STEM pursuit. Anticipated *STEM occupation at the age of 30* across multiple STEM taxonomies and longitudinal collection points are the categorical dependent variables and *psychometric; experiential and learning; contextual-environmental; and demographic influences* are independent variable groupings. Typographic models within and between groups will support a larger comparative analysis of the roles of these factors in STEM career pursuit amongst underrepresented students.

Research Questions

The objective of the research is to examine how students make occupational and educational decisions in their longitudinal pursuit of STEM careers. As a basis for this research, the following research questions consider the purpose for and approaches toward re-assessing STEM pursuit models:

Research Question 1: What is STEM and how is it defined within education and the workforce?

Research Question 2: What combination of influencing factors across student characteristic groupings contribute to expected STEM pursuit across secondary and postsecondary levels of education?

Research Question 3: What influencing factors across student characteristic groupings act as supports for or barriers to an anticipated STEM career across secondary and postsecondary levels of education?

Research Question 4: What typological models predict the successful pursuit of underrepresented groups of students into STEM fields?

Research Question 5: Is there a STEM taxonomy that encompasses inclusive typologies for underrepresented groups of students?

Research Question 6: How do these results compare to traditional pipeline model approaches to STEM pursuit and policy?

Hypothesis

Research surrounding Research Question 1 is inseparable from the historical contexts of STEM education in the United States and the evolving educational policies enacted throughout the modern era (post-WWII). Since STEM was derived from educational policy, addressing this question will necessitate a policy analysis. The results are hypothesized to follow a STEM definitional structure aligned to occupational, national, and political interests. As a basis for Research Question 2-6, understanding career-connected definitions of STEM (e.g., through the Bureau of Labor Statistics, Department of Labor, and National Science Foundation) will reset the perspective for who enters STEM fields, how they are supported, and the barriers that exist to their pursuit of STEM careers. Building on prior research that specifically considers factors affecting

STEM pursuit, it is hypothesized that many typologies exist for students entering STEM careers from a multitude of directions.

Significance of the Study

Recent contributions to the field of STEM education have centered on the significance of promoting diversity by examining the limiting conditions of students with an initial interest in these disciplines. However, an overreliance on traditional one-dimensional approaches to educational policy, such as the "pipeline model", have given way to more modern beliefs about the factors affecting student career goals and attainment outcomes as well as the frameworks for understanding the development process. Social Cognitive Career Theory (amongst a backdrop of other motivational and persistence theories) examines specifically how students shape their future careers and are shaped by their environment, forming a triadic relationship between social stimuli, self-influences, and achievement outcomes. Although the model has shown promise in predicting achievement outcomes of students through its derivative Social Cognitive Career Theory, it has yet to be applied longitudinally across secondary and postsecondary schooling and in the context of student motivations and career outlooks. The aim of this research is to uncover how students are making occupational and educational decisions longitudinally – those factors which affect their pursuit of a STEM major and beliefs about obtaining a STEM degree – and serve as model predictors. By disaggregating the STEM pipeline into factors and correlates, a cursory examination of the definitions surrounding traditional STEM careers with student career outlooks may give rise to an aggregate understanding of student motivations and persistence in these fields. The ability to provide educators, researchers, and policy makers with a deeper understanding of the gaps in the overall participation of women and underrepresented groups, including ways to close these divides and link opportunity pathways that may better align with a changing demographic of U.S.

citizenry, advances the state of the field. Success through these means will have a direct effect on increasing student agency in STEM and the well-being of all individuals in our society.

Operational Definitions

The following definitions are provided to give clarity to their use, operationalization, and context due to the interdisciplinary nature of the proposal. Since this proposed study combines literature from the individual STEM disciplines, education, economics, psychology, philosophy, educational policy, and the teaching profession, the included definitions offer a bridge toward connecting these parts throughout the document. To provide clarity in interpreting the terms presented, all researcher-developed definitions are not accompanied by a citation.

Academic Identity: how we see ourselves in an academic domain.

Academic Self-concept: how an individual regards their own academic achievement – a content-specific self-rating of skills, abilities, enjoyment, and interest.

Agency: the active role of students in their learning through voice or choice.

Classification of Instructional Programs (CIP): "a taxonomic scheme that supports the accurate tracking and reporting of fields of study and program completions activity" (U.S. Department of Education, 2020).

Cost: financial or personal strain of performing a specific task.

Expectancy: the probability that a desired outcome is achieved through a specific behavior or action.

Iron triangles: "communities of specialists operating out of the political spotlight" (Baumgartner et al., 2017).

Marginal effects: instantaneous rates of change of a predictor with an individual covariate under defined conditions (e.g., moderating factors).

North American Industry Classification System (NAICS): "the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business economy" (U.S. Census Bureau).

*The Occupational Network (O*NET)*: "the nation's primary source of occupational information". The O*NET database contains "standardized and occupation-specific descriptors on almost 1,000 occupations covering the entire U.S. economy" (Department of Labor, 2020).

Policy images: "a mixture of empirical information and emotive appeals" (Baumgartner et al., 2017).

Policy monopoly: "a definable institutional structure responsible for policymaking in an issue area, and its responsibility is supported by some powerful idea or image. This image is generally connected to core political values and can be communicated simply and directly to the public" (Baumgartner et al., 2017).

Policy window: generic term to include both "agenda windows" (i.e., pushing "pet solutions" or garnering attention to "special problems [Kingdon, 2011]) and "decision windows", which advocate for "getting policies adopted" (Herweg et al., 2017).

Punctuations: "political processes" that "occasionally produce large-scale departures from the past" (Baumgartner et al., 2017).

Self-efficacy: an individual's belief in their capacity to perform the behaviors necessary to produce specific performance attainments (Bandura, 1977; 1986; 1997).

Standard Occupational Classification (SOC): "a federal statistical standard used by federal agencies to classify workers into categories for the purpose of collecting, calculating, or disseminating data" (U.S. Bureau of Labor Statistics, 2020).

Stasis: a long period "marked by stability and incrementalism" (Baumgartner et al., 2017)

STEM Pipeline: a metaphor describing the singular path to pursuit of a career in science, technology engineering, and mathematics.

Supply-side Economics: a theory that postulates how an infusion of capital, jobs, and labor into a marketplace (the "supply-side") will stimulate the economy.

Task-value: perceived importance, usefulness, enjoyment, or benefit to the individual successfully completing a task.

Triadic Reciprocal Causation: the triadic, simultaneously causal effects of personal, environmental, and behavioral determinants on each other.

Utility Value: the perceived usefulness of a task.

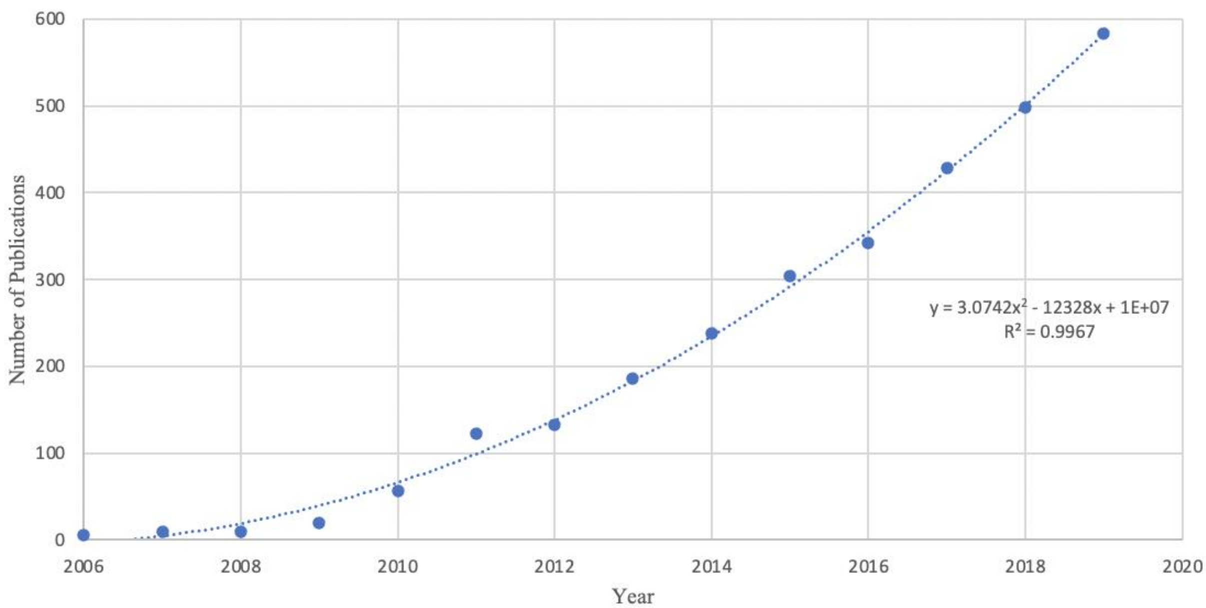
Chapter 2. Literature Review

The lack of a clearly defined and rigorous classification of STEM careers has led to a disparate set of approaches for explaining how secondary and postsecondary students in the United States reach these outcomes as well as their effect on the U.S. economy. Since the popularization of “STEM” by the National Science Foundation, as a loosely abstracted group of fields in science and engineering, the evolution of STEM as a non-operationalized term has produced reflexive interpretations over the last fifteen years since its emergence. Most of these interpretations are fitted around labor-market economic models (e.g., the STEM pipeline) that aim to predict the STEM workforce and guide the overall effectiveness of STEM training programs. Classifications of STEM center primarily on the traditional disciplines (the natural and physical sciences, engineering, and mathematics), though many also branch outward toward non-traditional STEM careers including the social sciences, health and medical professions, the technical trades, and management positions. The result is a significant variance (Teitelbaum, 2014; Xue & Larson, 2015) in the overall labor market through which “STEM” is defined – differences which may have had ripple effects across underrepresented groups of students, including on the models and educational policy decisions that have come as a result.

By all accounts, the origin of STEM grew from within the national policy landscape prior to the early 1990s (Sanders, 2009). Before 2000, “SME&T” was the *dernier cri*, representing the “collective” disciplines of Science, Mathematics, Engineering, and Technology. Other acronyms launched throughout this time including “SMET”, “SET”, and “MET”, though only SET remains today in international contexts. It was within an interagency meeting on science education that the former director of the National Science Foundation’s Education and Human Resources Division, Judith Ramaley, was credited with cementing this change (Christenson, 2011; Koonce et al., 2011;

National Science Foundation, 1996). Although insignificant at the time, this simple arrangement became a catchy, well-utilized descriptor in economic and educational policy. By the early 2000s the term was widely accepted throughout academe and by 2009 “STEM” began bracing Education Week headlines (Loewus, 2015) and its usage exhibiting a quadratic growth in Web of Science search results (Figure 3), an acknowledgement that it had entered the vernacular.

Figure 3. *Distribution of STEM Publications on the Web of Science from 2006-2019*



Note. The search criteria included the following search terms: “STEM” AND “science, technology, engineering, and mathematics”

Lacking an operationalized definition of STEM from the onset, the economic models undergirding national educational policy decisions have become highly criticized (Lowell & Salzman, 2007; Teitelbaum, 2014; Xie & Killewald, 2012; Xue & Larson, 2015). Depending on the economic model chosen (i.e., the inclusion or exclusion of agricultural, social science, or health occupations), labor market calculations have been shown to fluctuate from surpluses to deficits

(Xue & Larson, 2015). Educational and governmental organizations, therefore, have struggled with reconciling interagency meta-analysis and with ways of comparing workforce data as a means of assessing STEM policy decisions, like those outlined in the America COMPETES act (2007) and reauthorization act (2010; 2017). As a result, several national organizational bodies have developed their own definitions for STEM occupations, appearing as taxonometric codes, or numeric job and instructional program indicators, that form a standard hierarchical definition of STEM occupations[1]. The approaches, such as those employed by the Bureau of Labor Statistics, leverage solutions dating back to the 1890 Census of Population which originally specified a multi-level taxonometric approach to account for industries, disciplines, disciplinary jobs within these industries, and for varying layers of job specificity to administer the census. In 1980, the National Center for Educational Statistics (NCES) developed the Classification of Instructional Programs (CIP), a "taxonometric scheme" supporting "the accurate tracking and reporting of fields of study and program completions activity" (NCES, 2020) to solidify a similar "accounting" methodology at the postsecondary level. Their approach diverged mainly from the unit of analysis presented by the Bureau of Labor Statistics (BLS) Standard Occupational Code (SOC) framework, by focusing on the instructional programs enrolling students as opposed to the skills defining the STEM occupations of working professionals. Seeking a way to connect to the BLS SOC for longitudinal alignment between programs of study and future careers, the NCES coordinated the development of "crosswalks" to link between the CIP and SOC taxonomies for pursuit research.

Table 1 illustrates the leading definitions of STEM by organization and according to their authority, taxonomy, methodology, STEM definition, and level of analysis (e.g., educational- or

[1] For example, the code 1.A 17-2011 within the Bureau of Labor Statistics data uses dot/dash-delimited numbers to represent hierarchical jobs levels, in this case "Aerospace Engineer", of sub-domain, occupation, and SOC code.

occupational-focused). Of the definitions, the top five authorities - as viewed in Table 1 from the top-down - are the most widely used and accepted. Each taxonomy offers a distinct perspective, yet each fall into either the SOC, CIP, or North American Industry Classification System (NAICS) taxonometric framework. Localized attributes are shown to exist within these perspectives independently as either career-focused or instructional-program hierarchies. The skills-based taxonomies including the BLS SOC, Census Bureau NAICS, and Department of Labor's O*NET are organized around specific STEM skill sets determined by the Office of Management and Budget (OMB). Following the approach of separating STEM into "Science, Engineering, Mathematics, and Information Technology" and "Science and Engineering Related" domains, each domain is associated with jobs that fulfill five key STEM skill sets: (1) research, development, design, and practitioner, (2) technologist and technician, (3) postsecondary teaching, (4) managerial, and (5) sales. Through this approach military, health and medical, managerial, and technical sales jobs may be included in the job outlook since each requires a combination of education and industry-specific professional training. The NAICS, which guides the Census Bureau's approach to STEM classification, similarly separates occupations into "STEM" and "STEM-related" categories, though with a production-orientation based on the goods produced by an "establishment" within a specific industry (NAICS, 2017, pp. 15-21). Conversely, instructional program-aligned taxonomies define STEM based on the NCES Classification of Instructional Programs (CIP) which offers a distinct organizational methodology aligned to postsecondary programs at institutions of higher education and affiliated organizations such as those supporting research, design, and emergent technologies. This taxonomy differs by classifying fields of study into three categories: (1) Science, (2) Engineering, and (3) non science or engineering fields of study. The National Science Foundation is an example of an organization adopting this framework.

In keeping with NCES policy, although the NSF has yet to explicitly define STEM, successful STEM-specific programs such as the Louis Stokes Alliances for Minority Participation (2020), NSF leaders (Fiegener, 2015; Green, 2007), and STEM researchers (Chen, 2011) have provided guideposts toward a tacit NSF definition.

With a wide array of STEM definitions, the problem has arisen as to which taxonomy "best" defines STEM for a select population. Since each one delimits the types of STEM careers that are included in their individual definitions (mostly at the fringes), a large-scale acceptance of any one taxonomy has not materialized. Emerging to the surface of this STEM occupational inclusion debate, therefore, is the selection criteria of "related" STEM occupations – those hierarchies accepting STEM-trained workers, but which do not fall into the traditional STEM career fields. The Census Bureau definition is an example of this classification method, separating into "STEM" and "STEM-related" professions. The Standard Occupational Classification follows this approach to differentiate the two STEM domains into "Science, Engineering, Mathematics, and Information Technology" and "Science and Engineering Related". A similar practice is also utilized by researchers to organize the STEM disciplines separately or in combination with one of the listed models (Koonce, 2011; Rothwell, 2013; Xu, 2008). This distinction is what separates these systems from the BLS SOC and Department of Labor's O*NET, the decision to either include or exclude STEM-related occupations, even as both taxonomies utilize the same overall classification hierarchy, the Standard for Occupational Classification.

To visualize the differences between each of the main taxonomies (see Table 1) and their distinguishing paths toward STEM careers, Figures 4 and 5 synthesize their attributes into instructional and career pathway perspectives. Figure 4 considers STEM and STEM-related careers, those approved for inclusion by the SOC Policy Committee, organized around the five key skill sets that the committee defined as meeting their criteria for "STEM" within the domains. This approach contrasts to those taken by organizations employing an instructional program-centered methodology (e.g., NSF, DHS, and ACT). Figure 5 shows this distinction as a collection of disciplinary programs of study falling into either the sciences, engineering, and non-science and engineering disciplines that are STEM-oriented. Distinctions between the two pathways are illustrated in situations where industry skills are developed on-the-job, or where unique skillsets are job-specific and disciplinary based, not allowing for an instructional program offering such as technical sales (i.e., sales engineering and sales representatives) and various management careers.

By examining each figure, and to an extent the individual taxonomies, a distinct definition of STEM appears to lie between the two perspectives – one that is career-based and instructional program-centered. A thoughtful alignment of these current (instructional and degree program) and future (career) pathways to an individual students' outlook may construct the foundation for the successful pursuit of a STEM career. Through a mix of STEM research (Funk & Parker, 2018; Kaleva et al., 2019; Palmer et al., 2017; Wang, 2013) and a review of grey literature (Harris Interactive Survey, 2011; Kennedy et al., 2018; Painter et al., 2017), a set of motivations for why students choose to enter STEM careers, and the subsequent impact of career orientations on STEM definitions, have been established. These outlooks include: (1) an enhanced quality of life, (2) a greater job outlook, (3) to make a larger societal impact, (4) having an interest, (5) having a perceived ability, (6) wanting to become cross-marketable, and (7) enjoy solving problems or like being challenged. Acknowledging a particular student viewpoint, anchors the cognitive foundation for students to align their individual outlook to a specific STEM career (Unfried et al., 2014). The career-oriented pathway described in Figure 4, offers students a long-range, future-looking endpoint. Figure 5, by contrast, provides a near-term perspective on instructional programs of study leading to a STEM career. In each perspective, an alignment of outlooks may serve different means to the same ends. For example, a student who has an interest in computers and technology but may not associate their interests with a specific program of study in their school, may take a long-term look at STEM careers meeting these interests and backward plan how to meet their goals. Another student, with an interest in science and high perceived ability in biology that wishes to make a larger societal impact, may look toward the near-term pathways in Figure 4 to identify a STEM instructional program that leads to a matching career path. The utilization of both pathways may help assign context and meaning to students' interest, perceived ability, and outlook as they, with the support of counselors and career mentors, determine a pathway of pursuit for a STEM career.

Augmenting the traditional interpretations of STEM through a set of emerging taxonometric models is the changing problem landscape. STEM problems and industries have become more unified, cross-disciplinary, globalized, socioscientific, and historico-cultural throughout the last two decades, resulting in a definition that has become more *transdisciplinary*, or relating to more than one branch of knowledge. Without a clear definition of STEM careers, pursuit research and the policy models built to examine the state of STEM training effectiveness remain at best limiting. Current models, those relying on the overwhelming supply-side input of students and demand-pulling output from industries, remain challenged by: (1) nudging students who may not have interest in STEM into the "pipeline" through many policy-driven supply-side pushes, (2) misinterpreting the demand-pull given a fluctuating definition of what defines STEM careers, (3) not acknowledging the role of alternative pathways for entry into STEM careers (e.g., through military service, through career changes, or as a transfer student from a 2-year college), and (4) perpetuating a homogeneity of students through which these models identify and support.

With a changing national demographic of citizenry, the U.S. should, and has acknowledged, the importance of inculcating all interested students with STEM talent (NSB & NSF, 2020). The underrepresentation of students based on race, ethnicity, gender, and socioeconomic status, however, remains undergirded by the lack of an operationalized definition of STEM and current models for predicting their pursuit of a STEM career. These challenges consider which factors affect – and are barriers to – STEM across secondary and postsecondary education, inclusive of the teaching approaches emerging out of a pipeline “worldview”. A shifting research perspective on student typologies as “multiple streams” of outlooks and pursuit factors, rather than the traditional “one-dimensional” models, offers a unique perspective on STEM pursuit for underrepresented groups of students. The definitional STEM frameworks outlined in Figures 4 and 5 connect student near- and long-term course taking, interests, and perceived STEM ability into account when planning pathways toward a specific STEM career. Both provide an illustrative look at STEM from a skills-based and instructional program-centered perspective. However, the emergence of “STEM” in the annals of the National Science Foundation owes its foundation to an evolution of policymaking decisions dating back to over a century.

__Table 1.__ Defining STEM by Authority, Taxonomy, Level, and Type of Classification

Authority	Taxonomy	Methodology	How is STEM Defined?	Level of Analysis and Type of Classification[a]
Bureau of Labor Statistics (BLS) Standard Occupational Classification (SOC)	4-level hierarchical coding system of 860 occupations (Bureau of Labor Statistics, 2020).	"Federal statistical standard used by federal agencies to classify workers into occupational categories for the purpose of collecting, calculating, and disseminating data" (BLS, 2020).	"STEM occupations include computer and mathematical, architecture and engineering, and life and physical science occupations, as well as managerial and postsecondary teaching occupations related to these functional areas and sales occupations requiring scientific or technical knowledge at the postsecondary level" (Bureau of Labor Statistics, 2020).	• Occupational (workforce) • Skills-based Occupation Classification • Interest and Job Outlook Definitional Pathways
Department of Labor O*NET	4-level hierarchical coding system Based on the BLS Standard Occupational Classification, consisting of 923 occupations centered around the same taxonomic model (Department of Labor, 2019).	Nations primary source of occupational information – providing data and online resources (e.g., My Next Move, O*NET Online, and developed applications) for understanding the changing nature of work and how it impacts the workforce and US economy (Department of Labor, 2020)	Over 300 STEM occupations including managerial, postsecondary teaching, traditional STEM, sales, and technical trades.	• Occupational (workforce) • Skills-based Occupation Classification • Interest and Job Outlook Definitional Pathways
Census Bureau	6-digit hierarchical coding system coordinated between the U.S., Canada, and Mexico known as the North	The NAICS is a production-oriented (supply-based) taxonomy employed by the U.S., Canada, and Mexico. The	67 occupations including "computer and mathematical occupations, engineers, engineering technicians, life scientists, physical scientists,	• Occupational (workforce) • Instructional Program-based

	American Industry Classification System (NAICS).	Census Bureau incorporates this classification methodology in their Current Population Survey (Census Bureau, 2020).	social scientists, science technicians, and STEM managers. STEM-related occupations consist of architects, healthcare practitioners, healthcare managers, and healthcare technicians" (NSF, 2014).	Occupation Classification • Cross-marketable Definitional Pathway
National Center for Educational Statistics (NCES) Classification of Instructional Programs (CIP)	3-level hierarchical coding system of academic majors of study and instructional programs. Cross-referenced 6-digit codes represent every discipline offered throughout academic universities in the U.S. and link the CIP to the BLS (National Center for Educational Statistics, 2020).	The CIP was designed "to facilitate the organization, collection, and reporting of fields of study and program completions" (NCES, 2020). These classifications are the accepted government standard and used in surveys and databases to inform academic, research, and industrial communities.	"Since there is such variation in how STEM is defined, NCES does not have a single definition" (NCES, 2020). Therefore, a specific set of CIP codes has not been categorized as a STEM for policy decisions.	• Educational (post-secondary) • Instructional Program-based Occupation Classification • Perceived Ability and Enjoy Solving STEM Problems Definitional Pathway
National Science Foundation	3-level hierarchical coding system from the NCES CIP.	The NSF adopted the NCES CIP as the standard for academic major and instructional program reporting. However, larger groupings of these classifications (e.g., STEM) differ from NCES.	The NSF funds research in mathematics, physical sciences, and engineering, as well as in psychology and Social Sciences (Granovskiy, 2018).	• Educational (secondary and post-secondary) • Instructional Program-based Occupation Classification • Cross-marketable definitional Pathway
Department of Homeland Security (DHS)	3-level, 6-digit hierarchical coding	DHS has fully adopted the Classification of Instructional Programs in	Four summary groups are emphasized within the DHS STEM taxonomy including	• Occupational (workforce)

	system from the NCES CIP	its STEM designated degree program list of fields designated as STEM.	engineering, biological and biomedical sciences, mathematics and statistics, and physical sciences. STEM-related fields involve “research, innovation, or development of new technologies using engineering, mathematics, computer science, or natural sciences” (DHS, 2016).	• Instructional Program-based Occupation Classification • Perceived Ability and Enjoy Solving STEM Problems Definitional Pathway
ACT	College Board designation of courses and disciplines	Bridge STEM majors with advanced course taking at the secondary level.	Emphasize four classifications of majors for continued STEM pursuit including science, computer science and mathematics, medical and health, and engineering and technology (ACT, 2018, p. 2).	• Educational (secondary) • Instructional Program-based Occupation Classification • Interest and Job Outlook Definitional Pathway

Note. [a] STEM occupations choice descriptor by taxonomy and the specific level of analysis

Figure 4. *Pathways to STEM Careers (Long-term)*

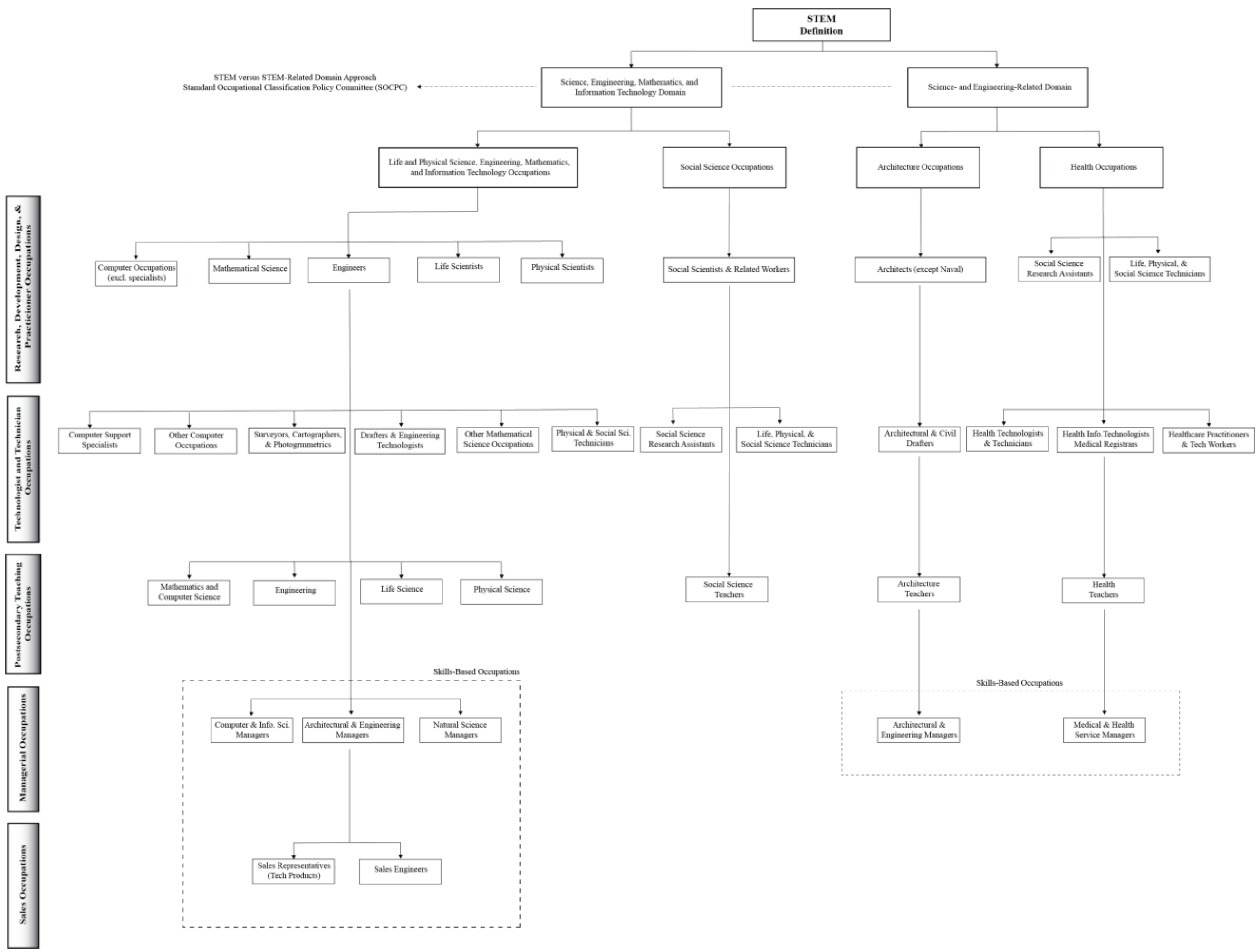
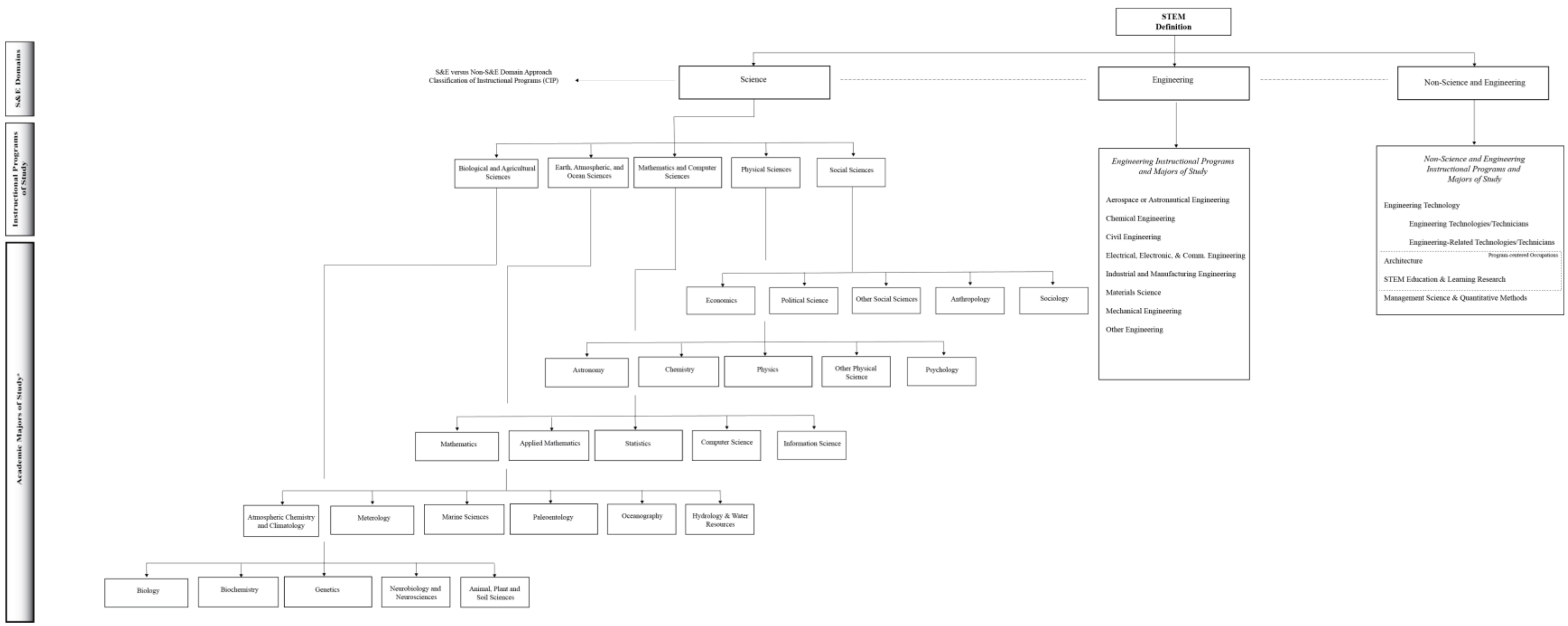


***Figure 5**. Pathways to STEM Careers through Instructional Programs (Near-term)*



Evolution of STEM

Science and Engineering (S&E) Policy Cycles

The usage of the term "STEM" in policy discussions of Science, Engineering, and S&E-related fields began to show a steep increase in its usage after 2007 (Figure 3). Coinciding with the implementation of the America COMPETES Act (2007)[2] – which aimed to promote STEM career pursuit and technical innovation – educators and educational researchers became challenged to successfully implement its innovation policies without an operationalized definition of STEM and an unclear interpretation of its meaning. Amidst the sorting for a workable meaning of "STEM" and as the proliferation of the term continued to climb along a quadratic path (Figure 3), its broad use became correlated with the macro policy that brought it to the micro levels within our U.S. educational system.

Historically, educational policy decisions have cycled through similar points of *punctuated change*, where policies are enacted, followed by lengthy periods of *stasis* – the "balancing" of policy implementation across educational levels. Baumgartner, Jones, and Mortensen (2018) characterize this type of phenomena – "marked by stability and incrementalism" but periodically invoking "large-scale departures from the past" – through Punctuated Equilibrium Theory (or PET), explaining how much of the policymaking in the United States is described through this exchange. Exhibiting a cyclical pattern of punctuation, where a geopolitical event, such as the events leading up to the implementation of the America COMPETES act (2007), alters the current public *policy image,* followed by years of stasis where policy solutions are implemented and evaluated, encapsulate the basis of PET (Baumgartner et al., 2018). The public has long had a U.S.

[2] The America Creating Opportunities to Meaningfully Promote Excellence in Technology, Education, and Science (America COMPETES) Act of 2007 legislated the recommendations from the seminal reports of 2005.

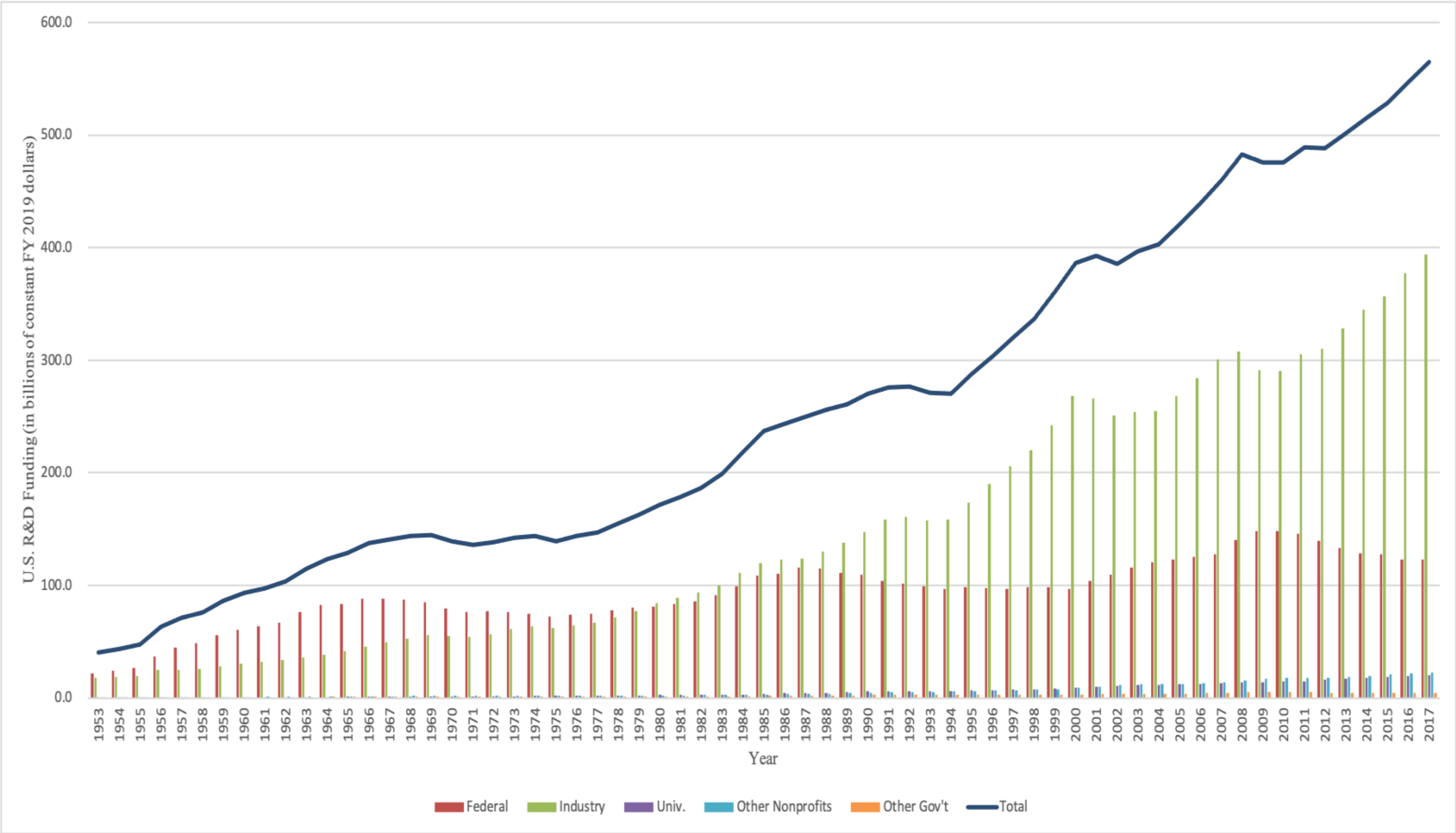
policy image of a nation leading the world in science and engineering innovation, research, and development with the means to compete with other challenging states. This image has maintained a tradition of incremental changes (stasis) in governmental and educational policies. However, as seen throughout our history since World War II, when the policy image begins to break down out of perceived competitive fears, policy monopolies, iron triangles, and issue networks force decision-makers to accept large-scale policy changes (or punctuations) from the subsystems within the larger governmental or educational network.

Figure 6 illustrates this cyclical change of state over the last 70 years based on the annual U.S. research and development (R&D) spending – a proven indicator of exogenous and endogenous factors in policy dynamics over long time periods (Baumgartner et al., 2017, pp. 72-74). Applied generally to the science and engineering fields, Figure 6 demonstrates agreeable yet revealing trends to stochastic cost study research modeling PET (pp. 75-78). Both small perturbations over long stretches of time and sharp punctuated crises have led to instabilities and significant changes. *Punctuations* represent these momentous changes to policy (through sigmoid-like functions, or S-curves), due to the breaking of a *policy monopoly*. This change is also characteristic of an unevenness of policy decision making with changing socio-political conditions where "the intersection of the parallel-processing capabilities of the policy subsystem and the serial-processing needs of the macro-political system creates the nonincremental dynamics of lurching" (Baumgartner, Jones, & Mortensen, 2018, p. 59). Times of *stasis* are subsequently indicated by time intervals where the policy does not represent a marked change. Identifying locations in time where public policy images are destabilized, called *policy windows*, characterize opportunities for in-depth analysis as to the nature of the destabilization. Figure 6 also reveals a philosophical shift in R&D funding from large governmental programs to industry-enhancing benefits, promoting innovation in the emerging fields of computer technology and integrated networks through industry enhancing policies starting in the early 1980s. Although beginning after the break-up of Germany following World War II, national pushes for large numbers of scientists and engineers, alongside the funding increases to implement these changes, have followed noteworthy events throughout our history. Whether the events of Sputnik 1 and 2 in the 1950s, the Apollo missions that jumpstarted the National Aeronautics and Space Administration (NASA) in the 1960s, the decades of Cold War between the 1950s and 1980s, and more recent innovations in information technology, biotechnology, and automation through the Internet of Things (IoT) between the 1990s up to today, the policy decisions advocating for more scientists and engineers were aimed at either countering the successes of our international rivals or assuaging the fears of the American public (Teitelbaum, 2014).

The most significant PET event of the modern era related to science and engineering policy was undoubtably the launch of Sputnik 1 and 2, occurring within a month of each other and meeting excessively complicated mission parameters. The events of Sputnik, more importantly, sparked considerable fear amongst the public and congressional leaders who vowed prompt action. George Reedy, one of Lyndon Johnson's staff members famously noted, "the simple fact is that we can no longer consider the Russians to be behind us in technology. It took them four years to catch up to our atomic bomb and nine months to catch up to our hydrogen bomb" (Launius, 2009, p.97)[3]. As a response to a series of failures culminating in Sputnik, in September 1958, Congress passed the National Defense Education Act (NDEA). The law placed an increased emphasis on STEM and modern foreign languages to bolster the science and technology disciplines to compete globally against the Soviet Union. To manage their robust plans for a strategic national movement,

[3] Based on the United States' "Fat man" design as a result of an intelligence breech (Haynes, 2012).

Figure 6. *Applied to U.S. R&D Spending from 1953-2017*



Congress gave power to the National Science Foundation to conduct research, direct programs, manage the distribution of federal grant monies, and aid with teaching, learning, and secondary and post-secondary program improvement (Mazuzan, 1994). A short- and long-term outlook for the NDEA was to increase the number of STEM graduates. Although concerns were emerging even before the NDEA was enacted that the USSR was graduating more engineers than the U.S. (70,000 to an estimated 30,000, or a ratio of just over 2:1) some disregard the idea that the NDEA was the primary policy responsible for the development and recruitment of engineers for the growing, and ultimately successful, U.S. space industry (Gunther, 1958; Teitelbaum, 2014). Nonetheless, efforts focused on identifying human capital shortages in engineering, while seeking policy solutions to resolve these identified gaps, would persist throughout the period of stasis into the 1960s and 70s.

Both preceding and following the Sputnik PET events of the 1950s were crises leading to policy windows that opened the opportunity for change (Teitelbaum, 2014). Figure 7 shows the cyclical nature of policy fluctuations that have led to punctuation and stasis over the last 70 years, and more recently to the evolution of "STEM". Four significant punctuation events are shown as "lurching" in the normalized trend in Figure 7 that exemplify the PET model. For example, following the changing public policy image of the U.S. as a world leader in S&E in the aftermath of Sputnik 1 and 2 launches, Congress quickly approved the development of NASA and the NDEA. As the public image continued to erode with another failure – the race to the first human in space, President Robert F. Kennedy's 1961 "We choose to go to the moon..." speech offered direct policy leadership in affecting the future direction of S&E in the U.S. The era of governmental funding on S&E programs peaked during this time, seeing a NASA budget increase by over 500% ($5.933M or 4.41% of total U.S. spending; USAFacts, 2019). Two decades later in the 1980s, economic concerns belied public confidence in U.S. S&E innovation with the rise of the Japanese manufacturing industry and lack of belief in the quality of programs training the next generation of scientists and engineers. As a result, in 1980 the U.S. Department of Education was developed to provide equal access to education, seeing a national need. One year later, the National Commission on Excellence in Education (NCEE), envisioned and led by Terrence Bell, examined the overall quality of education considering a “widespread public perception that something is seriously remiss in our educational system”, commissioning a review of the state of U.S. education. Out of the NCEE’s investigation emerged a historicizing report, *A Nation at Risk* (1983), which sought to "affirm” a “rising tide of mediocrity” in U.S. schools “that threatens our very future as a nation” (NCEE, 1983). Alongside these punctuations in education were the National Cooperative Research Act (1984) which aimed to promote R&D, innovation, trade, and amend historic antitrust laws. The 1980s were also witness to a rise in emergent technology fields and personal computing (e.g., Microsoft Windows) as well as their introduction into education – seeing personal computers introduced in schools in 1986. The policy changes in funding streams from government program-centered to the innovation-inspired infusion of dollars into emergent technology fields, are illustrated in Figure 7 as “cusps” in the years of stasis. In each case and occurring with periodicity in successive decades, were a supporting economic model and push for fulfilling a scientific or engineering workforce gap. From the 1940s Cold War drives for physics Ph.D. graduates, the War on Cancer of the 1970s (and resulting National Cancer Act which sought molecular biologists), to the high-tech industry boom of the 1990s and demand for information technology (IT) workers (e.g., computer engineers and programmers), to the web developments of the 2000s, Punctuated Equilibrium Theory centers these historical events within their defining policy perspective.

In each decade, talks of "gaps" have also transcended the policy debate while supporting punctuated change. The gap argument has been used since WWII to instill a sense of shock when comparing the U.S. to other industrialized nations. These gap arguments are almost exclusively system-level and rarely connected to the individual as a point of resonance, reflection, identity, or solution. For example, science and engineering fields, following the events of WWII, saw their emerging disciplines elevated from the milieu of the classic disciplines, to become a source of national and economic importance. A shifting focus on the quality and quantity of the individuals pursuing S&E degrees, as compared to competing nations, served as both a point of pride and recognition of U.S. hegemonic status. Many economic models accompanying these macro analyses, compare PISA and TIMSS scores[4] to validate global S&E standing or to stoke policy changes, typically accompanied by a gap analysis. The educational models and outcomes used to describe current and to project future gaps acknowledge S&E disciplines "in the tradition" through a hierarchical alignment (e.g., the physical sciences then the natural sciences). This hierarchy (which can be traced back to the historical events following WWII and policy pushes for well-trained Ph.D. students throughout the Cold War era) places a historic emphasis on educational and economic needs within the disciplines at the top of the hierarchy. Nevertheless, the S&E disciplines became established over forty-five years through national, economic, and policy adaptations until the evolution of a new acronym, STEM, was penned into policy by the National Science Foundation in the late 1990s – a response to the emergence of information and technology sectors from the prior decade.

[4] This existence of a gap has persisted; however, it has not appeared to widen. In 2019, TIMSS and PIRLS data show the United States trailing Chinese Taipei and the Russian Federation in 8th – grade mathematics and science scores (Mullis et al., 2020).

The Rise of STEM

What is commonly believed to have generated a fervent proliferation of STEM and cemented the acronyms status in education and policy is the convergence of three seminal reports released in 2005 – comprised of unique coalitions of non-profit organizations and corporate, academic, and educational leaders (Breiner et al., 2012; Koehler et al., 2012; Lantz, 2009; Teitelbaum, 2014). Each report had a similar goal, to bring to light the shared belief that the United States was failing to produce a quality science and engineering workforce, that the U.S. was quickly being surpassed by rising foreign nations, and to provide policy recommendations for addressing these forecasted challenges. As a basis for their calculations, the authors employed generalized economic models based around interpretations of the STEM occupations, showing a crisis on the horizon.

The first and most influential report in 2005 was developed out of an ad hoc committee from the National Research Council (NRC), *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future* (2005). Leaning on Thomas Friedman's (2005) controversial text, *The World Is Flat: A Brief History of the Twenty-First Century*, the NRC report simmers on what Friedman calls the "creeping crisis", that the lack of preparation of the United States in this "flattening" global economy[5] will reduce its ability to compete on the international stage. However, this perspective has been largely criticized for developing a portrait of globalization that opens the door for the use of cheap labor as a multinational corporate strategy (Ikenberry, 2005). Nonetheless, the charge of the committee was to develop a top-ten list of actions that "federal policymakers could take to enhance the science and technology enterprise so that the

[5] Friedman (2005) defines "flattening" as the re-setting of the economic playing field putting competing nations on pace with the United States. He postulates that the convergence of personal computing and data transmission speeds with the efficiency multiplier in workflow software level, or "flatten", the global marketplace.

United States can successfully compete, prosper, and be secure in the global community of the 21st century" (National Academy of Sciences, 2005). Two challenges were deemed tightly coupled to future scientific and engineering successes: (1) "creating high quality jobs for Americans" and (2) "responding to the nation's need for clean, affordable, and reliable energy" (National Academy of Science, 2005). Therefore, each of the suggested actions included an ambitious training and development push to increase the talent pool (supply-side pipeline model) through improvements to K-12 education, increase funding for research positions to promote innovation, and attract local and foreign talent.

Tapping America's Potential: The Education for Innovation Initiative (2005), primarily made up of business coalitions including the Business Roundtable, Business-Higher Education Forum, and Council on Competitiveness, viewed similar "warning signs" in STEM labor market indicators as compared to past measures and with foreign governments (e.g., number of degrees in engineering, investment in research, and STEM pursuit). With a focus on education as a national priority, this report was unique in that it acknowledged the importance of promoting NSF programs and other efforts to guide underrepresented groups into STEM fields. In addition, the report sought to promote more pragmatic means of delivering high-impact courses for students with an interest in STEM as well as increasing funding for research efforts to boost innovation throughout the national research laboratories.

The final report was entitled *Innovate America* (2005), a product of the Council on Competitiveness, a nineteen-member committee comprised of Chief Executive Officers (CEOs) and university presidents. Although the scope of the project was extensively broad, the section on "talent" provided similar recommendations and models as the previously mentioned reports. The focus was a call for more federal funding for graduate fellowships, an expansion of science master's programs, and measures to attract international science and engineering students.

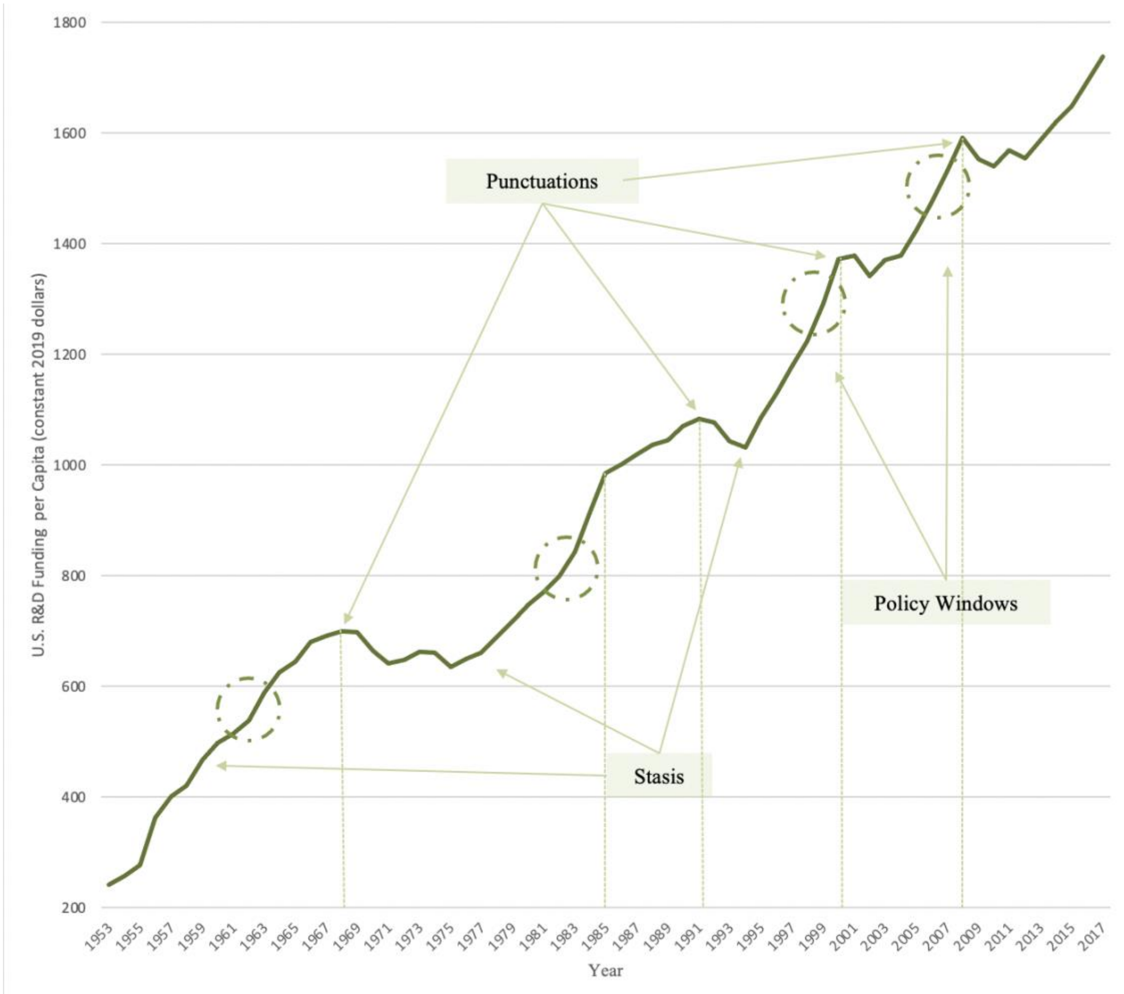
In each of these three historicizing reports, STEM is not explicitly defined but is referred in-context to the job sectors that support Science, Technology, Engineering, and Mathematics. As a result, most of the economic models used within these studies have generated substantial criticism over the years as to the extent to which the predictions for, and concerns surrounding, their validity are correct. In Lowell and Salzman (2007), *Into the Eye of the Storm*, the authors provide contrary evidence to the economic data presented in *Rising Above the Gathering Storm* (2005). "S&E occupations make up only about one-twentieth of all workers, and each year there are more than three times as many S&E four-year college graduates as S&E job openings" (Lowell & Salzman, 2007). A more recent comparative look by the National Science Board's *Science and Engineering Indicators* (2020) also supports these findings. Additionally, Xie and Killewald (2012) address similar concerns in *Is American Science in Decline?* Although their conclusions differ from Lowell and Salzman (2007), they point to one of the initial signs of a STEM operationalization problem in the economic and educational models presented. Xie and Killewald (2012) could not produce any evidence from their research indicating shortages of scientists and engineers entering the STEM pipeline. In fact, they discovered a ratio of degrees awarded in science and engineering compared to those employed in science and engineering occupations of approximately 2:1 (Xie & Killewald, 2012) – prompting questions from the larger research community if there is "a STEM crisis or surplus"? The discrepancies in the findings of Lowell and Salzman (2007) with Xie and Killewald (2012) was in the decision of Xie et al. (2012) to exclude all social sciences from their definition of "science and engineering".

In 2007 with the passage of the America COMPETES act, a response to the 2005 reporting of the “STEM crisis”, a call for promoting “promising practices in STEM teaching” redressed the traditional K-12 teaching pedagogies through an integrated curriculum. Although STEM may have been believed to contain a straightforward arrangement of disciplines, as the grouping caught fire in policy debates, it lacked the stabilizing groundwork in an operationalized definition. As a result, many definitional forms emerged and led to the gradation of STEM.

Gradations of STEM

Since STEM evolved from national-educational policy, a cyclical pattern of S&E PET events leading to federal policies since WWII, and has lacked an operationalized definition, the onus relied on organizations across PK-16 and the workforce (e.g., Department of Labor, Bureau of Labor Statistics, Department of Homeland Security, NSF, NCES, and ACT) to develop their own. As a result, multiple definitions and taxonomies were developed as others evolved, such as “STEM education” at the elementary and lower-secondary educational levels as an interdiscipline. At the workforce level, the Standard Occupational Classification (SOC) system, a 6-level taxonomy for breaking down all work for pay or profit, became the leading classification system. Managed by the Bureau of Labor Statistics (BLS), the SOC has been in existence since 1977 and is organized around similar skill sets or “worked performed”. Established by the Office Management and Budget, the BLS SOC STEM definition consists of two major domains (1) science, engineering, mathematics, and information technology domain and (2) the science and engineering-related domain (Bureau of Labor Statistics, 2018). Both contain two related subdomains, for example (1) life and physical science, engineering, mathematics, and information technology occupations and (2) social science occupations are subdomains of the first STEM

Figure 7. *PET Model to U.S. R&D per Capita Spending (1953-2017)*



Note. The PET model is adopted from Baumgartner et al. (2018).

domain (Bureau of Labor Statistics, 2018). Since the domains are broken up by skill, and skills may crossover between subdomains at both levels, OMB suggests data users and researchers decide “whether and how to split employment in this occupation between subdomains” (Bureau of Labor Statistics, 2018). This approach, however, is fundamentally flawed. For STEM, which already suffers from a non-operationalization problem, allowing users to choose definitions contributes to widening gaps in our understanding and implementation of STEM pursuit.

Built on the BLS SOC in 1998 as a foundational framework, The Department of Labor’s Occupational Network (O*NET) formed a database “vital in helping people find the training and jobs they need, and employers the skilled workers necessary to be competitive in the marketplace” (Department of Labor, 2020). Through services such as O*NET online, My Next Move, and other public and privately established applications to the dataset, O*NET services millions of individuals each year (Department of Labor, 2020). Through this dataset, a task-centric collection of over 300 jobs that require “STEM” skills have been established through the O*NET hierarchy. These jobs take on a wide range of offerings including (1) managerial, (2) postsecondary teaching, (3) research, development, design, and practitioners, (4) sales, and (5) technologists and technicians. Although these subdomains differ from the BLS SOC they may be categorized into similar domains.

At the postsecondary level, CIP codes were developed separately for the Department of Education to track majors and educational programs, and recently have been linked through crosswalks to BLS occupations as major-to-career progressions of STEM pursuit. The breakdowns of science, engineering, and mathematics in each of these systems remain in the standard tradition, however, interpretations of technology (such as computer programming, technician, and architect) and the adoption of ancillary classifications which re-define STEM take liberties in including “associated careers,” viewed by many as outside the tradition (i.e., medical and health professions, social sciences, and management). Furthering this point, the National Science Foundation is viewed to have included the social sciences in their definition of STEM but has left the medical and health professions from the definitional space. As highlighted in the prior research on STEM supply-side dynamics (Lowell & Salzman, 2007; Tanenbaum, 2003; Xie & Killewald, 2012), this decision has a significant impact on the description of the STEM workforce. The inclusion of the social sciences has the direct effect of increasing the labor market of STEM but has not shown to predict market trends more adequately, lead to gap reducing policies, or capture the pursuit of all students into STEM fields.

Over the last decade researchers at RAND Corporation (Anderson et al., 2018), the Census Bureau, and those working independently have developed classification models based on alternatives to the skill-based methods of the traditional taxonomies from the BLS. These recent taxonomies include more holistic approaches that have led to the development, and inclusion, of non-traditional STEM disciplines including those in the health and medical professions, social sciences, technical trades, and emerging industries (e.g., cybersecurity).

Educational and governmental organizations have also struggled to reconcile interagency meta-analysis and compare overall workforce data. As a result, several organizational bodies have developed modern definitions for STEM occupations and majors as well as crosswalks for comparing codes between the systems. These crosswalks, however, are limited to the postsecondary-workforce level and have furthered stratifications amongst secondary and elementary levels while processing policies and research traditionally handed-down during implementation.

Some researchers have attempted to re-define STEM through unique methods and adaptations to accepted classifications (Rothwell, 2013), but these results have shown either a lack of unity, clarity, or robustness to become accepted by the larger educational communities. Lacking an operationalized definition of STEM has, therefore, resulted in a pick-and-choose approach to examining the nature of STEM pursuit. A consistent definitional pattern of the "traditional STEM" disciplines is observed, broadly including the sciences (physical and life), mathematics, and engineering. However, at the margins (i.e., STEM management, medical, social science, and some technician occupations), the selection criteria fall uniquely upon one of two perspectives undertaken: a taxonomy that is either (1) clearly situated within the discipline and at the level of analysis or (2) "endorsed and validated" by independent researchers. These resulting overall gradations of STEM have allowed for its stratification across longitudinal levels of education producing a two-fold effect on pursuit by: (1) segmenting the layers of education and (2) constraining career pathways to pursuit (e.g., the discontinuities in engineering between secondary and postsecondary schools form misalignments between student outlooks and their understandings about engineering careers), therefore rendering current one-dimensional economic models of STEM inaccurate and impractical at the individual level.

The aerospace industry provides a striking example of the vast sub domains of STEM careers contained within the sector and a corollary to why near- and long-term perspectives can support all students' pursuit of STEM careers. Although Southern California, regionally, has the greatest density of aerospace engineers (those with a minimum of a bachelor's degree; Cooper et al., 2016, pp. 14-18), the manufacturing and aircraft industry has large population pockets throughout the United States. The range of educational achievement required for jobs within the sector stretch from a high school degree through a Ph.D., though both are rare. Most STEM careers within aerospace revolve around aerospace products (i.e., aircraft, spacecraft, satellites, rockets, and military hardware/software), providing a range of job opportunities to support the research and development, design, fabrication, sustainment, and planned obsolescence of these products. Whereas an aerospace engineer has either a bachelor's or master's in their respective specialty area, aerospace technologists support sustainment and maintenance efforts and have bachelor's degrees. Aerospace technicians, by contrast, perform the actual technical work and are highly trained though without a bachelor's degree, usually an associate degree but at a minimum a high school diploma and extensive on the job training. Even with just a high school diploma and some in-demand certifications (such as computer-aided design) a newly graduating high school senior or 2-year skilled postsecondary program graduate can enter the aerospace workforce and contribute in a meaningful way.

Not all jobs within the industry, however, center around a technical design-development mission but are critical for their operations. For example, the commercial aircraft industry employs aircraft cabin cleaners to tidy cabins and lavatories for new outbound public travelers. Cargo technicians also haul, stack, and arrange luggage for commercial passengers. Both positions are STEM-related and could be associated with STEM careers. However, from a skill-oriented perspective, these careers do not meet the criteria for a "STEM occupation" compared to the skills required to perform other STEM-specific jobs. Viewing the STEM taxonomies in Figures 4 and 5 in combination with student outlooks provide a multiple streams approach to developing and understanding pathways to STEM careers in the context of what defines a STEM occupation. This methodology diverges from the traditional STEM pipeline perspectives for developing models of pursuit.

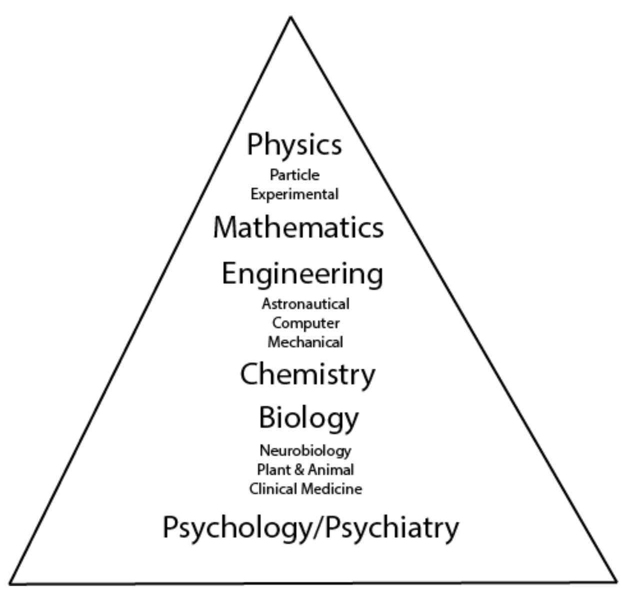
The STEM Pipeline

Following the events of World War II (1945), a time of reconstruction of our American society, parallel efforts were underway by social efficiency advocates and political leaders to establish a core curriculum which was heavily skills-based (i.e., helping students develop skills essential for fulfilling societal needs). This movement came to be known as “life adjustment” education and witnessed strong motivations from vocational educators through efforts within the Prosser resolution, a campaign which garnered significant support from the US Office of Education (Kliebard, 2004). The movement was short-lived, however, collapsing under significant public fear and political pressure in 1958 when the United Soviet Socialist Republic (USSR) launched Sputnik I.

In response to the launch of Sputnik, the 85th Congress pushed forward the National Defense Education Act which garnered federal funding to improve secondary and post-secondary schools under the national security needs encultured by the Space Race. The law more importantly placed an increased emphasis on Science, Technology, Engineering, and Mathematics (STEM) and modern foreign languages to bolster the science and technology disciplines to compete globally against the Soviet Union. To manage their robust plans for a nationally planned movement, Congress gave power to the National Science Foundation to conduct research, direct programs, manage the distribution of federal grant monies, and aids with teaching, learning, and secondary and post-secondary program improvement (Mazuzan, 1994). The increased federal role was viewed by the government as a necessary result but one which diverged from tradition (Hunt, 2019). In addition to the increased federal role, interdisciplinarity became a lost artifact in the modern-day curriculum. The disciplines were becoming stratified again and more prestige given to subject areas which were "highly desired" or met the perceived needs of the country to grow our global competitiveness.

The 1970s were recognized as a time of social, historical, and political reestablishment – one which also witnessed the NSF reach for positional power and find its limitations. Firmly entrenched into our "grammar of schooling", the disciplines as different and distinct areas of study, began to give way to hierarchical groupings such as liberal arts and the sciences. Soon after the acknowledgement of civics, geography, English, and reading became less trivialized with their funding through an amended National Defense Education Act (1964), they quickly fell in line with these hierarchical disciplinary structures. Figure 8 illustrates a similar trend within the STEM fields. The disciplines which are perceived as theoretical, more cognitively difficult, and objective approach the pinnacle of the pyramid versus those which are perceived as more clinical (or hands-on), less cognitively demanding, and less objective.

Figure 8. *Applied standard hierarchy to the STEM disciplines*



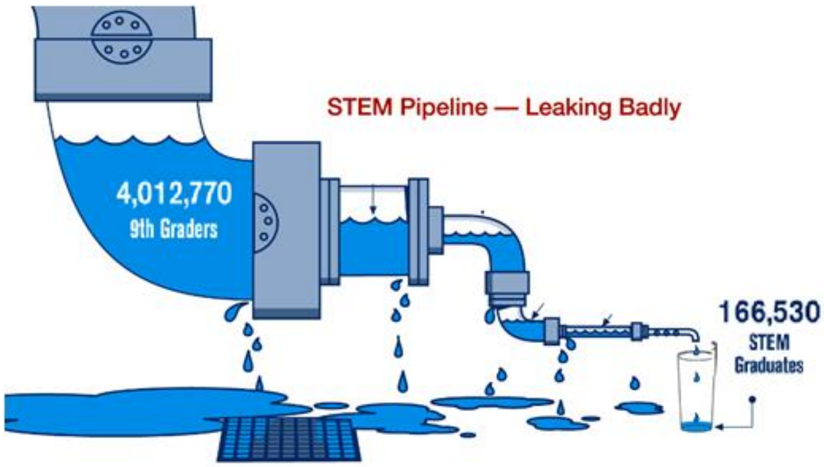
As a divergence from the objective nature within "the tradition" of these disciplines (Koppman, Leahey, & Cain, 2014), the NSF attempted to write curriculum centered around issues of humanity in the 1970s – it became a well-documented failure of power and tradition. "Man: A Course of Study" was a social science educational project for 5th grade students developed and implemented by the NSF and released to elementary schools within 47 states to national controversy. At the surface was an axiological debate over the distortion of family values. The underlying tension, however, was rooted in the both the divergence from an objective science curriculum and the national wrestling of control over the devolution of power to the states on the implementation of educational policy.

The earliest reference to the *STEM pipeline* as a metaphor in workforce predictive models was first introduced to the National Science Foundation in the 1980s (Lucena, 2000; 2005). As the economic recession of the 1970s lingered, long-term economic projections were sought amidst fears of a growing gap between the U.S. and foreign economic markets, particularly from Japanese exports. As a result, there was a stronger movement toward more governmental involvement in education. Differing from the proliferation of the national controlling features of the National Defense Education Act (1958), a new era situated in the evolving dominance of a global free market economy gained traction called *supply-side*[6], or "trickle-down", economics. The pipeline model, depicted in Figure 9, was developed by engineers at the National Research Council (NRC) as a systems-level model based on the movement of human capital (supply-side inputs and demand-pulling outputs) within the STEM fields. On the supply-side, students enter as 9th graders, graduating from secondary educational institutions, progressing through their post-secondary

[6] Supply-side economics is an economic theory during the Regan era which postulates that supply is the central determinant of economic growth and producers and their willingness to create products and services set the pace.

studies, and entering a career (National Research Council, 1986). Throughout the model, curriculum is individualized to specific discipline areas and scaffolded longitudinally throughout the entirety of the pipeline (9th-grade pre-requisites to post-graduate work). Under this model no points exist for entry outside of the supply year, however many points for "leakage" or movement out of the career path are availed by the model calculation.

Figure 9. *Supply-driven STEM pipeline model*



Note. Retained from NCES: Science and Engineering Indicators (2008)

The construct of a "leaky pipeline," or human capital losses prior to the pursuit of a STEM career, was first revealed by Bickenstaff (2005). Since this time, researchers have debated the size and type of these losses based on race, ethnicity, and gender (National Academy of Sciences et al., 2007; 2010; Teitelbaum, 2003; Xue & Larson, 2015). More recent debates by researchers such as Miller and Wai (2015) have concluded closure based on gender through their operationalized definition of STEM – which follows the National Science Foundation model, encompassing a broad set of fields such as those in the social sciences. As more data have become available through the National Boards, NSF, NRC, National Center for Educational Statistics (NCES), and other national longitudinal databases, traditional frameworks and perspectives have synthesized into new viewpoints. While today, the analogy of a STEM pipeline is well-employed in the lexicon of educational research surrounding scientific and engineering career pursuit, it is more of a reflection of the competitive consciences of the United States' – a stance fostering little risk with trained STEM workers across industries – than it is a reliable predictive logic or series of guide markers supporting STEM pursuit. Research supports movement away from these one-dimensional pipeline approaches. Secondary and postsecondary students who are not well informed about their career prospects or face additional skilled training requirements are at a great risk of not achieving their STEM career goals. Disaggregating the components of the STEM pipeline including entry conditions, linear progression, falling out, and completion allows for the restructuring of a model that may become more predictive for underrepresented groups of students.

The "Leaky" Workforce Path

Critiques surrounding the unsound predictions of the STEM pipeline model have been recorded beginning with NSFs initial pipeline studies throughout the mid-to-late 1980s. Lucena (2000) describes a specific flawed NSF claim from the pipeline model: In 1988 the Policy Research and Analysis Division published a pipeline study claiming for an assumed fixed percentage of students entering into the fields of science and engineering and without any efforts to increase the flow into these majors, an approximate 675,000 shortfall of graduates with degrees would result by 2006. As a poor conceptual model of a near 20-year trend, the prediction not only lacked research on the mediating relationships occurring both within and extant to the model (Lucena, 2000) but did not allow for the operationalization of science and engineering careers into an evolving STEM definition. Yet, since the development of the STEM pipeline, researchers routinely attempt to predict large shortages of individuals in the STEM workforce, particularly within underrepresented populations and along strategic points of the pursuit model. What has resulted are: (1) flawed measurements, a heavy research emphasis on the build-up of the supply-side feed of the model (Lucena, 2005; Teitelbaum, 2003), (2) one-dimensionality of career paths and career entry points, and (3) homogeneity of people and fields (Hammonds & Subramaniam, 2003). Although the latter critique is diminishing amongst the female population and specific racial and ethnic groups of students, it is due to a re-definition of STEM and finer (as opposed to coarser) gap analysis of STEM majors (Science and Engineering Indicators, 2020).

The “leaky path” model continues to analogize human capital flow into and out of a pre-defined educational path without regard for the multiple dimensions of inputs. This approach perpetuates problematic binary relationships, such as singular inputs and outputs of students through post-secondary institutions, negative connotations of STEM exit, the establishment of disciplinary hierarchies, and the resulting rejection of re-entry. Contemporary research has not only highlighted the flawed nature of these approaches but also the structural policies and measures of student success (Dixon-Román et al., 2013; Romero, 2016). It has also been attributed to a reductionist philosophical approach and to furthering of the divide between the applied disciplines. Pawley (2007) counters the reductionist approach, arguing for studying STEM in a newly formed aggregate. While each discipline has its own methods, histories, and axiology, they have similarities across generalized practices which when viewed together has shown to promote transfer across problems (Lindahl, et al., 2019). This aggregate coupling may help support the development of STEM definitions and pathways that consider many correlates for STEM pursuit.

Figure 10. *Timeline of Motivation and Retention Theoretical Models*

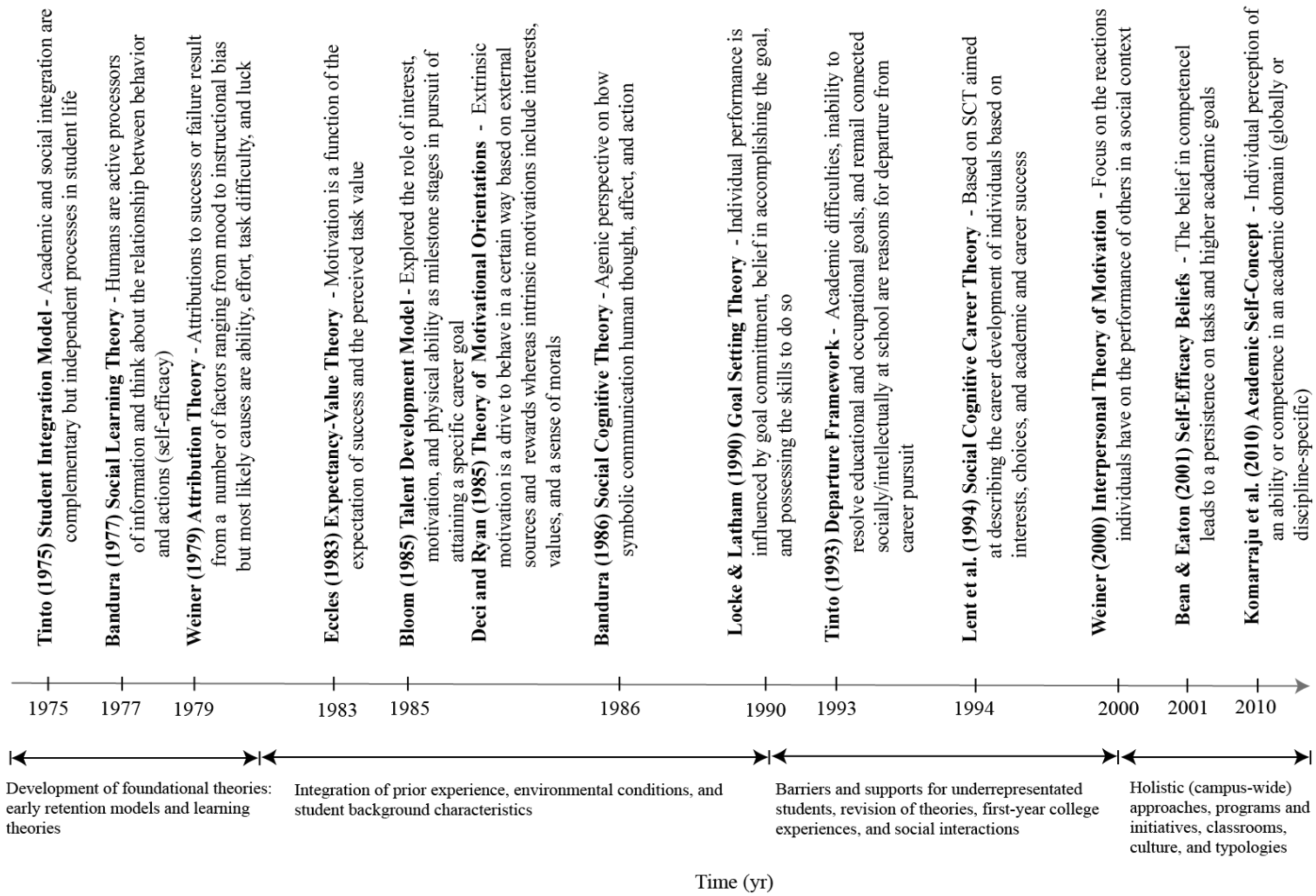
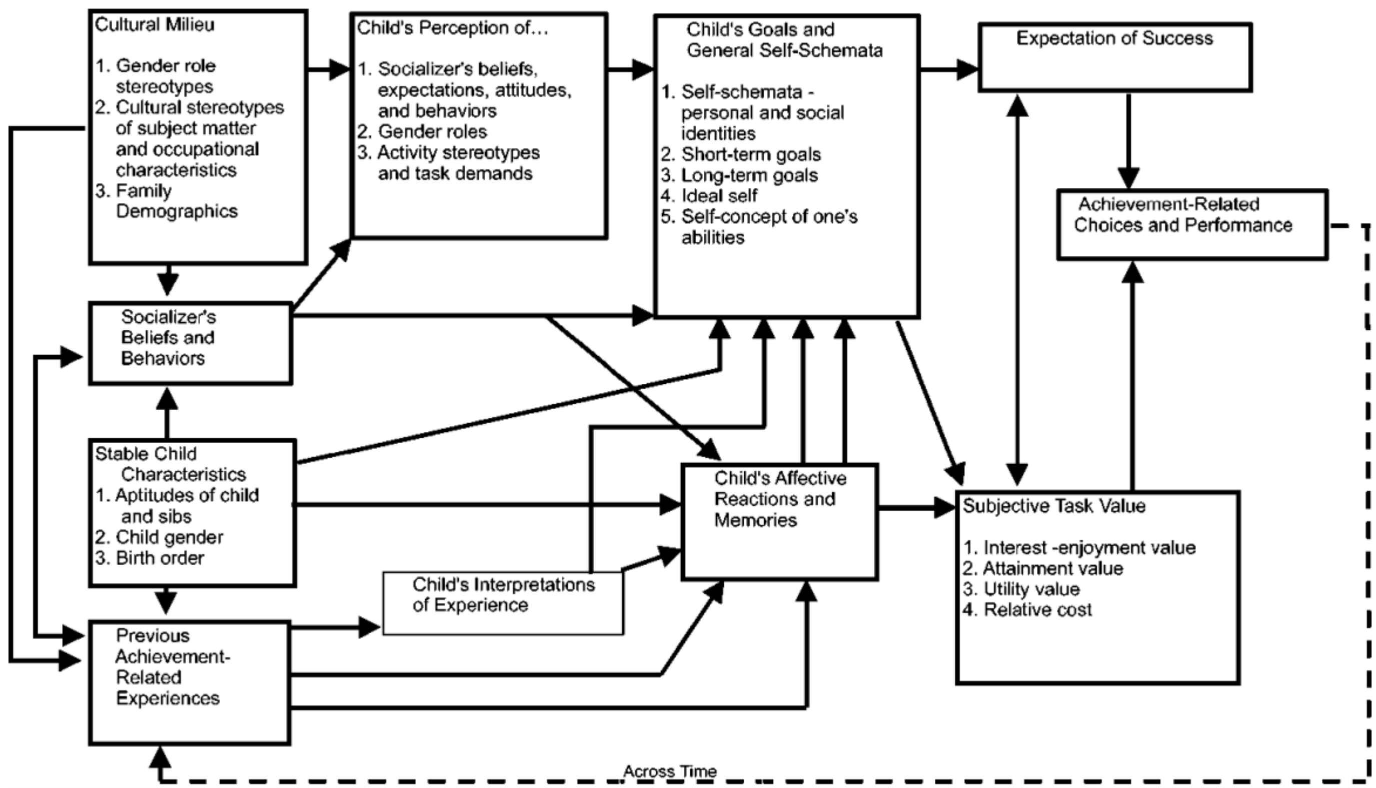


Figure 11. *Eccles et al. (2002) EVM of Achievement, Performance, and Choice*



Theoretical Framework

Models for Pursuit

Instead of relying on high-level system models of human capital input-outputs for understanding the factors that affect the attainment outcomes in students pursuing STEM careers, theoretical models have recently focused on constructs rather than on numbers to adjust to internal and external motivations, persistence, and diversity of students. Two main frameworks have emerged (see Figure 10) to explain the educational attainment outcomes of STEM students: Expectancy-Value Theory (EVT) and Social Cognitive Career Theory (SCCT).

Expectancy-Value Theory describes how achievement-related choices, such as a career and college major, are motivated by expectations of success and subjective task value (Eccles et al., 1983; Wigfield, 1994). For example, if an individual performs well in an activity and values the activity, they are more likely to pursue it. Figure 11 illustrates the two major constructs within the expectancy-value model: (1) achievement behaviors (e.g., performance and choice) and (2) belief and value (Wigfield, 1994). Subscribing to motivational explanatory variables around subjective task values (i.e., interest, utility, attainment value, and cost), expectancies for success, achievement goals, and beliefs about competence, the EVT model is the grounding perspective in many contemporary national longitudinal data sets (HSLS:09; Ingles et al., 2011). *Social Cognitive Career Theory* is derived principally on the perspective that people are actively shaped by and shape their environment (Lent, Brown, & Hackett, 2002). SCCT follows the triadic-reciprocal model of causality, proposed in Bandura (1986) and illustrated in Figure 12, which details how individuals are both "products and producers of their environment" (Wood & Bandura, 1989) with an ability for self-regulation – the guiding of ones' thoughts, behaviors, and feelings to reach personal goals. Within the SCCT framework, three central variables from social cognitive theory are incorporated as building blocks of career development: (1) self-efficacy, (2) outcome expectations, and (3) personal goals, key mechanisms for exercising personal agency (Lent, et al., 2002). Figure 13 represents the SCCT choice model tracing learning and individual experiences toward interests in STEM and onto an intent to pursue a STEM major, the selection of a STEM major, and entry into a STEM career (Lent, et al., 1994; 2002). Three career-related models are incorporated into the SCCT framework which subsumes a perspective of "conceptually and developmentally related processes of vocational interests, choice, and performance" (Lent, et al., 2002). SCCT also acknowledges the cyclical nature between self-efficacy and interests and bidirectional variable influences in each model over time. This perspective has opened opportunities for research on intrinsic and extrinsic barriers and supports to STEM pursuit amongst women and underrepresented racial-ethnic groups, and those living in poverty.

Figure 12. *Bi-directional Model of Triadic Reciprocal Causation (Bandura, 1986)*

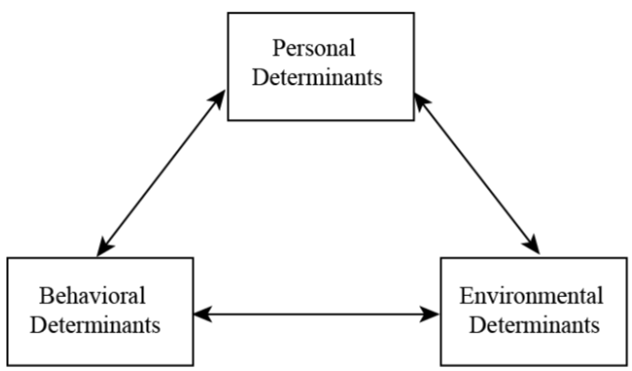


Table 2. *Summary of Contemporary Factors in Motivation and Retention Theories*

Factor	**Conceptual Overview**	**Theory**	**Source**
Self-efficacy[a]	Perceived ability to learn or perform at a specific level based on past accomplishments	SCT, SCCT, SDT	Bandura (1994)
Task-value	**Perceived importance**, usefulness, **enjoyment,** or benefit to the individual successfully completing a task (**felt- recognition**)	EVT, SCT, AT	Eccles & Wigfield (2002)
Attributions	Individual explanations for causes of behavior in relation to events	AT, RT	Weiner (1979)
Mindsets	An individually held set of **attitudes** about a specific task	GOT	Dweck (2000)
Environmental Influences	Informal learning exposure, **family social supports**, **parental education**, **classroom culture/environment** (**sense of belonging**), and **teacher academic qualifications** and **experience**	SCT, SCCT	
Academic Engagement	Combination of academic identification (interactions, interests, attitudes, behaviors) and participation (in-class and out-of-class work)	RT	Bean (1980)
Academic Preparation	Prior academic coursework (**aptitude [GPA, math grades]**, identity, **course sequencing**, and **participation in formal/informal learning**) will influence future success in academic work	RT, SCT, SCCT	Tinto (1993)
Cognitive Ability	Mental capability to plan, reason, comprehend ideas, and learn - especially through experience		
Social Engagement	Peers, **mentors**, and teacher/faculty-student connections are important connective social structures	RT	Tinto (1993)
Demographic Characteristics	Characteristics based on **race**, **ethnicity**, **gender**, **socio-economic status**, and **locale**	RT, SCT, SCCT, EVT	

Academic Interest	Wanting to know more about a specific topic, idea, or method (**science interest**, **early major declaration**)	EVT	Lent, Brown, & Hackett (1994)
Academic Efficacy	Belief that one can successfully achieve an intended goal at a designated level in an academic subject area (**math self-efficacy**)	EVT	Eccles & Wigfield (2002)
Academic Utility Value	Belief in how a specific task relates to future goals	EVT	Eccles & Wigfield (2002)
Attainment Value	Importance students' attach to a specific task as it relates to their conception of their identity and ideals or given domain	EVT	Eccles & Wigfield (2002)
Cost	Financial or personal cost of performing a specific task	EVT	Eccles & Wigfield (2002)
Motivational Orientations	Intrinsic and extrinsic motivations adjustment and perceived stress	SDT	Ryan & Deci (2000)
Identity	The distinguishing character or personality of an individual, however part of persons concept of self comes from the groups they belong (**parents' and students' future identity**, **gender-matching**)	SCT, SCCT, EVT	Tajfel & Turner (1979)
Academic Self-concept	Content-specific self-rating of skills, abilities, enjoyment, and interest (**math self-concept**, **science self-concept**)	SDT	Marsh & Shavelson (1985)

Note. Contemporary theories on motivation and retention include attribution theory (AT), retention theory (RT), Expectancy-Value Theory (EVT), social-cognitive theory (SCT), Social Cognitive Career Theory (SCCT), self-determination theory (SDT), and goal orientation theory (GOT).

[a] Bolded constructs are represented within the narrative literature selection as contemporary factors that have shown a positive effect on STEM pursuit (9-16W).

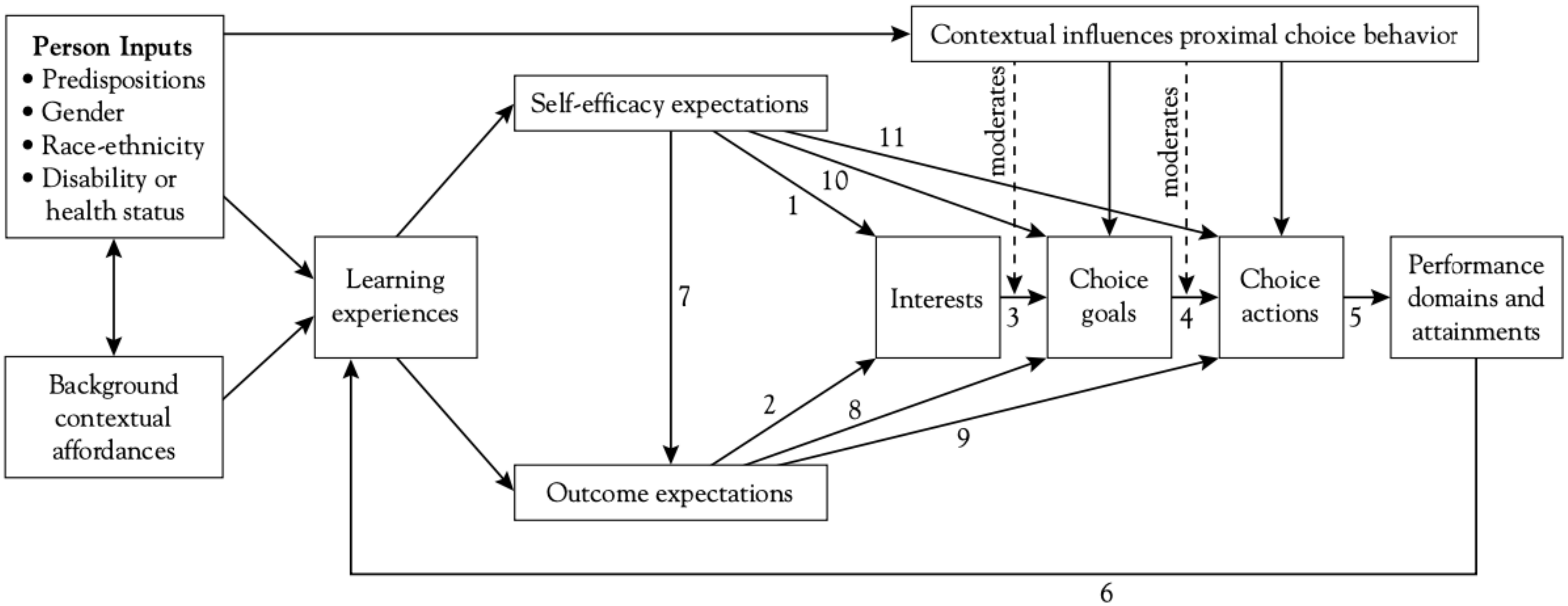
In addition to EVT and SCCT frameworks, motivational theories have also played a vital role in understanding why students participate in and pursue STEM careers (see Figure 11 and 13). Goal orientation and self-determination models have propelled ground-breaking research from Dweck (2000), describing how mindsets may not be fixed and can be taught or transformed, and Ryan & Deci (2000), on intrinsic and extrinsic factors on social development. Four reoccurring themes amongst the contemporary retention and motivation theories have emerged, crystalizing into the following key concepts: (1) competence beliefs, (2) value beliefs, (3) attribution, and (4) social-cognitive interactions (Cook & Artino, 2016, p. 1011). Table 2 provides an overview of these models in relation to other leading theories of motivation.

Dimensions and Constructs

Recent pursuit research studies on women and other underrepresented groups have begun to reveal the barriers to and factors influencing educational and career choices – acknowledging the influence of peers, families, teachers, and classrooms (Yang & Degol, 2013). Potential predictor variables for quantitative research have been theorized using Eccles' Expectancy-Value Theory as a framework broadly including: (1) intellectual aptitude and motivational beliefs (identity, self-efficacy, interest, and utility), (2) sociocultural factors (classroom setting, curricular differentiation, teaching foci), and (3) contextual influences (parental behaviors and peers), each providing a set of variable assemblages for the construction of robust quantitative models. Similarly, within the SCCT framework, studies have focused on the same dimensions but through the lens of barriers or supports and racial, ethnic, socioeconomic, and gendered considerations. Sequences of STEM courses (e.g., applied and advanced courses), the role of mathematics placement and instruction on interest and self-efficacy are some of the educational constructs explored. Parental influences and expectations, work-family planning, and perceived support were environmental factors researched in-depth. More generalized research on pursuit occurred between both frameworks including access to informal STEM programs (Lynch et al., 2018), career aspirations (Tai et al., 2006; Trusty, 2002), persistence, and attainment goals have reached for solutions to balancing the underrepresentation of women and minorities whose participation in these career fields is far below their employment participation (Funk et al., 2018).

Although progress has been made in certain STEM subfields (e.g., life sciences and mathematics), significant gaps still exist in engineering, computer science, and the physical sciences (The Pew Research Center, 2018). From a curricular lens, relevancy, informal learning opportunities, increased engagement, continuity, and self-efficacy are curricular attributes which have been associated with positive individual outcomes and increased entry into STEM careers (Lyon, et al., 2012). The inclusion of these attributes (particularly social influences) proposed through social cognitive theory (Bandura, 2001) and its derivative Social Cognitive Career Theory (Lent, Brown, & Hackett, 1993), encapsulate some of the longitudinal learning aspects across grades 9-20 and the workforce (9-20W). In response to the growing STEM gap, states such as California have begun exploring large-scale admissions changes to the California State University system based on research suggesting a correlation between fourth-year mathematics, or math-equivalent courses (i.e., statistics, computer science, career technical education, or personal finance), and an increase in STEM attainment outcomes (Asim, Kurlaender, & Reed, 2019). What the overall research has yet to completely consider are how career aspirations are formed longitudinally beginning around the early entry points for STEM training (Yang & Degol, 2013).

Figure 13. *SCCT Model of Person, Contextual, and Career-Related Choice)*



Note. Solid lines indicate direct relationship between variables while dashed lines indicate moderator effects (*Lent et al., 1994)*

Factors Affecting STEM Career Pursuit

Factors affecting STEM career pursuit highlighted in the research over the last 15 years has evolved from a one-dimensional focus on curricular effects to contextual factors based on race, ethnicity, gender, region, or socioeconomic status. This evolution has followed a progression from researching system-level changes to those at the individual student level, as more data continues to emerge about gap persistence in STEM pursuit amongst underrepresented groups of students. Applied course taking, course sequencing, and advanced coursework encompassed a significant percentage of the research energies over the last ten years. Gottfried (2015) discovered that students who had taken an applied STEM course early in high school had greater odds (37% higher) of taking an advanced course later in their secondary education. Two key findings: (1) student sociodemographic data and family (socioeconomic) covariates in either mathematics or science models and (2) critical school investments (i.e., prior math ability, self-efficacy, and college expectations) were noted by Gottfried (2015) for not attenuating these results. Moreover, enrolling in an information technology course within this early timeframe (9th or 10th grade) correlated to a higher probability (30% greater odds) of taking an advanced math or science course in grades 11 and 12 (Gottfried, 2015, p. 392). This range of course sequencing at the secondary level (from integrated to advanced courses for underrepresented students) is also highlighted in the research of Bozick et al. (2007; 2008) and to an extent by Sadler et al. (2012) in the early secondary years on developing interest in STEM.

The importance of secondary educational research on the pursuit of STEM careers is also documented throughout the last two decades (Gottfried, 2015; Warne et al., 2019; Wolniak, 2016). Wolniak (2016) provides in-depth research on the predictive factors of STEM major selection (i.e., demographics and high school academics) and the moderating influence of STEM dispositions, highlighting the need for more focus on first-year transitions and concentrating resources on those who do not fit traditional profiles of STEM students.

Discipline-based research on early interest in science, mathematics-related ability beliefs (Seo et al., 2019), math self-concept (Sax et al., 2015; Wang et al., 2017), and cognitive ability (Wang et al., 2017) were additional psychological constructs explored throughout the literature. Negative math self-concepts were discovered in female adolescents, whereas Black adolescents had a positive math self-concept when controlling for race/ethnicity, displaying “similar rates of STEM career attainment to White men” (Sax et al., 2015). As a result, model covariates (career expectancy, STEM achievement, and family background) are suggested to play a larger role in acting as barriers to STEM pursuit (Sax et al., 2015). Wang et al. (2017) investigated cognitive ability and task value (or interest) on student chances of STEM employment using the Longitudinal Study of American Youth (LSY:89) through the creation of three ability typologies characterized by math, science, and verbal abilities. Their findings suggested that youth with relatively low math and science abilities were more likely to be employed in a STEM career if they had greater math self-concept (Wang et al., 2017).

New research settings for social engagement, such as those occurring within undergraduate research experiences (Hernandez et al., 2018) and end of high school summer apprenticeships (Tai et al., 2017), revealed the mediating effects of mentorship on student pursuit of STEM majors and careers. Hernandez et al. (2018) investigated the intent of students interested in pursuing research careers in STEM, discovering these interests cycled through the declines and rebounds of the research work. Most revealing from their research was the strong mediating effect of *inspirational role-modeling* (i.e., having accomplished researchers talk about their careers and career paths with mentees) on the pursuit of STEM research careers. Similarly, Tai et al. (2017) corroborated prior research on the effects of "close mentorship and hands-on experiences with authentic scientific endeavors" as factors leading to increased student interest in pursuing STEM degrees through participation in a summer laboratory apprenticeship. The explanatory belief in these results is that an apprenticeship (or internship) builds a cognitive scheme for a future STEM career (Tai et al., 2017).

Environmental influences have also been well-researched within the literature. Parental motivation (Rozek et al., 2017), education (Svoboda et al., 2016), and family context (Rinn, 2013) were factors of STEM pursuit in the corresponding research. Rozek et al. (2017) evaluated the long-term effects of a theory-based intervention promoting math and science course taking amongst high school students – a motivational intervention – on their STEM career pursuit (interest, courses taken, and attitudes). As a follow-up to the positive findings from the same intervention on math and science course-taking in high school, Rozek et al. (2017) found that the intervention improved ACT mathematics and science test scores by 12 percentile points. Matching their findings onto a recursive process model, the results suggest that students' motivation is a key factor to enhance STEM competence and career pursuit (Rozek et al., 2017). Leveraging the impact of motivations on student career pursuit, Svoboda et al. (2016) determined that parental education, mediated by parents' and students' future identity and motivational beliefs of science and mathematics, predicted STEM course taking in secondary and post-secondary schools. The authors explain that although low-SES students are less likely to take STEM courses in high school (Tyson et al., 2007), a psychological perspective encompasses an important role due to the beliefs about the value of STEM and STEM-related future identities in parents and students. Intersectional factors, such as those described above, emerged most recently through the research with studies on gender-matching (Chen et al., 2020), sense of belonging (Rodriguez et al., 2020) and internal disciplinary biases in STEM classrooms, and felt recognition and classroom climate (Starr et al., 2020). Each of these factors describe intersectional influences on individual science and math classroom experiences. Amongst the studies, motivation, perception, identity, and demographics were key mediating constructs (Chen et al., 2020; Rodriguez et al., 2020; Starr et al. 2020).

Research over the last fifteen years on STEM education pursuit has focused on secondary, postsecondary, and careers with much of the research identifying early educational constructs that affect pursuit. These have been proven to be critical in understanding the supports and barriers to STEM pursuit milestones such as identifying early interest, choosing a STEM degree, graduating with a STEM degree, and entering a STEM career field. Therefore, much of the research over the last two decades has sought to resolve pursuit questions around choices of STEM courses, sequencing, pathways, and institutions (see Table 2 for a contextualized summary of this research).

The Emergence of Typological Models

Typologies have also emerged as models and methods for understanding underrepresented groups of students who may experience differences in the contextual factors describing their experiences of pursuit. Addressing these differences by investigating typologies, has shown the ability to support an understanding of students who were not adequately described by the high-level one-dimensional models depicted within the STEM pipeline. Moreover, contemporary research on interest (Su & Rounds, 2015) and ability (Yang & Barth, 2017) typologies has well-predicted student choices throughout their pursuit of a STEM career at level (e.g., secondary or postsecondary). Su and Rounds (2015) describe how interests in people-oriented versus product-producing careers have been shown to describe pathways for female students pursuing STEM careers (Su & Rounds, 2015). This research illustrates the potential explanatory ability for underrepresented populations of students using a typological methodology. It also provides the flexibility to align STEM pathways with orientations to ensure a more granulized approach to understanding the complexities surrounding pursuit.

The use of uniquely derived typologies has shown promise in recent pursuit studies (Yang & Barth, 2017) and serves as a guide for analyzing pursuit between student demographic subgroups, STEM orientations, motivations, and the STEM sub-disciplines. This central methodological shift alters the research approaches inherent within traditional STEM pipeline models – singularly placing every student within the same pipeline. Using typologies to understand the longitudinal progressions across high schools, colleges, and universities additionally provides adjustments for multiple entry points for STEM career pursuit not well-researched (e.g., military transitions, 2-year college pathways, and apprenticeships) and accounts for the intersectional relationships between demographics and predictive constructs of career attainment (see Table 2). With the lack of an operationalized definition of STEM and its application to research and institutional policy decisions, those that drive pathways and programs, a typographical approach could provide for nuanced investigations of the factors that support students' pursuit of STEM careers.

Chapter 3. Research Methodology

A quantitative methodological approach is undertaken herein to examine the extent to which motivational and persistence factors predict U.S. secondary and postsecondary students' occupational career choice and how their arrangement fit derived typologies of STEM pursuit. In the prior section, the factors supporting STEM pursuit were examined from the research over the last 15 years following the seminal reports of 2005 and are depicted in Table 2 and Table 6. The purpose of this proposal specifically seeks to outline an approach to answer the first three research questions below as current gaps in the STEM research literature:

1. What is STEM and how is it defined within education and the workforce?
2. What combination of influencing factors across student characteristic groupings contribute to an anticipated STEM career across secondary and postsecondary levels of education?
3. What influencing factors across student characteristic groupings act as supports for or barriers to expected STEM pursuit across secondary and postsecondary levels of education?

Utilizing the definitional pathway models through STEM instructional programs and toward STEM careers as a framework (see Figures 4 and 5), a set of multinomial logistic regressions are proposed for developing typologies that guide the pursuit of STEM careers for underrepresented students based on positive factors supporting STEM career aspirations. The generation of typological models as well as the factors encompassing their designs provide the basis for the final three research questions:

4. How can typological models predict the successful pursuit of underrepresented groups of students into STEM fields?

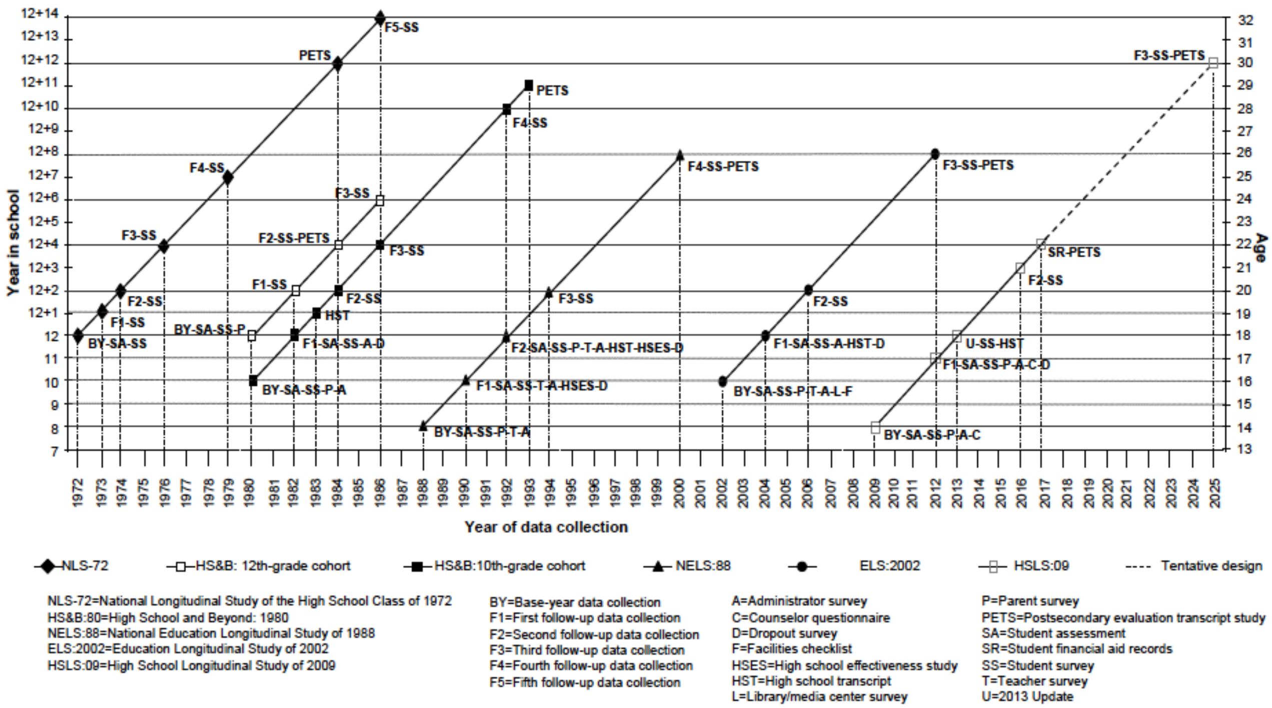
5. Is there a STEM taxonomy that encompasses inclusive typologies for underrepresented groups of students?
6. How do these typological model results compare to traditional pipeline approaches to STEM pursuit?

To capture student data that ranges across secondary and postsecondary contexts, a longitudinal panel was sought that would be representative of the research factors supporting the pursuit of STEM careers, demographically representative of students within the United States, and occurring within the research timeframe. Meeting each of these criteria, along with the specified delimiters, was the High School Longitudinal Study of 2009 (HSLS:09; Ingels et al., 2009). HSLS:09 was developed based on an approach consisting of waves of survey questions that aim to collect S&E educational construct data within an expectancy-value framework. The overall alignment of HSLS:09 to the proposed research purpose, goals, and potential outcomes supports its choice as a representative dataset for conducting STEM pursuit research.

The High School Longitudinal Study of 2009 (HSLS:09)

HSLS:09 is a nationally represented longitudinal study comprising over 23,000 9th-graders beginning in 2009 with a planned lifecycle of 16 years. Organized through the National Center for Educational Statistics (NCES), the study is situated as the most current data collection effort amongst the Secondary Longitudinal Studies (SLS) program (see Figure 14). The SLS program comprises five studies (four completed) including *HSLS:09*: The National Longitudinal Study of 1972 (NLS-72), the High School and Beyond Longitudinal Study of 1980 (HS&B:80), the National Education Longitudinal Study of 1988 (NELS:88), and the Education Longitudinal Study of 2002 (ELS:2002). A chronology of each study is illustrated in Figure 14, detailing the coordinated efforts to investigate the secondary and post-secondary experiences of students over the last fifty years (Ingels et al., 2018, pp. 2-4). The High School Longitudinal Study (HSLS:09), was designed to follow secondary

Figure 14*. Design for NCES Secondary Longitudinal Studies (1972-2025)*



Note. From the "High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation" by Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

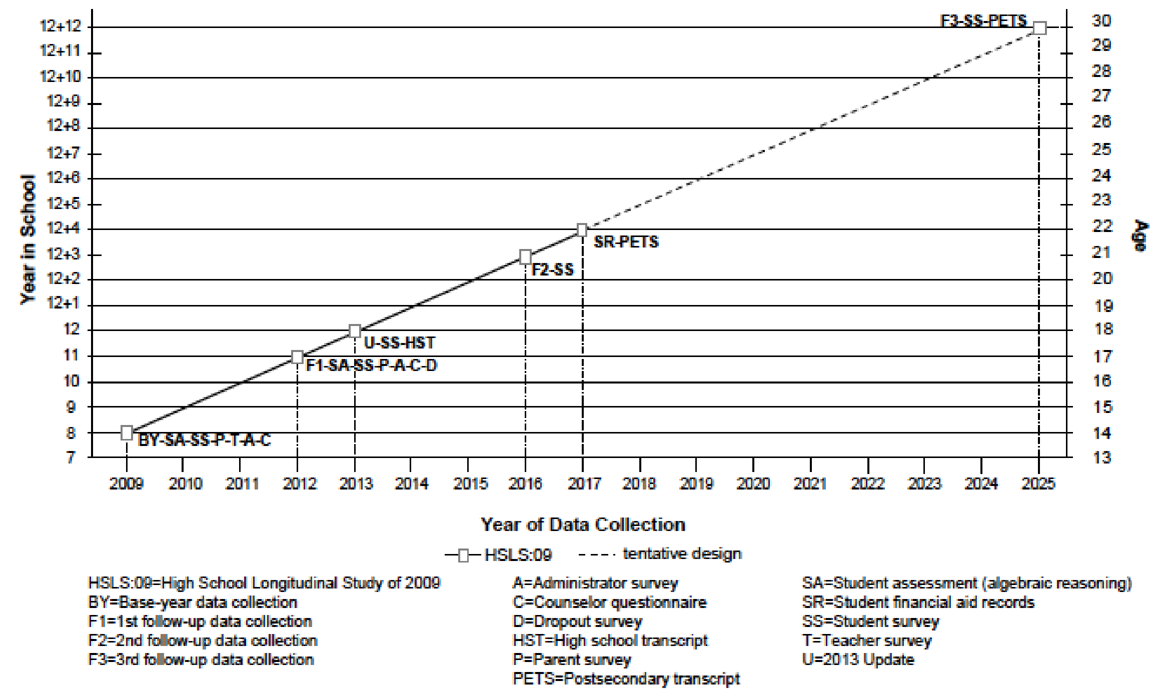
students from high school through their post-secondary education and entry into their respective career fields. Supporting longitudinal analysis for current policy objectives, HSLS:09 serves as a data source for investigating: (1) student retainment and STEM pursuit through multiple entry points, (2) the individual experiences of students (especially English language learners), (3) longitudinal pursuit models within STEM, and (4) the educational and social experiences of students including how these outcomes, decisions, and experiences affect their pursuit of STEM attainment goals

(Ingels et al., 2018, p. 5). The central focus, therefore, is on how students plan and make decisions about their current and future career goals. *HSLS:09* is inclusive of students, parents, math and science teachers, administrators, and counselors which allows for multi-level analysis across schools, classrooms, and households. Subsequently, educational goals and outcomes; psychometric; experiential and learning; contextual-environmental; and demographic influencing variables are available for analysis. What makes this study unique for assessing STEM pursuit is a unit of analysis focus on the same panel of students, without refreshment[7], throughout the duration of the data collection period.

HSLS has been used extensively to describe the educational experiences of underrepresented groups of students based on research employing this dataset since 2017. Of the 24 studies identified within the Inter-university Consortium for Political and Social Research (ICPSR) relating to student STEM pursuit - those including achievement outcomes (Howard, N. R., et al., 2019; Jackson et al., 2020; Jang, 2019; Kremer, 2020; Young et al., 2018; Yu & Singh, 2018), aspirations (Edwin et al., 2019; Gottlieb, 2018), barriers (Holzman et al., 2019; Saw et al., 2018; Shi, 2018), and factors (Alvarado, et al., 2018; James et al., 2019; Sanone, 2017; Young et al., 2017; Young et al., 2019) – 67% (n = 16) identified applied a primary or secondary focus on race, ethnicity, or gender. This intersectional focus is a significant attribute to HSLS:09 to which other panel data do not provide in-depth. With an additional concentration on science and engineering coursework at the student unit of analysis, most of the recent research using this dataset considers questions surrounding either the STEM disciplines generally (Alvarado & Muniz, 2018; Edwin et al., 2019; Gottlieb, 2018) or science (Anderson & Chen, 2016; Young et al., 2017) and mathematics (Howard, N.R. et al., 2019; Young et al., 2019; Yu & Singh, 2017) disciplines specifically.

[7] *Refreshment* refers to the cycling of new panel participants, used in prior SLS program studies.

Figure 15. *Longitudinal Design for HSLS:09*



Note. From the "High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation" by Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Due to the data collection methodology of HSLS, a complete look at student experiences from multiple perspectives is captured through student, parent, teacher, administration, and counselor surveys. This is particularly relevant to the research presented herein which considers the role educational leaders (such as counselors) maintain in providing career pathway advice to students seeking STEM careers, matching student job outlooks to careers, and aligning the coursework sequence to achieve those attainment goals (Engberg & Gilbert, 2014; Li et al., 2017; Mwangi et al., 2019). HSLS:09 also provides some depth within the overall instructional pedagogies offered throughout 9th-grade S&E classes in addition to student motivations (Liu et al., 2019) that is believed to be an early STEM entry point from prior research. Regression-type analysis, including multilevel and multinomial logistic regression, have also been employed successfully using this dataset (Engberg & Gilbert, 2014; Gottlieb, 2018; James et al., 2019; Kremer, 2020).

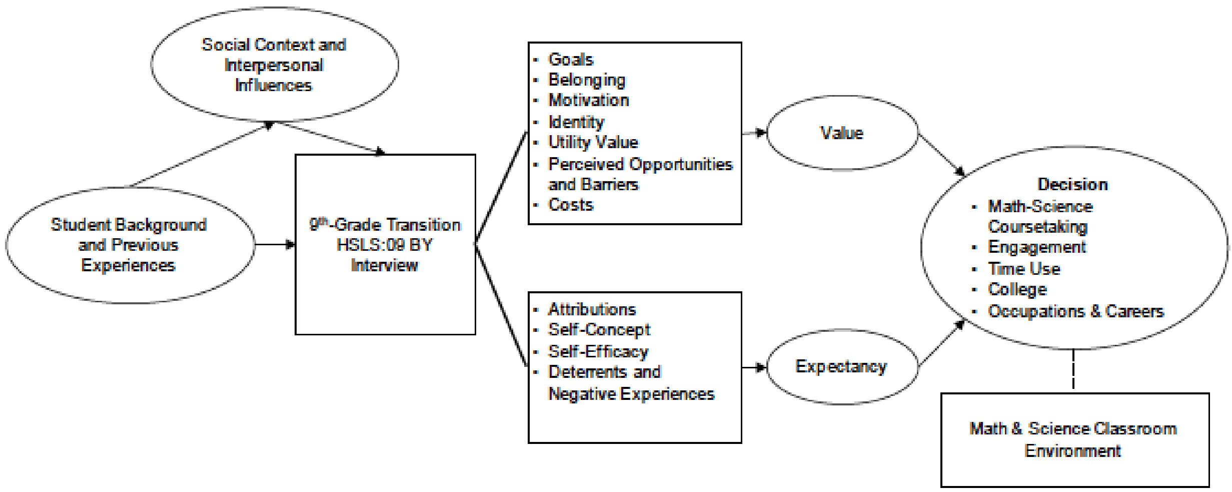
Survey Design

HSLS:09 utilizes a stratified, two-stage random sample design with schools and students as the primary sampling units (Ingels et al., 2018, p. 17). Figure 15 presents the *HSLS:09* longitudinal design beginning in 2009 with the base year data collection and extending through 2025, the third follow-up at age 30 (twelve years beyond secondary graduation date). A first and second follow-up report released in 2012 and 2016, respectfully, employed mixed survey methods which includes data from students, their parents, school administrators, counselors, and math and science teachers. Supplementary transcript data were collected in 2013 (secondary) and 2017 (post-secondary) in addition to student updates and financial aid records collection. The dataset is unique due to its comprehensive set of survey questions (students, teachers, parents, administrators, and counselors) surrounding many contextualized features of the students' educational experience in math and science.

The research agenda of the *HSLS:09* dataset employs an expectancy-value theoretical framework to guide questionnaire content and select data for inclusion. Figure 16 illustrates this conceptual approach, selecting the student as the unit of analysis to "identify factors that lead to academic goal setting and decision making" (Ingels et al., 2018, p. 9). Many influencing variables are provided within the model including science and mathematics interest, perceived opportunities, barriers, costs, motivation, and values and expectations of attainment goals. An end-of-year 8th grade mathematics assessment was also included in the design and administered on-site (at the participating schools), aligning to the vast amount of research supporting the inclusion of prior mathematics ability on STEM course taking, STEM major selection, and STEM career pursuit

(Bozick & Ingels, 2007; 2008; Gottfried, 2015; Lichtenberger et al., 2013; Sadler et al., 2012; Seo et al., 2019; Svoboda et al., 2016; Wang, 2013; Wolniak, 2016). Overall, student persistence and motivation for pursuing STEM careers are active areas for research within *HSLS:09*.

Figure 16. *HSLS:09 Base-year (9th Grade) Conceptual Map*



Note. From the "High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation" by Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Survey Instrument and Data Collection

The design structure of the study for data collection relies on a two-phase random sample. Phase 1 focuses on the identification of schools in all fifty states including the District of Columbia (Ingels et al., 2018, pp. 53-57). Of the 1,889 schools identified, 944 high schools agreed to participate, producing a weighting factor of 55.5%. Phase 2 moved onto selecting students within the individual schools. Seeking approximately 25 students per school, 25,206 total students were selected and participated in the school-based web survey and mathematics assessment (Ingels et al., 2018, pp. 53-60).

The second-year follow-up design consists of panel tracing and locating procedures of students and their parents using Lexus-Nexus social security numbers and telephone locators within the National Student Loan Data System (NSLDS). This advanced tracing method then produced and delivered a letter explaining the survey selection. Emails, postcards, and mailings were subsequently used for the follow-up and as reminders to complete the survey (see Figure 15 for a timeline of the data collection procedure). The surveys were multi-modal and could be accomplished either through a paper-pencil form, web-based data management system, telephonically, or through an in-person interview. Rerouting procedures were additionally utilized to reduce the length of in-person/web-based/telephonic interviews. Table 3 classifies the overall longitudinal data collection based on role, educational constructs assessed, and the data collection method for a holistic view of the alignment between the conceptual approach taken by the study designers and the range of pursuit factors collected.

Analytic Weights

The *HSLS:09* data follows a complex sampling design, which is coded to compensate for the oversampling of smaller subgroups of schools and students; a set of 200 sample weightings is used to adjust the standard errors for this type of sampling. This design ensures a representative sampling of local populations and maintains accuracy in hypothesis testing procedures undertaken by researchers. Following this approach, a Balanced Repeated Replication (BRR) method is suggested by the study designers and can be employed throughout the variable selection and overall model development in Stata 17.0, matching the survey design (Heeringa et al., 2017; Hosmer et al., 2013).

Herringa et al. (2016) provide a strategic method, through a BRR approach, for analyzing the data using the bias-adjusted weighting method (pp. 121-122). Balanced Repeated Replication of variance estimation is a method used within *HSLS:09* for evaluating sample variances under two

Table 3. ***HSLS:09 Educational Construct Assessed by Role***

Role	Educational Constructs Assessed	Data Collection (Year)[a]
Student	(1) STEM or school interest and goals; (2) identity formation, academic behavior; (3) attitudes and beliefs; (4) social and cultural experiences; (5) formal/informal STEM environment; (6) negative experiences	BY-SA-SS (2009), F1-SA-SS (2012), U-SS-HST (2013), F2-SS (2016), SR-PETS (2017), F3-SS-PETS (2025)
Parent	(1) Sources and quality of information; (2) expectations; (3) discussions about courses, postsecondary options, and careers; (4) school involvement	P (2009 and 2012)
Math/Science Teacher	(1) Personal preparation or experience; (2) depth of math and science at school; (3) perceptions of leadership and parental involvement; (4) attitudes toward work	T (2009)
Administrator	(1) Outreach and transition programs for 8th-graders; (2) course availability and planning; (3) planning for transition to postsecondary education	A (2009 and 2012)
Counselor	(1) Caseload; (2) duties; (3) pathway entry to college or postsecondary and careers; (4) course placement and advising; (5) student supports	C (2009 and 2012)

[a] Each code is defined at the bottom of Figure 14

primary stage unit[8] (PSU)-per-stratum designs. The original strata[9] in the sample were distilled into 199 BRR-specific strata accounting for differing school and student characteristics (i.e., type of school, region, and locale; Ingels et al., 2018, p. 126). Within this partial balance of BRR variance

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[8] *Primary Stage Units* (PSUs) represent the highest-level clusters, or groupings, of sample observations. "Two-per-stratum" allocation designs, such as HSLS:09, are the most common due to the minimum two PSUs per primary stage stratum requirement for estimating sampling variances (Heeringa et al., 2017).
[9] *Strata* are stratifications, or homogeneous groupings, of population elements formed *a priori* by the study designers. In the case of the *HSLS:09* dataset, these strata represent school and student samples.

estimates, two PSUs were subsequently formed to produce base weights from a 200 x 200 Hadamard matrix[10] analysis (p. 126). The solution to this Hadamard matrix produces precise values for the standard errors and is reported in Stata 17.0 using the "brr" option appended to the "mlogit" function for a MNLR. An initial setup, however, is required in identifying the weighting (see Tables 4-5 for weighting details) prior to running the statistical procedure.

Validation and Reliability

The High School Longitudinal Study utilizes the National Center for Educational Statistics (NCES) statistical standards for survey planning, design, data collection, and evaluation. NCES requires an evaluation which includes information about the quality and limitations of the data collected within the survey (for future surveys and survey replication) as well as a systematic assessment of the sources of error for key statistics resulting from the survey items. For *HSLS:09* this includes: (1) descriptive statistics on item response rates, (2) weights, (3) standard errors and design effects, (4) non-response bias item-level declined to answer analysis, and (5) single-value item imputation. Table 4 represents some descriptive statistics on base-weighted unit response rates for waves up to and including the second follow-up (Ingels et al., 2018, p. 93). Each wave has a set of weighting factors which are used to account for the population of survey non-respondents and calibration adjustments considering sampling frame coverage (using a balanced repeated replication method) for analysis performed by researchers utilizing the survey data. Table 5 highlights these weighting factors for the second follow-up.

Other forms of validity and reliability, including construct and internal consistency reliability, are provided for specific factors and measures. For instance, Ingels et al. (2018) report that the HSLS:09 mathematics 8th-grade assessment was field tested at an IRT-reliability of 0.92

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[10] *Hadamard matrices* are square matrices with elements +/- 1 and mutually orthogonal. Individual replicates in the BRR method are similarly formed (as either "0" or a value considering the complimentary half).

(after sampling weights were applied). Specific item sets across student, teacher, counselor, and administrator surveys analyzed using psychological scales (e.g., student self-efficacy and identity for math and science) were evaluated for internal consistency using Cronbach's alpha (Ingels et al., 2011, pp. 109-113). In total 24 constructs -12 in science and 12 in mathematics - reported internal consistency reliability, though only as psychological factors.

Throughout the survey, only 11 items indicated an unacceptable rate of missing data (significance greater than 5%) – tied primarily to income, loans, and parental salary (Ingels et al., 2018, p. 133). HSLS designers additionally performed inferential statistical tests on the data following the implementation of each wave to estimate bias (i.e., if a survey item represented a level of 0.05). As indicated by the data file documentation, "[t]he results of these nonresponse bias analyses suggest that there is not a substantial bias due to nonresponse after adjusting for that nonresponse" (Ingels et al., 2018). The statistics prior to and following the addition of a nonresponse adjustment is detailed by Ingels et al. (2018) and proves the above claim by maintaining validity and reliability of the survey data following NCES standards. Given that these data are valid and reliable, it provides a contemporary data collection repository for quantitative analysis including multinomial logistic regression.

Table 4. *Base-weighted Unit Response Rates*

Unit	Participation Definition	Eligible[f]	Participated[f]	Weighted Percent
	Base Year			
School	School agreed to participate	1,880	940	55.5[a]
Student	School questionnaire completed	25,210	21,440	85.7[b]
	Student assessment completed	25,210	20,780	83.0[b]
	First Follow-up			
Student	Student questionnaire completed[c]	25,180	20,590	82.0[b]

	Student assessment completed[c]	25,180	18,510	73.0[b]
	Parent questionnaire completed[e]	11,950	8,650	72.5[d]
	2013 Update and H.S. Transcript Component			
Student	Student questionnaire completed	25,170	18,560	73.1[b]
	High school transcripts collected	25,170	21,930	87.7[b]
	Student questionnaire completed and high school transcripts collected	25,170	17,660	70.2[b]
	Second Follow-up			
Student	Student questionnaire completed	25,120	17,340	67.9[b]

Note. From the "High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation" by Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. [a] School base-weight was used to calculate the weighted percentage. [b] Student base-weight was used to calculate the weighted percentage. [c] Ineligible first follow-up students totaled 20 students. [d] Student base-weight adjustment for parent subsampling was used to calculate the weighted percentage. [e] Includes a subsample of 11,950 eligible students for the first follow-up data collection. [f] Rounded per IES data security requirements.

Table 5. *Second Follow-up Survey Weights*

Weight	**Number of Respondents[c]**	**Mean[c]**	**Standard Deviation[c]**	**Maximum[c]**	**Sum[a]**
W4STUDENT	17,3340	240	311.0	7,890	4,183,280
W4W1STU	15,910	260	343.2	7,950	4,133,580
W4W1W2W3STU	13,280	310	412.4	9,240	4,133,880
W4W1STUP1	12,890	320	427.37	10,130	4,157,770
W4W1STUP1P2[b]	5,430	770	976.31	18,340	4,153,490

Note. From the "High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation" by Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. [a] Weight sums differ across population counts due to the suppression of data for excluded students. [b] Respondents restricted to a parent subsample of the first-year follow-up. [c] Rounded per IES data security requirements.

Exogenous Variables and Descriptive Statistics

The following exogenous variables were retained and employed in the research analysis. As outlined in Chapter 3, a balanced repeated replication was implemented to account for the survey weights applied to this complex survey data set. Each variable, therefore, is outlined by a sample size, weighting effect, range (minimum and maximum values), respondent frequencies (or percentages), missing data, and how each variable was coded.

Educational Goals and Outcomes

Major will be Considering – 2-digit CIP Code (S3FIELD2)

This independent variable represents the field of STEM study considered by the sample population of students as a 2-digit CIP code. The following survey question was administered to postsecondary students as of November 1, 2013: "What field of study or program [will/were/was] [you/he/she] [be] considering? To reduce the number of categories for achieving numerical convergence on each model, the variable was re-coded to acknowledge if the respondent was considering a STEM field of study or program. STEM fields were categorized using the BLS SOC[11].

[11] Bureau of Labor Statistics Standard Occupational Classification (BLS SOC) System

Table 6. Major Selection Descriptive Statistics

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	Non-STEM Major	8,690	40.0	46.40
1	STEM Major	2,810	12.0	13.55
	Missing/Non-response	12,010	51.0	40.05

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Highest Level Math/Science Course Taken (X3TGPAHIMTH/X3TGPAHISCI)

This variable is a composite of X3TGPAHIMTH and X3TGPAHISCI which attains the student GPA in their highest math and science courses, respectively. The resulting Cronbach's alpha was moderate at 0.74.

Table 7. Highest Level Math and Science Course GPA Descriptive Statistics

Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
Continuous	-2.43	1.77	-.063	.018	-.098	-.027

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Psychometric Influences

Math and Science Efficacy (X1/X2MTHEFF and X1/X2SCIEFF)

X1MTHEFF, X2MTHEFF, X1SCIEFF, and X2SCIEFF represent a scale of the participant's mathematics self-efficacy in their 9th-grade and 11th-grade years (waves 1 and 2 respectively). These variables are composites of S1/S2MTESTS, S1/S2MTEXTBOOK, S1/S2MSKILLS, and S1/S2MASSEXCL. Similarly, X1SCIEFF and X2SCIEFF represent a scale of the participant's science self-efficacy by wave. S1/S2STESTS, S1/S2STEXTBOOK, S1/S2SSKILLS, and S1/S2SASSEXCL are the composites. The resulting Cronbach's alpha for both math and science efficacy were adequate at 0.65.

Table 8. *Math Efficacy Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-2.92	1.62	.038	.019	.001	.076
2	Continuous	-2.50	1.73	.017	.016	-.016	.049

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Table 9. *Science Efficacy Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-2.91	1.83	.025	.022	-.018	.067
2	Continuous	-2.47	1.64	.030	.018	-.006	.065

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Math and Science Utility (X1/X2MTHUTI and X1/X2SCIUTI)

X1MTHUTI, X2MTHUTI, X1SCIUTI, and X2SCIUTI represent a scale of the participant's mathematics self-efficacy in their 9th-grade and 11th-grade years (waves 1 and 2 respectively). These variables are composites of S1/S2MUSELIFE, S1/S2MUSECLG, and S1/S2MUSEJOB. Similarly, X1SCIUTI and X2SCIUTI represent a scale of the participant's science self-efficacy by wave. S1/S2SUSELIFE, S1/S2SUSECLG, and S1/S2SUSEJOB are the composites. The resulting Cronbach's alpha for both math and science efficacy were adequate at 0.65.

Table 10. Math Utility Descriptive Statistics

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-3.51	1.31	.018	.019	-.019	.055
2	Continuous	-3.94	1.21	.023	.016	-.009	.055

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Table 11. Science Utility Descriptive Statistics

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-3.10	1.69	.013	.022	-.029	.056
2	Continuous	-.23	.10	.000	.001	-.002	.003

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Math and Science Interest (X1/X2MTHINT and X1/X2SCIINT)

X1MTHINT, X2MTHINT, X1SCIINT, and X2SCIINT represent a scale of the participant's mathematics self-efficacy in their 9th-grade and 11th-grade years (waves 1 and 2 respectively). These variables are composites of S1/S2MENJOYING, S1/S2MWASTE, S1/S2MBORING, S1/S2FAVSUBJ, and S1/S2MENJOYS. Similarly, X1SCIUTI and X2SCIUTI represent a scale of the participant's science self-efficacy by wave. S1/S2SENJOYING, S1/S2SWASTE, S1/S2SBORING, S1/S2FAVSUBJ, and S1/S2SENJOYS are the composites. The resulting Cronbach's alpha for both math and science efficacy were adequate at 0.65.

Table 12. *Math Interest Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-2.46	2.08	.029	.017	-.005	.062
2	Continuous	-2.02	1.99	.023	.018	-.012	.059

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Table 13. *Science Interest Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-2.59	2.03	.016	.025	-.033	.065
2	Continuous	-2.24	1.71	.020	.019	-.017	.057

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Student Expectations (X1/X2STUEDEXPCT)

This independent variable represents how far in school the participant (9th-grade and 11th-grade year) thinks he/she will get. To reduce the number of categories for achieving numerical convergence on each model, the variable was re-coded into categories depicting the major levels of academic achievement longitudinally.

Table 14. *Student Expectations (Wave 1) Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	High School Diploma/GED	2,760	11.7	14.69
1	Associate Degree/Some College	1,310	5.6	6.85
2	Bachelor’s Degree	3,740	15.9	17.48
3	Master’s Degree	4,450	19.0	20.19

4	Ph.D./M.D./Law/Other	4,460	18.98	19.39
	Non-response/Don't Know	6,780	28.86	21.39

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Table 15. *Student Expectations (Wave 2) Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	High School Diploma/GED	2,930	12.5	15.84
1	Associate Degree/Some College	2,190	9.3	10.96
2	Bachelor's Degree	5,800	24.7	28.21
3	Master's Degree	4,640	19.7	22.06
4	Ph.D./M.D./Law/Other	2,930	12.5	12.98
	Non-response/Don't Know	5,020	21.3	9.95

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Student Belonging (X1SCHOOLBEL)

This variable describes the participant's perception of school belonging (9th-grade year). This scale (higher representing a higher sense of belonging) was developed using principal components factor analysis standardized between 0 and 1. The inputs included S1SAFE, S1PROUD, S1TALKPROB, S1SCHWASTE, and S1GOODGRADES. The resulting Cronbach's alpha for both math and science efficacy were adequate at 0.65.

Table 16. *School Belonging Descriptive Statistics*

Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
Continuous	-4.35	1.59	.020	.019	-.017	.058

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Experiential and Learning Influences

Math and Science Identity (X1/X2MTHID and X1/X2SCIID)

X1MTHID, X2MTHID, X1SCIID, and X2SCIID represent a scale of the participant's mathematics identity in their 9th-grade and 11th-grade years (waves 1 and 2 respectively). These variables are composites of S1MPERSON1 and S1MPERSON2 which correspond to participants who agree with the statements: "You see yourself as a math person" and "Others see me as a math person". Similarly, X1SCIID and X2SCIID represent a scale of the participant's science identity by wave. S1SPERSON1 and S1SPERSON2 are the composites. The resulting Cronbach's alpha for both math and science efficacy were adequate at 0.65.

Table 17. *Math Identity Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-1.73	1.76	.046	.017	.013	.078
2	Continuous	-1.54	1.82	.034	.017	.001	.068

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Table 18. *Science Identity Descriptive Statistics*

Wave	Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
1	Continuous	-1.57	2.15	.033	.017	-.000	.066
2	Continuous	-1.74	1.86	.026	.016	-.007	.058

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Formal STEM Program for Underrepresented Students (C1PURSUE)

C1PURSUE is a dichotomous factor variable determined from the following survey question: "Does your school have any formal programs to…encourage underrepresented students to pursue mathematics or science?"

Table 19. *STEM Program for Underrepresented Students Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No	14,630	62.2	59.26
1	Yes	6,390	27.2	29.56
	Non-response/non-response	2,490	10.6	11.17

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

School Raises Math/Science Interest (A1MSOTHER)

A1MSOTHER is a dichotomous factor variable determined from the following survey question: "Does your school do any of the following to raise high school students' interest and achievement in math or science?" Ingels et al. (2018) lists 12 items in which participants have the option to select including:

- Hold school-wide math or science fairs, workshops, or competitions

- Pair students with mentors in math and science
- Sponsor a math or science after-school program
- Partner with Mathematics Engineering Science Achievement (MESA) or similar program

Table 20. *School Raises Math/Science Interest Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No	600	64.0	60.90
1	Yes	210	21.7	25.86
	Non-response/non-response	140	14.3	13.24

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Informal STEM Partnership (A1MSSUMMER)

This variable is a dichotomous factor variable determined from the following survey question: "Does your school do any of the following to raise high school students' interest and achievement in math or science?" Ingels et al. (2018) lists 12 items in which participants have the option to select in-line with A1MSOTHER:

Table 21. *Informal STEM Partnership Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No	600	64.0	46.45
1	Yes	210	21.7	40.31
	Missing/non-response	140	14.3	13.24

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

8th Grade Math Scores (S1M8GRADE)

This variable was coded by letter grade (A through Below D) based on each participant's response to "What was your final grade in this math course?" The grade indicated was the final score for the 9th grader's most advanced 8th grade math course.

Table 22. *8th Grade Math Scores Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	A	7,730	32.9	33.62
2	B	7,820	33.3	36.75
3	C	3,680	15.7	18.61
4	D	1,030	4.4	5.67
5	Below D	570	2.4	2.46
	Missing/Non-response	2,510	11.4	2.89

[a] Balanced Repeated Replication survey method was used to calculate the weight15ed proportion.

[b] Rounded per IES data security requirements.

Contextual-Environmental Influences

Teacher Gender Bias (S1MTCHMFDIFF and S1STCHMFDIFF)

S1MTCHMFDIFF and S1STCHMFDIFF considers how the participant felt their Fall 2009 math teacher treated males/females differently. The variable results were based on a four-point Likert scale which corresponds to participants who agree with the statements: "Your math teacher…treats males and females differently."

Table 23. *Math Teacher Gender Bias Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	Strongly Agree	670	2.8	3.30
2	Agree	1,540	6.6	7.40
3	Disagree	8,700	37.0	41.57
4	Strongly Disagree	7,940	33.8	36.31
5	Missing/Non-response	4,660	19.8	11.43

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Table 24. *Science Teacher Gender Bias Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	Strongly Agree	640	2.7	2.79
2	Agree	1,540	6.5	6.96
3	Disagree	8,230	35.0	38.73
4	Strongly Disagree	6,950	29.6	32.54
5	Missing/Non-response	6,150	26.2	18.98

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Gender Matching (X1GENMATCH)

X1GENMATCH is a composite variable determined by matching the student's gender with their math (M1SEX) and science teacher (N1SEX) in the 2009 year.

Table 25. *Gender Matching Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	Not Matched	14,880	63.3	65.00
2	Matched	8,620	36.7	35.00

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Parental Education Level (X1DADEDU and X1MOMEDU)

X1DADEDU and X1MOMEDU represent a sample member's father/mother's highest educational level attained.

Table 26. *Father's Educational Level Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No bio/Adoptive/Stepfather	3,720	15.8	19.40
1	Less than High School	1,210	5.1	6.77
2	High School Diploma/GED	5,410	23.0	27.47
3	Associate Degree	1,490	6.4	7.07
4	Bachelor's Degree	2,910	12.4	12.17
5	Master's Degree	1,220	5.2	4.86
7	Ph.D./M.D./Law/Other	820	3.5	2.48
	Missing/Non-Response	6,720	28.6	19.77

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Table 27. *Mother's Educational Level Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No bio/Adoptive/Stepfather	1,160	4.9	5.10
1	Less than High School	1,280	5.5	7.77
2	High School Diploma/GED	6,340	27.0	32.07
3	Associate Degree	2,520	10.7	12.86
4	Bachelor's Degree	3,690	15.7	15.69
5	Master's Degree	1,370	5.8	5.39
7	Ph.D./M.D./Law/Other	430	1.8	1.35
	Missing/Non-Response	6,720	28.6	19.77

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Parental Expectation (X1/X2PAREDEXPCT)

This independent variable represents how far in school the parent (9th-grade and 11th-grade year) thinks their student will achieve. To reduce the number of categories for achieving numerical convergence on each model, the variable was re-coded into categories depicting the major levels of academic achievement longitudinally.

Table 28. *Parent Expectations (Wave 1) Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	High School Diploma/GED	1,440	6.1	7.38
1	Associate Degree/Some College	1,390	5.9	7.45
2	Bachelor's Degree	5,030	21.4	23.66

3	Master's Degree	3,390	14.4	15.55
4	Ph.D./M.D./Law/Other	3,780	16.1	16.75
	Non-response/Don't Know	8,470	36.1	29.21

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Table 29. *Parent Expectations (Wave 2) Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	High School Diploma/GED	2,700	11.5	14.69
1	Associate Degree/Some College	1,810	7.7	9.55
2	Bachelor's Degree	6,470	27.5	29.89
3	Master's Degree	4,140	17.6	18.36
4	Ph.D./M.D./Law/Other	3,310	14.1	14.43
	Non-response/Don't Know	5,080	21.6	13.09

[a] BRR survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Parental Expectation (X1/X2PAREDEXPCT)

The parental involvement scale was advanced by Howard (2016) for use with HSLS:09 as no measure currently exists. This factor variable combines P2DISCOURSES, P2DISCCLGEXAM, P2DISCCLGAPP, and P2DISCCAREER inputs. Each variable corresponds to the following survey questions, respectively:

- How often the parent has discussed selecting courses or programs at school
- How often discussed preparing for college entrance exams

- How often discussed applying to college/other school safter high school
- How often discussed careers he/she might be interested in

To use the scale, a similar principal component factor analysis was conducted with an equivalent Cronbach's alpha equal to .82.

Mentorship (C2HAMENTOR)

This mentorship variable seeks to identify which schools support high achievers with an adult mentor. The survey question asks, "In which of the following ways does [school name] support high-achieving students…a school-arranged match with an adult mentor".

Table 30. *Mentorship Descriptive Statistics*

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
0	No	15,810	67.3	68.48
1	Yes	3,330	14.2	15.23
	Missing/Non-Response	4,370	18.6	16.29

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Demographic Influences

Race (X1RACE)

X1RACE is an ethnicity-composite variable which combines six dichotomous race/ethnicity variable as inputs: X1HISPANIC, X1WHITE, X1BLACK, X1ASIAN, X1PACISLE, and X1AMINDIAN. To simplify the later analysis and reach numerical stability, the variables considered were X1HISPANIC, X1WHITE, X1ASIAN, and X1BLACK.

__Table 31__. Race Descriptive Statistics

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	Asian	1,950	8.3	3.53
2	Black/African American	2,620	11.1	14.32
3	Hispanic/Latin American	3,800	16.2	21.95
4	More than one Race	1,940	8.3	7.93
5	White/European American	12,080	51.4	51.79
6	Missing/Non-response	1,120	4.8	.48

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Gender (X1SEX)

This variable inquiries about the sample members' gender from the categories of either Male or Female.

__Table 32__. Gender Descriptive Statistics

Category	Label	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
1	Male	11,980	51.0	50.29
2	Female	11,530	50.0	49.71

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

[b] Rounded per IES data security requirements.

Socioeconomic Status (X1SES)

This variable is a composite scale measuring the socioeconomic status of participants. The construct is calculated using parent/guardian education (X1PAR1EDU and X1PAR2EDU), occupation (X1PAR1OCC2 and X1PAR2OCC2), and family income (X1FAMINCOME).

Table 33. *Socioeconomic Status Descriptive Statistics*

Category	Minimum	Maximum	Mean Weighted[a]	Std. Error[a]	95% CI	
Continuous	-1.93	2.88	-.062	.018	-.097	-.026

[a] Balanced Repeated Replication survey method was used to calculate the weighted proportion.

Considering the array of exogenous variable types in this study including dichotomous, categorical, ordinal, and continuous covariates are paired with endogenous categorical variables to predict whether a participant expects to enter a STEM career at the age of 30, a multinomial logistic regression was chosen.

Methodological Procedure

Multinomial logistic regression (MNLR) is a statistical method for evaluating and predicting nominal[12] dependent variables given multiple independent variables. Matching other regression procedures, both continuous and categorical covariates may be employed (separately or in combination) as well as any interactions between these variables. MNLR, therefore, is a uniquely suited statistical method for predicting how factors such as mentorship, parental support, course sequencing, and teacher instructional methodologies affect an individual's pursuit of a STEM career. *HSLS:09* additionally provides a direct measurement of this dependent outcome, student occupation

[12] Nominal outcomes are unordered categories such as those describing educational progression (e.g., secondary, post-secondary, and careers). These categories can be used in evaluating questions that seek to understand motivations and persistence in pursuing STEM careers - such as by race, ethnicity, gender, and socioeconomic status.

at the age of 30 (X1/X2/X4STU30OCC_STEM1) and offers several variables for assembling models that predict STEM pursuit. Table 6 considers possible motivational and persistence covariates in a STEM pursuit model, including the univariate results from considering their independent impact on perceived pursuit. These variables are situated in historic and current research categorized by their respective area (see Table 6). MNLR offers a method for assembling these factors into multiple categories (beyond three and including controls) to evaluate their interactions longitudinally across demographics and educational experiences.

Generalized Linear Model

The multinomial logit model (MNLM) is the most widely used and employed nominal regression model (Long & Freese, 2014) – one that is also featured in Stata 17.0. The challenge, however, for a multinomial versus a traditional binary logit model is in merging the probabilities of each combination of logits[13] in addition to their interpretations. The difference between the logits of two distinct probabilities is defined as the odds ratio (OR). MNLM fits these binary logit combinations simultaneously for comparisons that account for all possible alternatives (sometimes referred to as "one-versus-all" multi-class classification method), determining their odds ratios. This method may also be thought of as comparing each logit to a control situation (i.e., comparing a control logit to multiple categories). Below is the generalized equation for an MNLM:

***Equation 1**. Generalized MNLM Equation*

$$\ln\, \Omega_{m|b}\,(x) = ln\; \frac{\Pr\,(y = m \,|\, x)}{\Pr\,(y = b \,|\, x)} = x\, \beta_{m|b} \qquad for\;\; m = 1\; to\, J$$

[13] *Logits* are log-odds functions that describe the probability of a binary outcome based on several covariates. These functions map probability values within a domain of 0 to 1 (two binary outcomes) following a logistic distribution.

where *b* is the base outcome (reference category or control), *m* is comparison outcome, and *J* is the total number of alternative categories. Comparing an outcome with itself, yields a value of 0. As a result, the number of logits produced from a MNLM is equal to *J*-1. To see this equation applied conceptually, consider a research question that seeks to determine the effect of course taking (college preparatory [CP], honors [H], and advanced placement [AP]) by three regressors (age, ethnicity, and gender) on the decision to pursue a STEM degree (either yes or no). The following set of equations are produced from equation (1) and account for categorical and continuous regressors established from the problem statement and researched factors,

Equation 2*. Example Set of MNLM Equations to Determine the Effect of Coursetaking on STEM Degree Attainment*

$$\ln \mathit{\Omega}_{CP|H} x_i = \beta_{0,CP|H} + \beta_{1,CP|H}\, age + \beta_{2,CP|H} hispanic + \beta_{3,CP|H}\, female$$

$$\ln\ \Omega_{CP|AP} x_i = \beta_{0,CP|AP} + \beta_{1,CP|AP}\, age + \beta_{2,CP|AP} hispanic + \beta_{3,CP|AP}\, female$$

$$\ln\ \Omega_{H|AP} x_i\ = \beta_{0,H|AP} + \beta_{1,H|AP}\, age + \beta_{2,H|AP}\, hispanic + \beta_{3,H|AP}\, female$$

Although additional constraints are imposed when solving the MNLM model based on individual logits, Hosmer et al. (2013) indicate that the differences are minimal. Stata 17.0 additionally provides a method for calculating each simultaneously (Long & Freese, 2014) which yields the slightly more precise results and will be approached whenever possible. However, some fit and diagnostic tests are not supported by current statistical software (including Stata 17.0) and therefore must be calculated using the set of individual logits with binary diagnostic methods (Hosmer et al., 2013).

Given this set of equations, Hosmer et al. (2013) illustrate how to interpret the coefficients (β's) from the logits obtained through an emerging MNLM and on how to evaluate their significance (pp. 273-278). Following the odds ratio model,

Equation 3. *Odds Ratio Model*

$$OR_m(a,b) = \frac{\Omega_{a|b}\ (\boldsymbol{x},\ x_k +\ \delta)}{\Omega_{a|b}(\boldsymbol{x},\ x_k)} = \frac{(\Pr\ (y = m \,|\, x = a)/\Pr\ (y = 0 \,|\, x = a)\ )}{(\Pr\ (y = m \,|\, x = b)/\Pr\ (y = 0 \,|\, x = b)\ )}$$

which represents the difference between logits *a* and *b* using logarithmic difference identities (see equation [1] and Long & Freese [2014, p. 387]). These odds ratios may also be obtained from a cross-classification of the dependent variable with the independent variables (Hosmer et al., 2013, pp. 273-278). Standard errors for the coefficients (β = ln [*OR*]) are calculated by determining the square root of the sum of the inverse cell frequencies (p. 274). Conversely, when using complex survey data, Stata is similarly employed to calculate the standard errors and account for the data collection design through a balanced repeated replication method.

Modeling with Complex Survey Data

Given adjustments to the bias in the HSLS survey data using a weighting methodology through balanced repeated replication, Herringa et al. (2016) provide a strategic method for analyzing the data using the bias-adjusted weighting approach (pp. 121-122). The design of a multinomial logistic regression model begins with the purposeful selection[14] and assembly of covariates. Hosmer et al. (2013, pp. 90-93) provide a step-by-step, research-based approach to selecting variables, identifying significant interactions between covariates, calibrating the preliminary model and testing the final main effects model for fit. Figure 17 details the procedure for each step and synthesizes the integration between Stata 17.0, complex survey data analysis with *HSLS:09*, and these methods. The approach follows through selecting and iteratively testing main effects covariates to develop a *preliminary main effects model* (see Figure 17 for a general map). Likelihood ratio tests strategically assess the covariates for inclusion while comparing their changes

[14] The purposeful selection of covariates was accomplished through the comprehensive literature review including motivation and retention theories as well as prior research on pursuit factors.

($\Delta\beta$ percentages) during the model updates. New and original models are additionally compared using partial likelihood tests (or Wald tests) as well as any unretained variables from the initial step for fit. Throughout each analysis, a balanced repeated replication is required for a correct calculation of the standard errors. Stata 17.0 allows for BRR adjustments using multinomial logit functions and hypothesis tests (Long & Freese, 2014).A final check is conducted for covariate linearity, an assumption for the multinomial regression model, using lowess smooth and fractional polynomial (or quartile design variable) plots. Variables that meet this criterion are retained and a *main effects model* is produced.

Covariate Interactions

Following the development of a main effects model, the process for determining the significance of variable interactions is approached through practical and statistical perspectives. Hosmer et al. (2013) suggest creating a list of all possible pairs of variables that have a "realistic possibility" of interacting with each other. Interpreted as arithmetic products, meaningful pairs (based on practical expertise) are assessed for statistical significance (p-value < 0.05) using a likelihood ratio test in a univariate analysis (pp. 92-93). Those selected are added to the main effects model as the logit coefficients are tested for large changes (i.e., $\Delta\beta > 20\%$). Retained interactions are then included into the main effects model forming the *preliminary final model*.

Fit and Diagnostics

An assessment of the preliminary final model adequacy and fit remain as the final step toward developing a completed version. The assessment of fit for a model seeks to determine how good of a job the model does in predicting outcomes. Therefore, "fit tests" evaluate the probability that the model will yield a binary outcome, events that are hypothesized to occur ($\Omega = 1$) or those that are predicted not to occur ($\Omega = 0$) based on a decision boundary. The probabilities of a positive or

Table 34. *HSLS:09 Variables of Interest*

Variable	Description	Variable Retained[a]
Educational Goals and Outcomes		
Student occupation at age 30	Intent to pursue a STEM career (X1/X2/X4STU30OCC_STEM1)	Dependent
Selection of a STEM major	Reference degree's first major is STEM	X4RFDGMJSTEM
Major will be considering	Major the secondary student will be considering (early-selection; 2-digit CIP)	S3FIELD2
Coursetaking	Academic track/concentrator and occupational track	X3TACADTRCK/ X3TOCCUCON
Highest level math/science course taken	GPA earned in the highest-level mathematics and science course taken	X3TGPAHIMTH/ X3TGPAHISCI
Psychometric Influences		
Math and Science Self-efficacy	Composite self-efficacy variable	X1/X2/MTH/SCIEFF
Math and Science Utility	Composite utility variable	X1/X2/MTH/SCIUTI
Math and Science Interest	Composite interest variable	X1/X2/MTH/SCIINT
Student Expectation	Variable to determine "How far a student believes they will get in school"	X1/X2STUEDEXPCT
Student Sense of Belonging	Composite of a student's sense of belonging	X1SCHOOLBEL
Experiential and Learning Influences		
Math and Science Identity	Composite identity variable	X1/X2/MTH/SCIID
Program to encourage underrepresented students in STEM	School has a formal program/engages in systematic efforts to encourage underrepresented students to pursue STEM	
Raises student math/science interest in another way[b]	12 factor variables representing how early-education teachers raise student interest in math and science	A1MSOTHER
Informal STEM participation	Indicators of whether the student's school holds math/science fairs, workshops, or competitions (A1MTHSCIFAIR), partners with colleges to offer math/science summer enrichment programs (A1MSSUMER), or afterschool programs (A1MSAFTERSCH)	A1MSSUMER
8th-grade Math Scores	Pre-assessment of mathematics cognitive ability entering high school	Initial Control

Contextual-Environmental Influences		
Teacher educational background	Teacher major field of study at the highest STEM degree-level (2-digit CIP code)	N1/M1HIMAJ_STEM
Teacher gender biases	Student's 9th-grade math/science teacher treats males/females differently	S1M/S1STCHMFDIFF
Gender matching	Teacher's gender in 9th-grade math and science	M1/N1SEX
Parental Education	Highest level of education achieved by biological, adopted, or stepfather/mother	X1DADEDU/ X1MOMEDU
Parental Involvement	4 factor variables, based on the work of Howard (2016) identifying how often a parent engages with their student (e.g., discusses course selection, entrance exam preparation, college, and/or careers)	PInv
Parental Motivation	Highest level of education the parent expects the student to achieve	X1PAREDEXPCT
Mentorship	Indicators of whether the student was paired with a math/science mentor (A1/A2MSMENTOR), supports high achieving students with a mentor (C2HAMENTOR), and/or school arranged mentors are provided by the school (C2XTRAMENTOR)	C2HAMENTOR
Demographic Influences		
Race	Student's race/ethnicity based on questionnaire data.	Initial Control
Sex	Sex of the student taken from the base-year questionnaire, parent questionnaire, and/or school-provided sampling roster (X1SEX)	Control
Socioeconomic Status	Composite for SES using parent/guardian income, occupation, and family income (X1SES)	Control

[a]PInv was obtained through a principal component analysis described by Howard et al. (2016) containing P2DISCCOURSES, P2ISCCLGEXAM, P2DISCCLGAPP, and P2DISCCAREER.
[b]The purposeful selection of variables utilized Hosmer et al. (2013, pp. 90-107) to determine if a variable was retained or not retained, and if it represents a dependent or control variable.
[c]Italicized variable names indicate multiple factors present in HSLS:09.
[d]Represents a variable that is part of the restricted-use HSLS:09 dataset.

negative prediction describes the model's sensitivity and 1-specificity, respectively. Plots of sensitivity versus 1-specificity[15] are commonly referred to as the Receiver Operating Characteristic (ROC)[16] curve and the area under this curve provides a characteristic of *discrimination* – the estimated probability of one outcome occurring versus another. Values of ROC > 0.7 are considered "acceptable" (Hosmer et al., 2013, p. 177), however the greater the area, the better the model does at predicting an outcome. The success rate of predictions statistic is provided in Stata 17.0 with a default cutoff at 50%. To determine the optimal cutoff (a value between 0 and 1) plotting sensitivity/specificity versus the range probability cutoffs will reveal this value at the intersection of each curve between sensitivity and specificity line graphs (Hosmer et al., 2013). An accurate quantity for determination may then be fed back into the Stata 17.0 statistical function to show the best result for classification. Lastly, jittered outcome (scatter) and density (histogram) plots provide clarity on the ability of the data to discriminate between predicted and unpredicted outcomes.

Regression diagnostics are the final measures of fit, examining how a model "fit" is supported over the entire set of regressor patterns. Hosmer et al. (2013) recommend a series of plots detailing the contribution of the estimated probability to the value of the following diagnostic statistics: (1) leverage (h), (2) change in Pearson chi-squared (ΔX^2), (3) change in deviance (ΔD), and (4) Cook's distance ($\Delta\hat{\beta}$). Since a statistical method is not available in Stata 17.0, the development of each plot requires breaking up the MNLM into individual logits. Data points in these plots at either the top left or right, generally indicate a poor fit (Hosmer et al., 2013, p. 197). The data points in these outlying covariate patterns are eliminated one-by-one, then completely, to test for their effect on the model. Assembling the results in a table by covariate and percent change, a

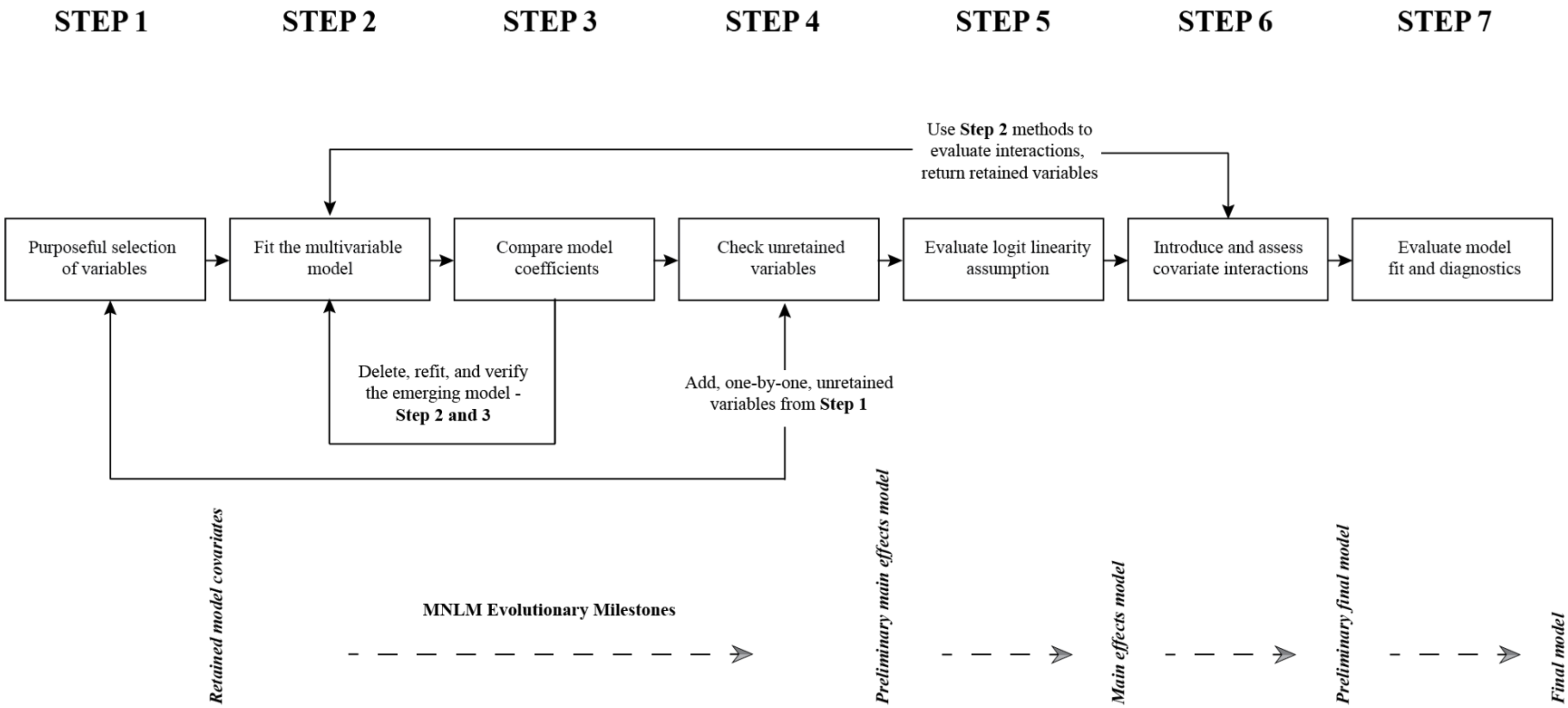
[15] 1-specificity describes the rate of false positives among the cases that should be negatives.
[16] The Receiver Operating Characteristic (ROC) curve originated from signal detection theory in describing the existence of a signal in the presence of noise (Hosmer et al., 2013, p. 174).

decision is subsequently made on keeping or eliminating covariates. Hosmer et al. (2013) further explain this decision point with a word of caution, "we use diagnostics statistics to identify subjects and subject matter considerations to decide on exclusion" (p. 199).

Methodological Limitations, Delimitations, and Ethical Considerations

Four significant challenges remain in implementing a multinomial logistic regression. The first is the resolution of multiple odds ratios across logits. The difficulty, here, lies more in the reporting and interpretation of the odds ratios rather than the calculation. With many comparisons across covariates, the researcher must carefully navigate the meaningfulness of the complete set of results against the questions for inquiry. An unintended stretching of the data could also result due to small subgroups of students represented in the sample being spread "thinly" across each logit. This was evaluated post hoc to verify that the sample sizes by subgroup fit within accepted levels. The second challenge is the lack of statistical software for fully testing the fit of a particular model under multinomial conditions. Although methods exist, they have not implemented in the leading statistical packages (e.g., Stata, SPSS, and SAS). As a result, testing for model fit of a MNLM requires reducing the model into individual logits and analyzing each logit for fit – a tedious proposition with more than a half dozen covariates. Since outliers in the data for these logistic models have a significant effect on the fit and diagnostics of the overall model, individual outlying data points will be excluded in the final model. A third difficulty is the pathway to convergence on a fitted MNLM. The number of covariates, especially when introducing categorical independent variables, may quickly reach numeric instability and a divergence of the fitted model. Additionally, while the steps provided by Hosmer et al. (2013) for developing an MNLM is one of the more straightforward approaches, it relies heavily on the researcher's empirical experience (statistical and subject area expertise) for reaching convergence on a well- fitted model. The selection of variables

Figure 17. *MNLR Model-Building Flowchart*



Note. A process flow map of the steps for conducting a thorough analysis using MNLR. Designed from the methodology in Hosmer et al. (2013).

is critically important to the model which leans on the researcher's ability to construct pragmatic, clinical, and testable covariate interactions. Finally, the last challenge considers model building methods with complex survey data designs (such as *HSLS:09*) and practical statistical procedures (e.g., in Stata 17.0). Debates over the most precise statistical methods for testing covariates and assessing their fit continues as methods are constantly evolving. For example, the Hosmer-Lemeshow statistic is viewed as being highly dependent on an arbitrary decision for the number of groups used. Independence of Irrelevant Alternatives (IIA) assumption tests, long used when reporting MNLMs, are also debated about their relevance in characterizing model behavior. Although the inclusion of IIA assumption tests is left to the individual journal reviewers, Long and Freese (2014) report these findings and do not recommend the measure for assessing fit (pp. 223-224) or performing an IIA analysis.

With the chosen study design, delimitations to the chosen number of variables are accomplished through a rigorous review of literature and practical experience teaching at both secondary and postsecondary levels of education. In addition to factor delimiters, the theoretical landscape will focus on transactional motivational and persistence theories to frame the models of student pursuit. Moreover, the choice of range between secondary and postsecondary education levels (i.e., 9-16) for the typological models, matches the research on early STEM pursuit progressions toward STEM careers. It also mirrors traditional STEM pipeline timescales for future study comparisons. A last delimitation includes the scope of accepted taxonomies of STEM to the most widely used systems and approaches in the research.

A significant ethical consideration considered through this proposal is the scope to which the results generalize across demographic and factor groupings. As more conditions are set onto the population of students within the study (n = 14,130), the sample sizes supporting the analysis begin to decrease dramatically. For instance, the population of students taking computer science courses is between 1 – 3% ($140 \leq n \leq 430$) of the total population. Careful consideration when utilizing this population must then be given to the generalization of these results based on the initial set of students the analysis was based on. Moreover, matched typologies are generalized guidelines that offer counselors, students, and parents better-matched pathways toward pursuit of STEM careers. This implies that a product resulting from the research has a usefulness only in its ability to transfer the research on STEM pursuit to the individual student and provide counselors, parents, teachers, and administrators pathway models for providing guidance toward these ends.

Expected Findings

Utilizing a quantitative methodology, the objective of the methodology section was to outline how a multinomial logistic regression could be used to perform a statistical analysis within the High School Longitudinal Study (HSLS:09). *HSLS:09* was chosen since it was one of the only longitudinal datasets available to study student progressions across educational levels with a focus on STEM and utilized current theoretical frameworks on student motivation and persistence aligned to the overall research focus on analyzing STEM pursuit. In meeting these goals, a synthesis between the *HSLS:09* survey design, regression techniques using Stata, and multinomial logistic regression modeling methods was explored in providing a roadmap toward answering this question pragmatically. Table 6 and Figure 16 illustrate a collective framework for conducting an analysis of *HSLS:09* data through multinomial logistic regression methods and practical applications. Utilizing this framework through a correlational quantitative research design, future studies will be able to determine how much of power educational attainment outcomes, self-influences, experiential-, contextual-, and personal-influences play in determining the selection of STEM occupational pursuit for underrepresented groups of students nationwide. Accordingly, potential implications for policy adjustments to the traditional STEM pipeline approaches describing pursuit for diverse groups of students suggest intersectional approaches using MLNMs as viable methods with contemporary data.

Chapter 4. Data Analysis and Results

A multinomial logistic regression was employed to evaluate the role of psychometric; experiential and learning; contextual-environmental; and demographic influences (see Table 6) on predicting anticipated STEM career attainment, longitudinally (secondary through postsecondary education), while controlling for socioeconomic status, race, and 8th grade math scores. Following the process outlined in step 1 of Figure 16, the purposeful selection of variables, a robust *a priori* and *posteriori* analyses of the assumptions required for completing a statistically significant multinomial regression analysis was conducted. Included in these assumption analyses were assessments of the overall (1) sample size, (2) multicollinearity in the independent variables, and (3) outliers in the data. Multinomial logistic regressions are particularly sensitive to these assumptions which needed to be evaluated prior to running the MNLR. Although tests for independence of observations and linearity are not required for a multinomial logistic regression, the latter is performed herein following the development of the logistic regression preliminary main effects models in step 4 of Figure 16. As described in Chapter 3, the MNLR analysis will closely follow the flow in Figure 16 which checks for outliers using special case-wise diagnostics for linearity prior to the main effects model in step 5. A final model was determined following calibration and discrimination through goodness of fit tests and ROC curve area values (Hosmer et al., 2013).

Sample Size

Long and Freese (2014, p. 85) proposed a general rule for determining the minimum number of samples required for maximum-likelihood estimates. At approximately $N \geq 500$, this amount correlates to, but is generally a higher threshold, then the calculated value approached by other researchers (Tabchnick & Fidell, 2005). The formula for calculating sample size using the later models is given by $N > 50 + 8m$, where *m* is the number of independent variables. Considering these significant differences, Long and Freese (2014) acknowledge that at least 10 observations per parameter (N > 220) is a reasonable sample estimation, which is in-line with Tabachnick and Fidell (2015; N > 226). However, they caution the researcher to evaluate each study individually for ill-conditioned data (i.e., for ordinal regression models or highly collinear data; p. 85). Under these conditions the sample size for the initial set of variables (n = 23) is much smaller than the minimum proposed by Long and Freese (2014, p. 85; N > 220). Considering the smallest sampled variable S3FIELD2 (N = 6,540) and the MNLR analyses, the sample size assumption appears adequate for our study as it far surpassed the size threshold.

As a redundant *a priori* measure for checking the minimum sample size, a power analysis was performed using a Monte Carlo simulation on a generalized set of logistic regression models (i.e., using researched coefficients for building the model).

Equation 4. *Monte Carlo Simulation Logit Model*

$$\begin{aligned}\Omega_{expected\ occupation\ at\ 30} &= \beta_0 + \beta_1(x_{sex}) + \beta_2(x_{science\ utility}) + \beta_3(x_{gender\ matching}) \\ &+ \beta_4(x_{gender\ bias}) + \beta_5(x_{reference\ major}) + \beta_6(x_{SES}) + \beta_7(x_{math\ identity}) \\ &+ \beta_8(x_{institutional\ level})\end{aligned}$$

Figure 18 illustrates the results of an estimated 80% power model with four combinations of sample and effect sizes for the control covariate – socioeconomic status. At an odds ratio of 1.36, an estimate of at least 80% power is obtained at sample sizes ranging from 800 to 1000. With larger odds ratios, 85% power levels are achieved through a significant reduction in the overall sample size. The remaining continuous covariates in the model are displayed in Table 35 with their respective power values. These results further confirm our prior sample size estimates and level of statistical confidence in the summary data.

Figure 18. *Monte Carlo Power Analysis over SES*

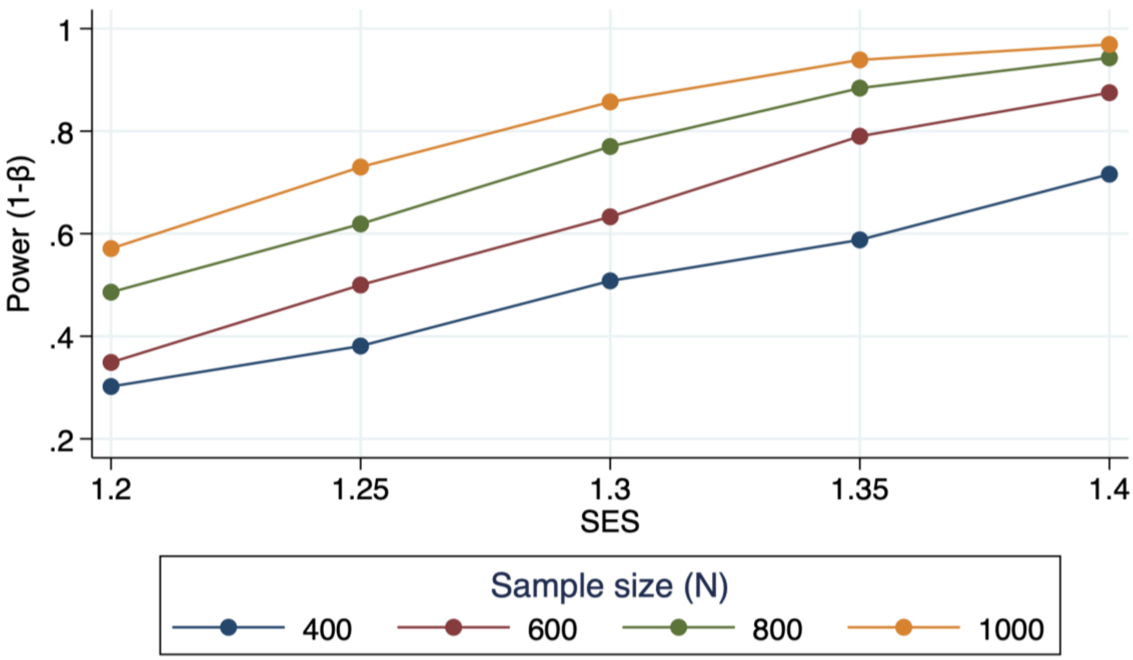


Table 35. *Monte Carlo Power Analysis for Continuous Covariates*

Continuous covariate	alpha	Power	Sample size (N)
Science utility	.05	.49	400
	.05	.65	600
	.05	.78	800
	.05	.86	1000
Socioeconomic status	.05	.63	400
	.05	.81	600
	.05	.89	800
	.05	.94	1000
Math identity	.05	.58	400
	.05	.79	600
	.05	.86	800
	.05	.94	1000

Note: Bolded values represent covariates with >.85 power

Multicollinearity

Tests for multicollinearity represent another significant verification step in preparing the data for analysis. Multicollinearity refers to the relationships amongst the independent variables in the sample set. For the multinomial logistic regression study, each variable was compared against each other using a linear regression technique in Stata 17.0. Since collinearity is a property of the predictors, not the model, the assumption for multicollinearity was simplified through correlation calculations using Spearman's ρ (between continuous and categorical variables) and Pearson's r statistics (between continuous variables). Tolerance and Variance Inflation Factors (VIFs) were later calculated and are displayed in Table 36. As a result, none of the independent variables were shown to have strong correlational results ($r \geq 0.9$), low Tolerance levels (less than 0.1), and VIFs greater than 10. Since each *a priori* assumption criteria were met, the next step of the model building process continued with a univariate analysis of each variable against the anticipated STEM occupation at the age of 30. Table 34 shows the results of this analysis in the column "Variable Retained?". Each variable was then carefully fitted to the multinomial models for each wave using the procedure in Figure 17 (steps 3-6; Hosmer et al., 2013).

Table 36. *Tolerance and Variance Inflation Factors (VIFs)*

Model[a]	Variable	Wave 1		Wave 2		Wave 4	
		VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
1	X1PAREDEXPCT	1.34	.74	–	–	1.10	.91
	X1STUEDEXPCT	1.31	.77	–	–	–	–
	S1M8GRADE	1.2	.82	1.2	.80	–	–
	X1SCIID	1.34	.74	–	–	–	–
	X1SES	1.22	.82	1.23	.81	1.04	.96
	X1SCIUTI	1.27	.79	–	–	–	–

	X1SEX	1.07	.93	1.10	.91	1.12	.89
	X1MGENMATCH	1.02	.98	1.03	.97	1.03	.97
	X1RACE	1.12	.89	1.11	.90	–	–
2	X2SCIEFF	–	–	1.47	.68	–	–
	X2SCIUTI	–	–	1.48	.68	1.14	.88
	X2SCIID	–	–	1.74	.58	–	–
	X2MTHID	–	–	1.19	.84	–	–
	X2STUEDEXPCT	–	–	1.30	.77	–	–
	S1MTCHMFDIFF	–	–	1.03	.97	1.03	.98
4	X4RFDGMJ123	–	–	–	–	1.25	.80
	S3FIELD_STEM	–	–	–	–	1.35	.74
	X2MTHID	–	–	–	–	1.14	.88

[a]First appearance of the variable in each model by ascending order

Outliers

Following the development of the *preliminary final multinomial logistic regression model*, diagnostics were performed to determine and eliminate outliers, high leverage values, and highly influential points. An initial review of outlying data points was first performed using the Cox (2017) *extremes* ado module in Stata 17.0. The results are presented in Table 37-38, showing the five highest and five lowest values for each continuous covariate by wave, were compared to those obtained from the diagnostic statistics outlined in Chapter 3 and following an individual logistic regression approach from Begg and Gray (1984). While most statistical packages, including Stata, do not allow for MNLR diagnostics on complex survey data, the abovementioned approach was employed by treating the MNLR as individual logits without survey estimation and weighting effects. Following the procedure provided by Begg and Gray (1984) in combination with that proposed by Hosmer, et al. (2013), which forces the iterative estimation process to start with coefficients from the MNLR analysis and fixes the iteration count to 0 (Hosmer et al., 2013, p. 284), diagnostic graphs of leverage, change in Pearson chi-square, change in deviance, Cook's distance versus estimated probability (see Figures B.4-B.27) revealed a set of outliers that were compared with those in Tables 37-38. Tables 39-41 shows the coefficients, confidence intervals, and percent differences in coefficients using model-based versus design-based analysis approaches for the first wave model results as outlined by Hosmer et al. (p. 241). The results indicate variable coefficients in the simplified model differed between 0-67% with larger coefficient values on S1M8GRADE and X1MGENMATCH. Figure 42 identified 10 covariate patterns with outliers on one or more of the diagnostic statistics. These patterns showed four large values for ΔX^2 and ΔD, one for h, three for ΔX^2, and two more outlying values of $\Delta\beta$ (see Table 42). Each covariate pattern was deleted individually to assess their effect on the overall model. Following their stepwise deletion, Table 42 describes the overall change in the covariate patterns deleted. Since the results indicated a positive association within each model after the deletion of the respective pattern, the decision was made to drop all the outlying data points in the final model.

Additional Assumptions

The remaining additional assumptions for running a multinomial logistic regression analysis hinge on proving linearity amongst the final model covariates. Since Long and Freese (2014) warn against using IIA tests to verify independence of irrelevant alternatives, the analysis was omitted after careful consideration of the recoding of the individual STEM taxonomies (into STEM1 and STEM3 categories). As previously discussed in Chapter 3, these tests may result in a negative χ^2 value, one that Hausmann and McFadden (1984) acknowledge as a limitation to the test and not evidence of a violation of IIA. Long and Freese (2014, p, 408) suggest only using

Table 37. *Outliers for Wave 1*

Variable	Observation Value	Observation Type[a]
Science Identity (X1SCIID)	-1.57	L
	2.15	H
Socioeconomic Status (X1SES)	-1.93	L
	-1.82	L
	-1.75	L
	2.57	H
	2.88	H
Science Utility (X1SCIUTI)	-3.10	L
	1.69	H

[a]Highest outlier is denoted by an "H" and lowest by an "L"

[c]Direct outlying observations are not shown per IES reporting guidelines

Table 38. *Outliers for Wave 2 and Wave 4*

Variable	Observation Value[c]	Observation Type[a]
Science Efficacy (X2SCIEFF)	-2.47	L
	1.64	H
Science Utility (X2SCIUTI)[b]	-.23	L
	.1	H
Science Identity (X2SCIID)	-1.74	L
	1.86	H
Mathematics Identity (X2MTHID)[b]	-1.54	L
	1.82	H
Socioeconomic Status (X1SES)[b]	-1.93	L
	-1.82	L
	-1.75	L
	2.57	H
	2.88	H

[a]Highest outlier is denoted by an "H" and lowest by an "L"

[b]Wave 4 variables

[c]Direct outlying observations are not shown per IES reporting guidelines

models in which the decision maker can distinctively and independently attest to their difference. Therefore, comparing the outlined STEM career models adds to the credibility of independence.

A final assumption analysis will, therefore, check for linearity between continuous covariates on the predicted multinomial logistic regression model results. Following step 4 of Figure 17 and the development of a preliminary effects model, each of the covariates in this model were checked for linearity by plotting a two-way lowess smooth scatter plot for each variable. As depicted in a combined linearity plots in Figures B.1-B.3, all continuous covariates in the study exhibit linearity.

Table 39. *Coefficients and 95% Confidence Intervals - Wave 1 Model 1*

Variable[d]	"Design-Based" Analysis[b]			"Model-Based" Analysis[c]			Pct. Diff. (%)
	Coeff.	95% CI		Coeff.	95% CI		
X1PAREDEXPCT	-.16	-.27	-.05	-.14	-.19	-.09	-14.3
X1STUEDEXPCT	-.35	-.61	-.10	-.38	-.51	-.90	8.6
(Master's Degree)							
(Ph.D./M.D./Prof.)	-.96	-1.2	-.66	-1.04	-1.18	-.90	8.3
S1M8GRADE	.37	.01	.73	.11	-.05	.27	-70.3
(Grade C)							
(Grade D)	.87	.14	1.60	.57	.26	.89	-34.5
X1SCIID_1	-.16	-.23	-.09	-.13	-.16	-.09	-18.8
X1SCIID_2	.10	.05	.16	.08	.06	.10	-20.0
X1SCIUTI	-.39	-.53	-.25	-.35	-.41	-.29	-10.2
X1SEX	-.38	-.60	-.17	-.33	-.45	-.26	-13.1
X1MGENMATCH	-.01	-.26	.26	.02	-.09	.13	100.0

[a] All waves and correlative models by sub-domain (i.e., [1] not a STEM occupation; [2] life and physical science, engineering, mathematics, and information technology occupations; and [3] health occupations).

[b] Design-based analysis include survey estimation and weights.

[c] Model-based analysis exclude survey estimation and weights, performed as a simple random sample.

[d] Control variables disregarded in the analysis

Table 40. *Coefficients and 95% Confidence Intervals - Model for Wave 1 Model 2*

Variable[d]	"Design-Based" Analysis[b]			"Model-Based" Analysis[c]			Pct. Diff. (%)
	Coeff.	95% CI		Coeff.	95% CI		
X1PAREDEXPCT	.12	-.07	.32	.04	-.05	.12	-66.7
X1STUEDEXPCT	.27	-.04	.59	.35	.14	.57	29.6
(Master's Degree)							
(Ph.D./M.D./Prof.)	-.17	-.67	.33	-.20	-.43	.04	17.6
S1M8GRADE	-.04	-.63	.54	-.11	-.39	.16	175.0
(Grade C)							
(Grade D)	-1.24	-2.07	-.42	-.58	-1.15	-.01	7.3
X1SCIID_1	.14	.05	.24	.15	.10	.19	7.1
X1SCIID_2	-.08	-.15	-.01	-.09	-.12	-.05	-12.5
X1SCIUTI	-.09	-.28	.11	.06	-.04	.16	33.3
X1SEX	-1.47	-1.86	-1.08	-1.29	-1.48	-1.11	12.2
X1MGENMATCH	-.07	-.42	.28	-.11	-.28	.07	-57.1

[a] Waves include 1, 2, and 4 with a correlative model 1-4 represented by the STEM occupation sub-domains (i.e., [1] not a STEM occupation; [2] life and physical science, engineering, mathematics, and information technology occupations; and [3] health occupations).

[b] Design-based analysis include survey estimation and weights.

[c] Model-based analysis exclude survey estimation and weights, performed as a simple random sample.

[d] Control variables disregarded in the analysis

Table 41. *Coefficients and 95% Confidence Intervals - Model for Wave 1 Model 3*

Variable[d]	"Design-Based" Analysis[b]			"Model-Based" Analysis[c]			Pct. Diff. (%)
	Coeff.	95% CI		Coeff.	95% CI		
X1PAREDEXPCT	.23	.11	.35	.21	.15	.27	-8.7
X1STUEDEXPCT	.25	-.07	.56	.21	.05	.36	-16.0
(Master's Degree)							
(Ph.D./M.D./Prof.)	1.42	1.14	1.69	1.35	1.20	1.50	-4.9
S1M8GRADE	-.31	-.73	.10	-.15	-.33	.03	51.6
(Grade C)							

(Grade D)	-.61	-1.53	.31	-.30	-.67	.07	-50.8
X1SCIID_1	.08	.01	.15	.07	.03	.10	-12.5
X1SCIID_2	-.06	-.12	-.01	-.05	-.08	-.03	16.7
X1SCIUTI	.43	.27	.58	.38	.31	.45	-11.6
X1SEX	1.12	.90	1.34	1.09	.97	1.22	-2.7
X1MGENMATCH	.03	-.23	.30	-.03	-.15	.09	0.0

[a] Waves include 1, 2, and 4 with a correlative model 1-4 represented by the STEM occupation sub-domains (i.e., [1] not a STEM occupation; [2] life and physical science, engineering, mathematics, and information technology occupations; and [3] health occupations).

[b] Design-based analysis include survey estimation and weights.

[c] Model-based analysis exclude survey estimation and weights, performed as a simple random sample.

[d] Control variables disregarded in the analysis

Table 42. *Subjects with Large Coefficient Values by Logit (1-3) in Waves 1-4*

Subject	Wave	Diagnostic	Deletion Effect
18072	1	Large ΔX^2 and ΔD in Logit 1 and Logit 3	No major effects on the estimates
33977	2	Large h in Logit 1	No major effects on the estimates
33195	2	Large ΔX^2 in Logit 2	No major effects on the estimates
29586	2	Large ΔX^2 in Logit 2	No major effects on the estimates
12597	2	Large ΔX^2 and ΔD in Logit 1 and Logit 3	No major effects on the estimates
33493	2	Large ΔX^2 and ΔD in Logit 3	No major effects on the estimates
33404	2	Large ΔX^2 in Logit 3	No major effects on the estimates
29556	2	Large ΔX^2 and ΔD in Logit 1 and Logit 3	No major effects on the estimates
33099	4	Large $\Delta\beta$ in Logit 1	No major effects on the estimates
28453	4	Large $\Delta\beta$ in Logit 1	No major effects on the estimates

Modeling Results

The data considered in the High School Longitudinal Study of 2009 (HSLS:09) consists of 23 independent variables (13 categorical), two dependent variables (STEM1 and STEM3 occupational expectations at the age of 30), three waves extending from early secondary to mid-postsecondary levels, and a minimum of 3,930 subjects, respective of the wave analyzed, per model. An evaluation of these modeling results was conducted using descriptive, factor, Wald, and marginal effects analysis techniques.

Research Question 1: *What is STEM and how is it defined within education and the workforce?*

Science, Technology, Engineering, and Mathematics is categorized in HSLS:09 using the criteria detailed in Table 43. Six STEM variables outlined by Ingels et al. (2018) follow the BLS SOC sub-domain (*STEM1*) and occupation type (*STEM2*) architecture. For *STEM1* designated variables, these include: (a) life and physical science, engineering, mathematics, and information technology occupations; (b) health occupations; and (c) split across two STEM or STEM-related sub-domains (e.g., social science, architecture, and health occupations). *STEM2* designated variables follow the occupational type designations in the BLS SOC: (a) research, development, design, or practitioner occupations; (b) technologist and technician occupations; (c) postsecondary teaching occupations; (d) managerial occupations; and (e) sales occupations. Although educational data mirrors what is used in workforce predictive models, HSLS:09 does not categorize STEM longitudinally through CIP and BLS SOC crosswalks. This alternative approach for describing STEM career pursuit in the secondary years follows the discovery of a near-STEM perspective in the review of literature. As a result, a new *STEM3* dependent variable was constructed using the 6-digit BLS codes provided by X1/X2/X4STU30OCC6. Both Figure 5 and the CIP-BLS crosswalks were employed as guidelines for the re-categorization of these codes into their respective designations. Table 44 provides a summary statistical data of this “near-STEM” outlook defined by: (a) science, (b) engineering, and (c) non-science and engineering majors/programs of study.

A descriptive evaluation of students with likely STEM career outcomes reveals a clearer image of the participant sample, the differences in expected STEM occupation by perspective, and how the sample changes based on these taxonometric definitions. Figures 43-44 indicate a significant increase in both the far-term ($\Delta n = 610$) and near-term ($\Delta n = 80$) career outlooks between the 9th-grade and 11th-grade years. By running descriptive statistics (frequencies and proportions) on the student sample between these years by race, ethnicity, and gender the results in Tables 43-44 and Figures A.1-A.2 were generated. What is revealed by the data are significant drops overall between the secondary and postsecondary years (9th-grade through early postsecondary years; $\Delta n = -2{,}370$; $\Delta n = -950$). Proportional numbers additionally show a 36% and 39% drop in expected STEM outcomes, respectfully (Figures A.1-A.2).

Table 43. *Descriptive Statistics for STEM code 1 – Sub-Domain Type (Far Term)*

Dependent Variable	Category	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
X1STU30OCC_STEM1	Not a STEM Occupation	13,970	55.4	65.95
	Life and Physical Science, Engineering, Info. Tech	1,730	6.9	8.33
	Health Occupations	4,350	17.3	19.44
	Split Across 2 Sub-Domains	410	1.6	1.98
	Missing/Non-Response/ Don’t Know	4,750	18.8	4.30
X2STU30OCC_STEM1	Not a STEM Occupation	12,990	51.5	63.82
	Life and Physical Science, Engineering, Info. Tech	1,880	7.5	9.20
	Health Occupations	4,620	18.3	21.58

	Split Across 2 Sub-Domains	600	2.4	3.07
	Missing/Non-Response/ Don't Know	5,120	20.3	2.33
X4OCC30STEM1	Not a STEM Occupation	6,540	25.9	37.82
	Life and Physical Science, Engineering, Info. Tech	1,190	4.7	6.56
	Health Occupations	2,650	10.5	14.22
	Split Across 2 Sub-Domains	280	1.1	1.79
	Missing/Non-Response/ Don't Know	14,550	37.7	39.61

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] Rounded per IES data security requirements.

Table 44. *Descriptive Statistics for STEM code 3 – Sub-Domain Type (Near Term)*

Dependent Variable	Category	Frequency Unweighted[b]	Percent Unweighted[b]	Percent Weighted[a]
X1STU30OCC_STEM3	Not a STEM Major	12,260	48.7	57.72
	Science	840	3.3	3.85
	Engineering	710	2.8	3.24
	Non-Science & Engineering	890	3.5	4.43
	Missing/Non-Response/ Don't Know	10,500	41.7	30.76
X2STU30OCC_STEM3	Not a STEM Major	12,050	47.8	58.94
	Science	800	3.2	3.84
	Engineering	960	3.8	4.68
	Non-Science & Engineering	760	3.0	3.95
	Missing/Non-Response/ Don't Know	10,640	43.9	28.59
X4OCC30STEM3	Not a STEM Major	9,190	36.5	52.15
	Science	470	1.9	2.69
	Engineering	530	2.1	2.70
	Non-Science & Engineering	500	2.0	2.96

Missing/Non-Response/ Don't Know	14,530	57.6	39.49

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] Rounded per IES data security requirements.

An evaluation of Tables A.4 – A.7 by race and gender reveals similar proportional trends between African American and Latin American participants. As the waves increase into the postsecondary years, there is a 2% jump in the proportion of European American participants whereas participants of color (including African American and Latin American students) remained at steady proportions.

Research Question 2: *What combination of influencing factors across student characteristic groupings contribute to expected STEM pursuit across secondary and postsecondary levels of education?*

The combination of influencing factors predicting student anticipated STEM career outlooks was evaluated using the multinomial logistic regression models. Six final models were developed across three waves of longitudinal data (secondary and postsecondary waves) and two STEM taxonomies for career expectations, the near-term (*STEM3*) and far-term (*STEM1*). Following the detailed, iterative process outlined in Chapter 3, and Figure 17, a set of final models was obtained and is described in Tables 46-51. The decision to accept these models was made after individually testing model logits for fit using Receiver Operating Curves (ROCs)[17] and comparing the results across the specialized diagnostic measures described in Chapter 3. The challenge with running diagnostic and fit tests is well-documented (Hosmer et al., 2013, pp. 284-287). However, following accepted procedures from Hosmer et al. (2013, pp. 233-242) an acceptable to excellent

[17] An ROC analysis was chosen as a test for fit since the study focuses on estimated probabilities – the expectation of choosing a STEM career at the age of 30.

discrimination of fit was obtained. After a thorough evaluation of each model for fit and diagnostics the logit covariate coefficients were compared to the MNLR models using a percent difference formula. The results are displayed and categorized in Table 39-41 as “design-based” and “model-based” analyses.

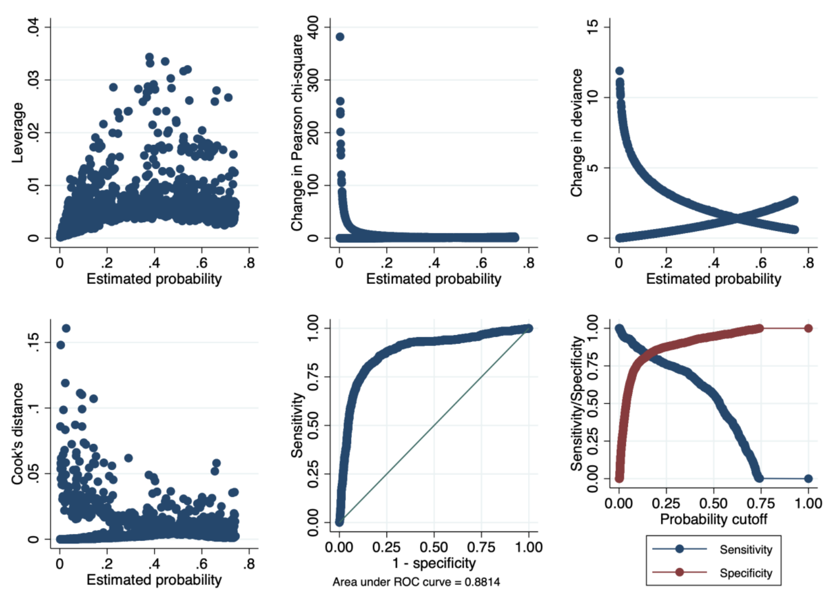
Each fit and diagnostic test result is presented formally in Figures B.4 – B.27. Figure 19 provides an example of an “excellent” discrimination of fit (Hosmer et al., 2013) as well as four diagnostic tests. As shown in the Appendix B figures, each ROC curve maintains an area greater than .70, which represents an acceptable discrimination between each STEM career category (Hosmer et al., 2013, p. 177), and has the characteristic left-right/right-left crossing curves without outliers. The first two waves of models have a high acceptable discrimination, whereas the final wave (post-secondary) model indicates an excellent discrimination (ROC > .80). The remaining graphs in Figures B.4-B.27 provide the MNLR diagnostics for goodness of fit[18]. Leverage (h), change in Pearson chi-square (ΔX^2), change in deviance (ΔD), and cook’s distance ($\Delta\beta$) versus the model estimated probability (π) are shown (left-right and top-down, respectively) in Figures B.4-B.27. The shapes of plots ΔX^2 and ΔD are distinguished by to crossing quadratic-like curves that correspond to the two distinct covariates with $y \geq 1$ (left to right) and $y = 0$ (right to left). Similarly, the plot of $\Delta\beta$ illustrates the same pattern and contains values less than 1.0 (Hosmer et al., p. 197) after their identification (see Table 42) and their removal. This influence diagnostic is critical in determining outlying values and their effect on the model. With diagnostic and fit measures in-line with the expected results, it can be concluded that the *STEM1* model provides a

[18] A Hosmer-Lemeshow goodness of fit test was not included in the analysis due to its high dependency on variable groupings in complex survey data (Long and Freese, 2013, pp. 223-224).

good approximation of the longitudinal changes in student expectations of a STEM career by the age of 30.

Following the analysis of a "far-term" STEM1 taxonomy, the same covariate sets were then fitted to a "near-term" STEM3 perspective[19]. The results from the fit and diagnostics are shown in Figures B.4-B.20. Using the same taxonomy of STEM pursuit to this group of participants resulted in half the models (e.g., model 2 science and model 4 non-science and engineering) falling below the discrimination threshold of .70. Model 3 (engineering), however, maintained a discrimination value greater than .80 which illustrates "excellent discrimination" in the logit. The split-alignment between the fitted models for different taxonomies of expected STEM career at the age of 30 highlight how specific subjects or career foci affect model convergence by the students' individual perspective. Additionally, the similar convergence of engineering models across both taxonomies acknowledges similarities in curriculum and outlooks.

Figure 19. *Individual Logit Fit and Diagnostics of STEM1 – Wave 4 Model 2*



[19] The STEM3 variable was developed specifically for this study using the synthesized taxonometric approach in Figure 5.

__Table 45.__ MNLR Final Model Results on Expected STEM Career Outcomes at 30

Taxonomy	Wave	*F*	Degrees of Freedom		*p*
			df1[a]	df2[a]	
STEM1	1	30.54	50	160	<.001
	2	25.91	50	150	<.001
	4	17.96	40	150	<.001
STEM3[b]	1	7.88	50	150	<.001
	2	11.55	50	150	<.001
	4	17.96	40	150	<.001

[a] Rounded per IES data security requirements.

[b] Developed as a near-STEM outcome from HSLS:09 X1/X2/X4STU30OCC6 variables using Figure 5 and the BLS-SOC/CIP crosswalks as a guideline.

Table 45 provides a statistical summary of the two taxonomies used to predict expected STEM careers at the age of 30. What emerges across each wave is the varied significance in predictor variables for student expectations of a STEM career (see Tables 46-51). Whereas a linear pipeline model for describing STEM career pursuit was initially built around educational policies that subsumes a consistency of student factors, it excludes the evolving student dynamic that is revealed across the three waves of results. For example, in the students' 9th grade year science identity, science utility (wave 1: $t = 2.77$, p = .006; wave 2: $t = 5.64$, p < .001), gender, and parent-student expectations for graduate school or higher predict early anticipated STEM occupations. However, moving into the 11th grade year science efficacy, math identity, science utility (wave 1: $t = 5.02$, p < .001; wave 2: $t = 7.92$, p < .001), gender matching, and teacher gender bias emerge as model predictors. Finally, at the post-secondary level a shift in predictors shows a strong evolution in student expectations of a STEM career. Teacher gender bias remains as a significant covariate (wave 1: $t = 2.09$, p = .028; wave 2: $t = 2.46$, p = .015) along with parent expectations, STEM major (or those considering a STEM major), gender, science utility, and math identity in the 11th-grade year.

Table 46. *MNLR for Expected Occupation at Age 30 (X1STU30OCC_STEM1)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	X1PAREDEXPCT	1.01	.01	.075	.20	.845	-.13	.16
	X1STUEDEXPCT							
	Master's Degree	1.16	.15	.209	.73	.468	-.26	.56
	Ph.D./M.D./Prof.	.78	-.25	.223	-1.10	.272	-.69	.19
	X1SCIID_1 [a]	**1.30**	.26	.041	**6.48**	**<0.001**	.18	.34
	X2SCIID_2 [a]	**.84**	-.17	.030	**-5.49**	**<0.001**	-.23	-.11
	S1M8GRADE							
	B	.71	-.34	.218	-1.54	.125	-.77	.09
	C	.59	-.54	.329	-1.63	.105	-1.2	.11
	D	**.18**	-1.71	.585	**-2.93**	**.004**	-2.87	-.56
	Below D	.76	-.28	3.08	-.09	.929	-6.35	5.8
	X1SES	1.05	.05	.099	.50	.615	-.15	.24
	X1SCIUTI	**1.28**	.25	.089	**2.77**	**.006**	.07	.42
	X1SEX	**.62**	-.47	.193	**-2.47**	**.015**	-.85	-.10
	X1RACE							
	Black/African Am.	.55	-.59	.493	-1.20	.233	-1.56	.38
	Hispanic/Latin Am.	.84	-.18	.435	-.41	.684	-1.04	.68
	White/Euro. Am.	.76	-.27	.384	-.71	.481	-1.02	.49
	Constant	.16	-1.85	.582	**-3.18**	**.002**	-3.00	-.70
2	**X1PAREDEXPCT**	**1.27**	.24	.067	**3.61**	**<.001**	.11	.37
	X1STUEDEXPCT							
	Master's Degree	**1.41**	.34	.157	**2.17**	**.031**	.03	.65
	Ph.D./M.D./Prof.	**4.16**	1.43	.160	**8.91**	**<.001**	1.11	1.74
	X1SCIID_1 [a]	**1.27**	.12	.041	**2.92**	**.004**	.04	.20
	X2SCIID_2 [a]	**.92**	-.09	.030	**-2.87**	**.005**	-.15	-.03
	S1M8GRADE							
	B	1.00	.004	.127	.03	.977	-.25	.25
	C	.67	-.41	.226	-1.80	.073	-.85	.04

	D	.45	-.79	.469	-1.68	.094	-1.71	.14
	Below D	.74	-.31	.733	-.42	.676	-1.75	1.14
	X1SES	.97	-.03	.097	-.32	.753	-.22	.16
	X1SCIUTI	**1.63**	.49	.087	**5.64**	**<.001**	.32	.66
	X1SEX	**2.69**	.99	.12	**8.08**	**<.001**	.75	1.23
	X1RACE							
	Black/African Am.	.94	-.06	.28	-.23	.821	-.61	.48
	Hispanic/Latin Am.	1.06	.06	.28	.22	.829	-.49	.61
	White/Euro. Am.	1.21	.19	.20	.94	.350	-.21	.59
	Constant	.06	-2.85	.36	**-7.91**	**<.001**	-3.56	-2.14
3	X1PAREDEXPCT	1.07	.07	.16	.40	.691	-.26	.39
	X1STUEDEXPCT							
	Master's Degree	**2.54**	.93	.41	**2.29**	**.023**	.13	1.73
	Ph.D./M.D./Prof.	**2.54**	.93	.40	**2.32**	**.021**	.14	1.72
	X1SCIID_1 [a]	1.16	.15	.09	1.70	.090	-.02	.31
	X2SCIID_2 [a]	.90	-.11	.07	-1.65	.100	-.24	.02
	S1M8GRADE							
	B	.67	-.39	.29	-1.34	.182	-.97	.19
	C	.42	-.86	.44	-1.94	.054	-1.73	.01
	D	.55	-.60	14.68	-.04	.976	-29.56	28.35
	Below D	**<.001**	-20.26	1.21	**-16.70**	**<.001**	-22.66	-17.87
	X1SES	.98	-.023	.21	-.11	.913	-.44	.39
	X1SCIUTI	1.26	.23	.13	1.82	.070	-.02	.48
	X1SEX	.60	-.52	.30	-1.74	.083	-1.10	.07
	X1RACE							
	Black/African Am.	.34	-1.07	2.61	-.41	.682	-6.22	4.08
	Hispanic/Latin Am.	2.02	.70	.52	1.36	.175	-.32	1.72
	White/Euro. Am.	1.38	.32	.44	.73	.466	-.55	1.19
	Constant	.03	-3.60	.69	**-5.20**	**<.001**	-4.97	-2.23

[a] Fitted using fractal polynomials

Table 47. *MNLR for Expected Occupation at Age 30 (X2STU30OCC_STEM1)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	X2SCIEFF	1.12	.11	.099	1.12	.263	-.08	.21
	X2SCIUTI	‡	6.54	1.304	**5.02**	**<.001**	3.97	9.11
	X2SCIID	1.54	.43	.445	.97	.336	-.45	1.31
	X2MTHID	**1.52**	.42	.082	**5.13**	**<.001**	.26	.58
	S1MTCHMFDIFF	.73	-.31	.276	-1.13	.259	-.86	.23
	X1MGENMATCH	1.20	.19	.138	1.35	.179	-.09	.46
	X1SEX	**.52**	-.66	.149	**-4.44**	**<.001**	-.95	-.37
	X1STUEDEXPCT							
	Master's Degree	**1.55**	.43	.147	**2.95**	**.004**	.14	.73
	Ph.D./M.D./Prof.	1.15	.14	.202	.69	.489	-.26	.54
	X1SES	1.11	.11	.081	1.33	.184	-.05	.27
	X1RACE							
	Black/African Am.	.71	-.35	.337	-1.04	.302	-1.01	.32
	Hispanic/Latin Am.	.95	-.05	.305	-.16	.872	-.65	.55
	White/Euro. Am.	.90	-.10	.205	-.51	.612	-.50	.30
	S1M8GRADE*X2SCIID							
	A	1.26	.23	.468	.49	.621	-.69	1.15
	B	1.15	.14	.461	.31	.760	-.77	1.05
	C	1.10	.09	.511	.18	.854	-.91	1.10
	D	.75	-.28	.600	-.47	.636	-1.46	.90
	X2SCIEFF*X2SCIID	.93	-.07	.077	-.91	.364	-.22	.08
	Constant	.17	-1.79	.362	**-4.95**	**<.001**	-2.50	-1.08
2	X2SCIEFF	.89	-.11	.057	-1.97	.050	-.22	.01
	X2SCIUTI	‡	7.82	.99	**7.92**	**<.001**	5.88	9.77
	X2SCIID	1.70	.53	.32	1.64	.102	-.11	1.17
	X2MTHID	1.06	.05	.042	1.31	.190	-.03	.14
	S1MTCHMFDIFF	1.17	.16	.161	1.00	.317	-.16	.48
	X1MGENMATCH	1.18	.16	.093	1.76	.080	-.020	.35
	X1SEX	**3.61**	1.28	.101	**12.77**	**<.001**	1.09	1.48
	X1STUEDEXPCT							
	Master's Degree	**1.60**	.47	.118	**4.00**	**<.001**	.24	.70

	Ph.D./M.D./Prof.	**3.92**	1.37	.149	**9.17**	**<.001**	1.07	1.66
	X1SES	.89	-.12	.065	-1.80	.074	-.25	.01
	X1RACE							
	Black/African Am.	1.31	.27	.213	1.27	.206	-.15	.69
	Hispanic/Latin Am.	1.32	.28	.197	1.42	.157	-.11	.67
	White/Euro. Am.	1.15	.14	.157	.88	.381	-.17	.45
	S1M8GRADE*X2SCIID							
	A	.93	-.07	.334	-.21	.833	-.73	.59
	B	.91	-.09	.332	-.28	.778	-.75	.56
	C	.86	-.15	.352	-.43	.666	-.85	.54
	D	.68	-.38	.414	-.92	.360	-1.20	.44
	X2SCIEFF*X2SCIID	.98	-.02	.050	-.44	.662	-.12	.08
	Constant	.07	-2.64	.24	**-11.08**	**<.001**	-3.12	-2.17
3	X2SCIEFF	1.03	.03	.112	.23	.820	-.20	.25
	X2SCIUTI	21.36	3.06	1.73	1.77	.078	-.34	6.46
	X2SCIID	1.67	.51	.299	1.70	.090	-.08	1.10
	X2MTHID	1.02	.02	.116	.13	.897	-.21	.24
	S1MTCHMFDIFF	1.44	.37	.294	1.25	.214	-.21	.95
	X1MGENMATCH	1.05	.05	.204	.24	.812	-.35	.45
	X1SEX	1.44	.37	.204	.24	.812	-.35	.45
	X1STUEDEXPCT							
	Master's Degree	**3.47**	1.24	.247	**5.05**	**<.001**	.76	1.73
	Ph.D./M.D./Prof.	**3.89**	1.36	.269	**5.07**	**<.001**	.83	1.89
	X1SES	**.74**	-.30	.15	**-2.00**	**.047**	-.60	-.01
	X1RACE							
	Black/African Am.	.69	-.38	.484	-.78	.439	-1.33	.580
	Hispanic/Latin Am.	1.25	.23	.448	.50	.614	-.658	1.11
	White/Euro. Am.	1.13	.12	.337	.36	.719	-.545	.79
	S1M8GRADE*X2SCIID							
	A	.66	-.41	.331	-1.25	.213	-1.07	.24
	B	.56	-.59	.366	-1.60	.111	-1.31	.14
	C	.39	-.95	.513	-1.84	.067	-1.96	.07
	D	.59	-.53	.440	-1.20	.231	-1.40	.34

	X2SCIEFF*X2SCIID	.98	-.02	.099	-.23	.816	-.22	.17
	Constant	.02	-4.11	.476	**-8.63**	**<.001**	-5.05	-3.17

‡ Data not meeting IES standards for reporting (standard errors > 70% of the recorded value).

Table 48. *MNLR for Expected Occupation at Age 30 (X4OCC30STEM1)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	**X4RFDGMJ123[a]**	**.43**	-.84	.118	**-7.15**	**<.001**	-1.07	-.61
	X1SES	1.04	.04	.144	.27	.789	-.25	.32
	X1SEX	.80	-.22	.266	-.84	.405	-.75	.30
	X1PAREDEXPCT							
	Ph.D./M.D./Prof.	.99	-.01	.247	-.05	.957	-.50	.47
	S1MTCHMFDIFF	**3.61**	1.28	.614	**2.09**	**.038**	.07	2.49
	X2SCIUTI	18.72	2.93	2.127	1.38	.170	-1.27	7.12
	S3FIELD_STEM							
	Considering a STEM Major	**5.17**	1.64	.317	**5.18**	**<.001**	1.02	2.27
	X1MGENMATCH	.87	-.14	.242	-.56	.576	-.61	.34
	X2MTHID	**1.34**	.29	.093	**3.15**	**.002**	.11	.48
	X1SEX*S1MTCHMFDIFF	4.63	1.53	1.04	1.47	.143	-.52	3.59
	X2SCIUTI*X1SES	.73	-.32	1.97	-.16	.872	-.422	.34
	X1RACE							
	Black/African Am.	.75	-.29	.63	-.47	.642	-1.53	.94
	Hispanic/Latin Am.	.67	.40	.39	-1.01	.315	-1.18	.38
	White/Euro. Am.	.90	-.10	.26	-.40	.688	-.62	.41
	Constant	.16	-1.81	.724	**-2.50**	**.013**	-3.24	-.38
2	**X4RFDGMJ123[a]**	**.50**	-.69	.060	**-11.62**	**<.001**	-.81	-.58
	X1SES	1.00	-.01	.105	-.03	.977	-.210	.204
	X1SEX	**3.42**	1.23	.193	**6.37**	**<.001**	.85	1.61
	X1PAREDEXPCT							
	Ph.D./M.D./Prof.	**1.84**	.61	.159	**3.84**	**<.001**	.30	.92
	S1MTCHMFDIFF	**3.16**	1.15	.468	**2.46**	**.015**	.23	2.07
	X2SCIUTI	‡	5.91	1.39	**4.25**	**<.001**	3.17	8.65
	S3FIELD_STEM							
		.66	-.41	.249	-1.66	.098	-.904	.08

	Considering a STEM Major							
	X1MGENMATCH	.75	-.29	.184	-1.53	.127	-.64	.08
	X2MTHID	1.04	.04	.077	.47	.636	-.11	.19
	X1SEX*S1MTCHMFDIFF	4.67	2.24	1.441	1.56	.122	-.601	5.08
	X2SCIUTI*X1SES	9.40	2.24	1.441	1.56	.122	-.65	.08
	X1RACE							
	Black/African Am.	.61	-.50	.349	-1.44	.152	-1.19	.19
	Hispanic/Latin Am.	.52	-.66	.264	-2.48	.014	-1.18	-.14
	White/Euro. Am.	.64	-.44	.189	-2.35	.020	-.82	-.07
	Constant	.37	-1.00	.482	**-2.08**	**.039**	-1.95	-.05
3	**X4RFDGMJ123[a]**	**.60**	-.51	.103	**-4.98**	**<.001**	-.72	-.31
	X1SES	1.22	.20	.236	.83	.410	-.27	.66
	X1SEX	1.06	.06	.430	.14	.886	-.787	.91
	X1PAREDEXPCT			.				
	Ph.D./M.D./Prof.	1.73	.55	358	1.52	.130	-.16	1.25
	S1MTCHMFDIFF	2.92	.66	6.157	.11	.915	11.48	12.80
	X2SCIUTI	64.99	4.17	3.70	1.13	.261	-3.13	11.48
	S3FIELD_STEM							
	Considering a STEM Major	.83	-.28	.571	-.49	.624	-1.41	.85
	X1MGENMATCH	1.14	.13	.305	.44	.662	-.47	.74
	X2MTHID	.83	-.19	.187	-1.02	.310	-.56	.18
	X1SEX*S1MTCHMFDIFF	2.92	1.07	6.66	.16	.872	-12.07	14.21
	X2SCIUTI*X1SES	.88	-2.47	4.27	-.58	.563	10.90	5.95
	X1RACE							
	Black/African Am.	.47	-.76	.685	-1.12	.266	-2.12	.587
	Hispanic/Latin Am.	.61	-.50	.779	-.64	.524	-2.04	1.04
	White/Euro. Am.	.50	-.70	.409	-1.70	.090	-1.50	.11
	Constant	.14	-1.94	6.306	-.31	.759	-14.37	10.50

[a] Coded as a comparison from traditional STEM majors

‡ Data not meeting IES standards for reporting (standard errors > 70% of the recorded value).

Table 49. *MNLR for Expected Occupation at Age 30 (X1STU30OCC_STEM3)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	X1PAREDEXPCT	1.03	.025	.098	.26	.796	-.167	.218
	X1STUEDEXPCT							
	Master's Degree	1.54	.430	.280	1.54	.126	-.122	.981
	Ph.D./M.D./Prof.	.97	-.028	.308	-.09	.927	-.636	.580
	X1SCIID_1[a]	**1.21**	.190	.056	**3.38**	**.001**	.079	.301
	X2SCIID_2[a]	**.90**	-.110	.041	**-2.65**	**.009**	-.191	-.028
	S1M8GRADE							
	B	1.00	.005	.247	.02	.984	-.482	.493
	C	1.21	.189	.334	.56	.573	-.470	.847
	D	.41	-.888	2.947	-.30	.764	-6.699	4.924
	Below D	.39	-.929	13.531	-.07	.945	-27.611	25.753
	X1SES	.87	-.139	.120	-1.16	.248	-.375	.097
	X1SCIUTI	1.03	-.031	.103	.30	.766	-.172	.233
	X1SEX	.94	-.064	.179	-.36	.722	-.418	.290
	X1RACE							
	Black/African Am.	.33	-1.094	.601	-1.82	.070	-2.278	.091
	Hispanic/Latin Am.	.93	-.074	.478	-.15	.877	-1.017	.869
	White/Euro. Am.	1.04	.039	.270	.15	.884	-.494	.572
	Constant	**.03**	-3.688	.421	**-8.76**	**<.001**	-4.518	-2.858
2	X1PAREDEXPCT	1.09	.084	.106	.79	.430	-.126	.294
	X1STUEDEXPCT							
	Master's Degree	1.03	.030	.222	.13	.894	-.409	.468
	Ph.D./M.D./Prof.	**.34**	-1.088	.340	**-3.20**	**.002**	-1.758	-.419
	X1SCIID_1[a]	**1.24**	.212	.059	**3.58**	**<.001**	.095	.328
	X2SCIID_2[a]	**.88**	-.130	.043	**-3.05**	**.003**	-.215	-.046
	S1M8GRADE							
	B	.56	-.574	.308	-1.86	.064	-1.182	.033
	C	**.20**	-1.633	.519	**-3.14**	**.002**	-2.657	-.609
	D	02	-3.704	5.006	-.74	.460	-13.576	6.169
	Below D	1.03	.031	4.802	.01	.995	-9.438	9.500
	X1SES	1.28	.246	.138	1.78	.076	-.026	.519

	X1SCIUTI	1.12	.118	.107	1.10	.272	-.093	.329
	X1SEX	**.08**	-2.495	.271	**-9.20**	**<.001**	-3.029	-1.960
	X1RACE							
	Black/African Am.	1.68	.518	.564	.92	.359	-.593	1.630
	Hispanic/Latin Am.	2.58	.950	.524	1.81	.071	-.083	1.983
	White/Euro. Am.	1.14	.127	.346	.37	.713	-.554	.809
	Constant	.06	-2.875	.539	**-5.33**	**<.001**	-3.938	-1.812
3	X1PAREDEXPCT	.88	-.124	.106	-1.16	.246	-.334	.086
	X1STUEDEXPCT							
	Master's Degree	1.40	.337	.346	.98	.330	-.344	1.019
	Ph.D./M.D./Prof.	.58	-.553	.339	-1.63	.104	-1.22	.115
	X1SCIID_1 [a]	**1.18**	.167	.050	**3.37**	**.001**	.070	.265
	X2SCIID_2 [a]	**.89**	-.113	.0383	**-3.01**	**.003**	-.188	-.039
	S1M8GRADE							
	B	.74	-.296	.221	-1.34	.183	-.733	.141
	C	.90	-.100	.427	-.23	.815	-.942	.742
	D	.60	-.519	2.280	-.23	.820	-5.016	3.978
	Below D	.38	-.975	13.778	-.07	.944	-28.144	26.194
	X1SES	1.12	.109	.127	.86	.391	-.142	.361
	X1SCIUTI	1.09	.084	.102	.82	.414	-.118	.285
	X1SEX	.66	-.415	.244	-1.70	.091	-.896	.066
	X1RACE							
	Black/African Am.	.30	-1.219	.697	-1.75	.082	-2.594	.156
	Hispanic/Latin Am.	.56	-.574	.604	-.95	.343	-1.764	.616
	White/Euro. Am.	.51	.683	.582	-1.17	.242	-1.831	.465
	Constant	.17	-1.759	.831	**-2.12**	**.035**	-3.398	-.121

[a] Fitted using fractal polynomials

Table 50. *MNLR for Expected Occupation at Age 30 (X2STU30OCC_STEM3)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	X2SCIEFF	1.02	.024	.114	.21	.831	-.200	.248
	X2SCIUTI	8.30	2.117	1.854	1.14	.255	-1.539	5.772
	X2SCIID	2.10	.744	.487	1.53	.129	-.218	1.705
	X2MTHID	**.76**	-.278	.102	**-2.72**	**.007**	-.479	-.077
	S1MTCHMFDIFF	1.11	.104	.335	.31	.756	-.555	.764
	X1MGENMATCH	1.02	.017	.159	.11	.915	-.297	.331
	X1SEX	**.97**	-.025	.197	-.13	.898	-.414	.362
	X1STUEDEXPCT							
	Master's Degree	**2.35**	.852	.233	**3.66**	**<.001**	.394	1.311
	Ph.D./M.D./Prof.	**1.81**	.594	.253	**2.34**	**.020**	.094	1.093
	X1SES	1.03	.025	.110	.23	.817	-.191	.242
	X1RACE							
	Black/African Am.	.67	-.402	.385	-1.04	.298	-1.161	.357
	Hispanic/Latin Am.	.74	-.306	.335	-.91	.363	-.967	.355
	White/Euro. Am.	1.01	.008	.248	.03	.974	-.482	.498
	S1M8GRADE*X2SCIID							
	A	.71	-.344	.483	-.71	.477	-1.295	.608
	B	.67	-.397	.490	-.81	.420	-1.364	.571
	C	.40	-.925	.590	-1.57	.119	-2.088	.239
	D	.43	-.834	.530	-1.57	.117	-1.881	.212
	X2SCIEFF*X2SCIID	1.09	.088	.072	1.22	.223	-.054	.230
	Constant	.04	-3.232	.472	**-6.85**	**<.001**	-4.163	-2.301
2	X2SCIEFF	1.31	.270	.141	1.92	.056	-.007	.548
	X2SCIUTI	‡	7.381	1.982	**3.72**	**<.001**	3.473	11.290
	X2SCIID	.88	-.131	.309	-.43	.671	-.740	.477
	X2MTHID	**1.85**	.617	.156	**3.97**	**<.001**	.311	.924
	S1MTCHMFDIFF	.55	-.698	.423	-1.42	.159	-1.432	.235
	X1MGENMATCH	1.16	.152	.173	.88	.381	-.190	.494
	X1SEX	**.15**	-1.894	.235	**-8.07**	**<.001**	-2.357	-1.432
	X1STUEDEXPCT							
	Master's Degree	1.34	.289	.204	1.42	.158	-.113	.691

	Ph.D./M.D./Prof.	**.46**	-.784	.324	-2.42	.017	-1.422	-.144
	X1SES	**1.44**	.363	.127	**2.86**	**.005**	.1112	.614
	X1RACE							
	Black/African Am.	.63	-.469	.478	-.98	.328	-1.411	.473
	Hispanic/Latin Am.	1.22	.196	.468	.42	.676	-.726	1.118
	White/Euro. Am.	.84	-.174	.292	-.59	.553	-.750	.403
	S1M8GRADE*X2SCIID							
	A	1.68	.518	.304	1.71	.089	-.080	1.117
	B	1.30	.259	.303	.86	.393	-.338	.857
	C	1.29	.253	.574	.44	.660	-.878	1.384
	D	.71	-.346	.545	-.64	.526	-1.420	.728
	X2SCIEFF*X2SCIID	.88	-.129	.090	-1.43	.154	-.306	.049
	Constant	.17	-1.771	.605	**-2.93**	**.004**	-2.964	-.577
3	X2SCIEFF	1.05	.049	.130	.38	.706	-.208	.306
	X2SCIUTI	.77	-.258	1.676	-.15	.878	-3.562	3.046
	X2SCIID	1.30	.261	.463	.56	.573	-.651	1.174
	X2MTHID	**1.67**	.514	.098	**5.23**	**<.001**	.320	.709
	S1MTCHMFDIFF	.98	-.023	.306	-.07	.941	-.627	.582
	X1MGENMATCH	.94	-.066	.187	-.35	.725	-.436	.304
	X1SEX	**.35**	-1.041	.193	**-5.41**	**<.001**	-1.421	-.661
	X1STUEDEXPCT							
	Master’s Degree	1.36	.309	.201	1.54	.126	-.088	.706
	Ph.D./M.D./Prof.	**.55**	-.602	.248	**-2.43**	**.016**	-1.091	-.114
	X1SES	.93	-.073	.144	-.51	.611	-.358	.211
	X1RACE							
	Black/African Am.	.66	-.419	.391	-1.07	.285	-1.189	.352
	Hispanic/Latin Am.	.95	-.052	.348	-.15	.882	-.738	.635
	White/Euro. Am.	.82	-.192	.238	-.81	.419	-.661	.276
	S1M8GRADE*X2SCIID							
	A	1.04	.035	.475	.07	.941	-.902	.972
	B	.91	-.089	.482	-.19	.853	-1.040	.861
	C	1.31	.271	.533	.51	.612	-.780	1.323
	D	1.17	.159	.674	.24	.814	-1.171	1.489

	X2SCIEFF*X2SCIID	.97	-.029	.088	-.33	.744	-.203	.145
	Constant	.11	-2.227	.364	**-6.11**	**<.001**	-2.945	-1.508

‡ Data not meeting IES standards for reporting (standard errors > 70% of the recorded value).

Table 51. *MNLR for Expected Occupation at Age 30 (X4OCC30STEM3)*

Logit	Covariate	OR	Coeff.	Std. Err.	t	p	95% CI	
1	**X4RFDGMJ123[a]**	**.69**	-.369	.090	**-4.12**	**<.001**	-.546	-.192
	X1SES	.82	-.195	.172	-1.13	.259	-.534	
	X1SEX	.79	-.230	.283	-.81	.418	-.788	.328
	X1PAREDEXPCT							
	Ph.D./M.D./Prof.	1.13	.121	.323	.38	.708	-.516	.758
	S1MTCHMFDIFF	2.33	.844	.849	.99	.322	-.831	2.52
	X2SCIUTI	3.50	1.25	1.88	.67	.505	-2.45	4.96
	S3FIELD_STEM							
	Considering a STEM Major	**2.18**	.77	.330	**2.36**	**.019**	.127	1.43
	X2MTHID	.95	-.054	.121	-.45	.655	-.292	.184
	X1SEX*S1MTCHMFDIFF	2.48	.907	1.01	.90	.371	-1.086	2.900
	X1RACE							
	Black/African Am.	.55	-.606	.481	-1.26	.209	-1.553	.342
	Hispanic/Latin Am.	.72	-.333	.564	-.59	.555	-1.445	.778
	White/Euro. Am.	.86	-.156	.352	-.44	.658	-.849	.537
	Constant	.07	-2.593	.902	-2.88	.004	-4.371	-.815
2	**X4RFDGMJ123[a]**	**.27**	-1.319	.487	**-2.70**	**.008**	-2.283	-.356
	X1SES	1.19	.178	.173	1.03	.306	-.164	.519
	X1SEX	**.35**	-1.063	.356	**-4.15**	**<.001**	-1.568	-.558
	X1PAREDEXPCT							
	Ph.D./M.D./Prof.	.73	-.321	.245	-1.31	.192	-.805	.162
	X2SCIUTI	1.98	.682	2.017	.34	.735	-3.29	4.66
	S3FIELD_STEM							
	Considering a STEM Major	**5.77**	1.753	.370	**4.74**	**<.001**	1.024	2.482
	X2MTHID	**1.82**	.596	.124	**4.83**	**<.001**	1.024	2.482
	X1SEX*S1MTCHMFDIFF	7.04	1.951	2.400	.81	.417	-2.783	6.686

	X1RACE							
	Black/African Am.	.99	-.006	.740	-.01	.993	-1.466	1.453
	Hispanic/Latin Am.	1.52	.418	.513	.82	.416	-.593	1.430
	White/Euro. Am.	1.24	.214	.330	.65	.518	-.438	.865
	Constant	.03	-3.413	.865	-3.95	<.001	-5.120	-1.707
3	**X4RFDGMJ123[a]**	**.63**	-.464	.136	**-3.41**	**.001**	-.733	-.196
	X1SES	1.21	.193	.151	1.27	.205	-.106	.491
	X1SEX	**.39**	-.949	.332	**-2.86**	**.005**	-1.602	-.295
	X1PAREDEXPCT							
	Ph.D./M.D./Prof.	.612	-.491	.331	-1.48	.139	-1.144	.162
	S1MTCHMFDIFF	1.52	.419	.834	.50	.616	-1.227	2.066
	X2SCIUTI	.13	-2.052	2.362	-.87	.386	-6.712	2.607
	S3FIELD_STEM							
	Considering a STEM Major	**4.54**	1.512	.433	**3.50**	**.001**	.659	2.366
	X2MTHID	1.12	.116	.155	.74	.457	-.191	.422
	X1SEX*S1MTCHMFDIFF	.44	-.826	6.719	-.12	.902	-14.077	12.425
	X1RACE							
	Black/African Am.	2.02	.701	.764	.92	.360	-.805	2.207
	Hispanic/Latin Am.	.79	-.235	.649	-.36	.718	-1.1514	1.044
	White/Euro. Am.	1.00	.000	.270	<.00	1.000	-.533	.533
	Constant	.08	-2.548	1.046	-2.44	.016	-4.610	-.485

[a] Coded as a comparison from traditional STEM majors

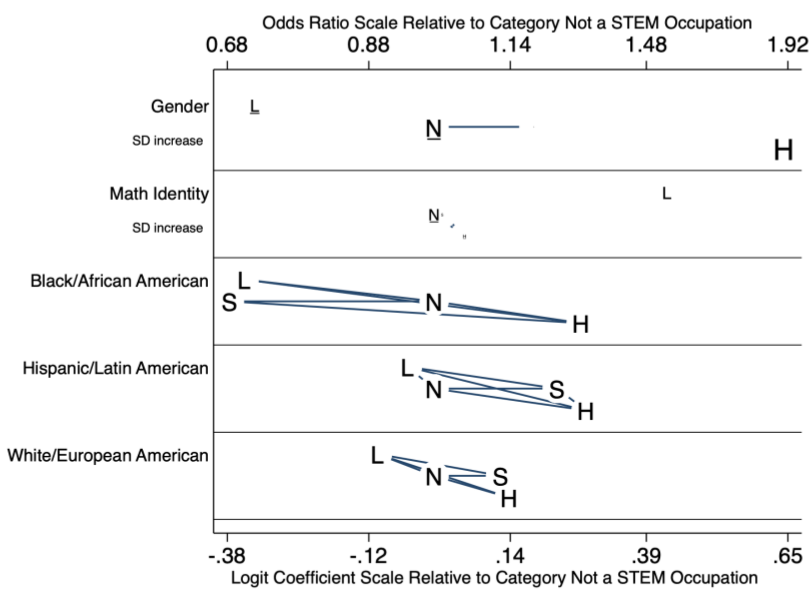
‡ Data not meeting IES standards for reporting (standard errors > 70% of the recorded value).

Research Question 3: *What influencing factors across student characteristic groupings act as supports for or barriers to an anticipated STEM career across secondary and postsecondary levels of education?*

Several tests were run independently after obtaining good discrimination on the fit and diagnostic statistics for each STEM definition. These tests focused on the marginal effects between the predictor variable (expected STEM career at the age of 30) and each exogenous variables fit to the models. *Marginal effects* seek to identify the instantaneous rate of change of a predictor with an individual covariate under defined conditions. For example, a marginal effect measure for early mathematics identity of Black/African American students in the 9th-grade year would describe graphically the rate of change of identity with respect to each type of expected STEM career. Although these "predicted probabilities" show the changes amongst each outcome with respect to each other, they won't indicate any internal dynamics between the outcomes. Odds ratios balance the marginal effects by providing a full view of the covariate effects on the outcomes.

Tables 46-51 use bolded formatting to identify significant coefficient and odds ratio results for each STEM perspective by wave and model. However, much of the results lying between the waves and logits emerged after using multinomial logit plots with graphical discrete changes and significance levels developed by Long and Freese (2014, pp. 435-444). Figure 20 is an example of a partial set of variables[20] from the second wave of the STEM1 set of outcomes by race and gender.

Figure 20. *Example mlogitplot on Wave 2 Outcomes (STEM1)*



[20] A maximum of eight covariates may be run at one using an mlogitplot (Long and Freese, 2014).

Results by Gender

Across each wave and amongst both STEM perspective, there exists a significant divide between female and male students, irrespective of race and ethnicity. Figures 21-23 show this effect through the predicted probabilities graphs. Relative to the case of a non-STEM career expectation, female students have significantly less odds (.62 odds ratio) of expecting traditional STEM careers. The data also highlights the role of early math/science identity and student/parent expectations on near-term and far-term perspectives. Health-related careers (viewed as long-term in this study) are preferred by female student participants (2.69, 3.61, and 3.42 odds ratios) over male students. The long-term nature of medical professions which require a Ph.D./professional degree are positively supported by parent expectations in the 9th-grade (1.27 odds ratio), followed by an evolving student expectation in the 11th-grade (3.92 odds ratio).

Figure 21. *Wave 1 MNLM by Gender for STEM1*

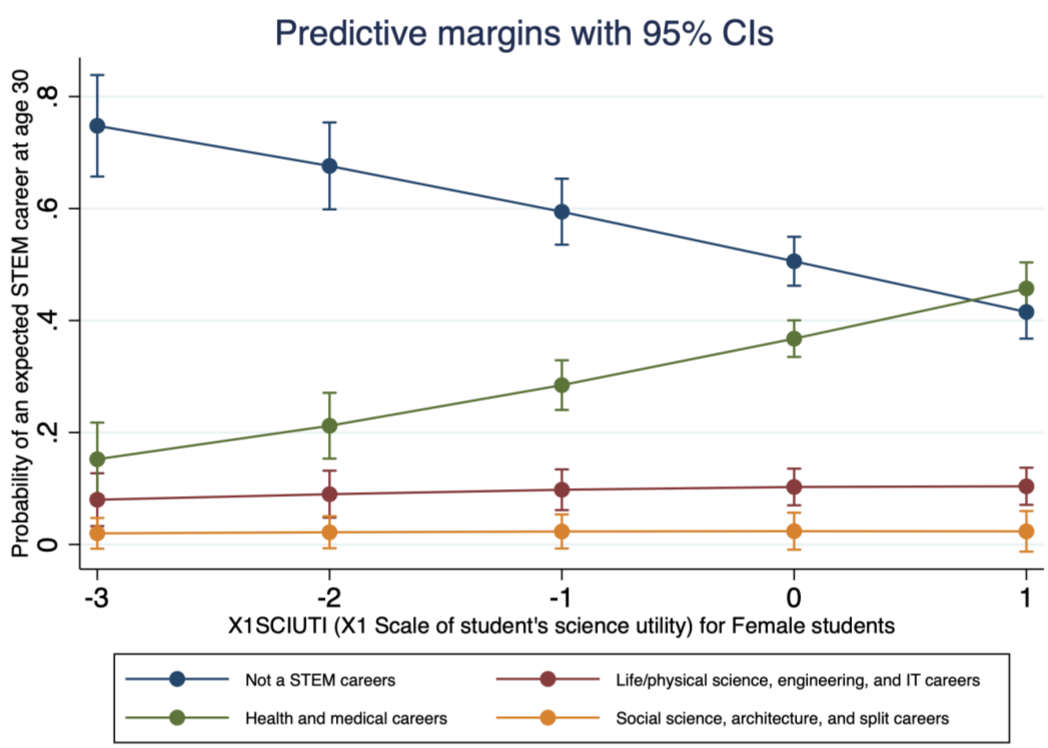


Figure 22. *Wave 2 MNLM by Gender for STEM1*

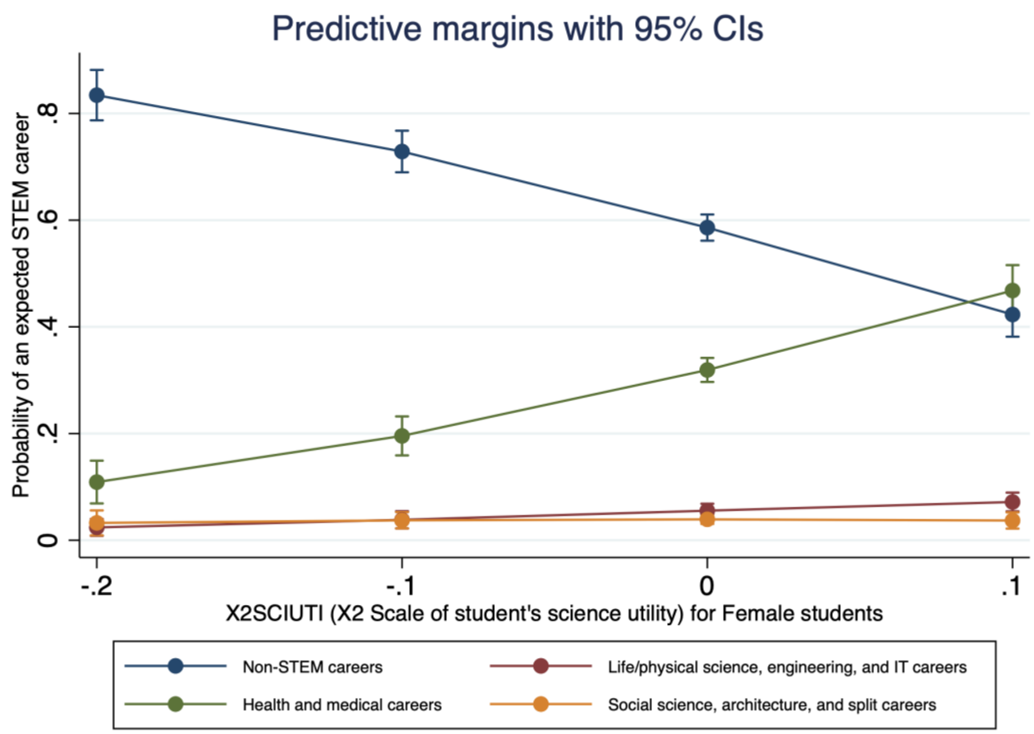
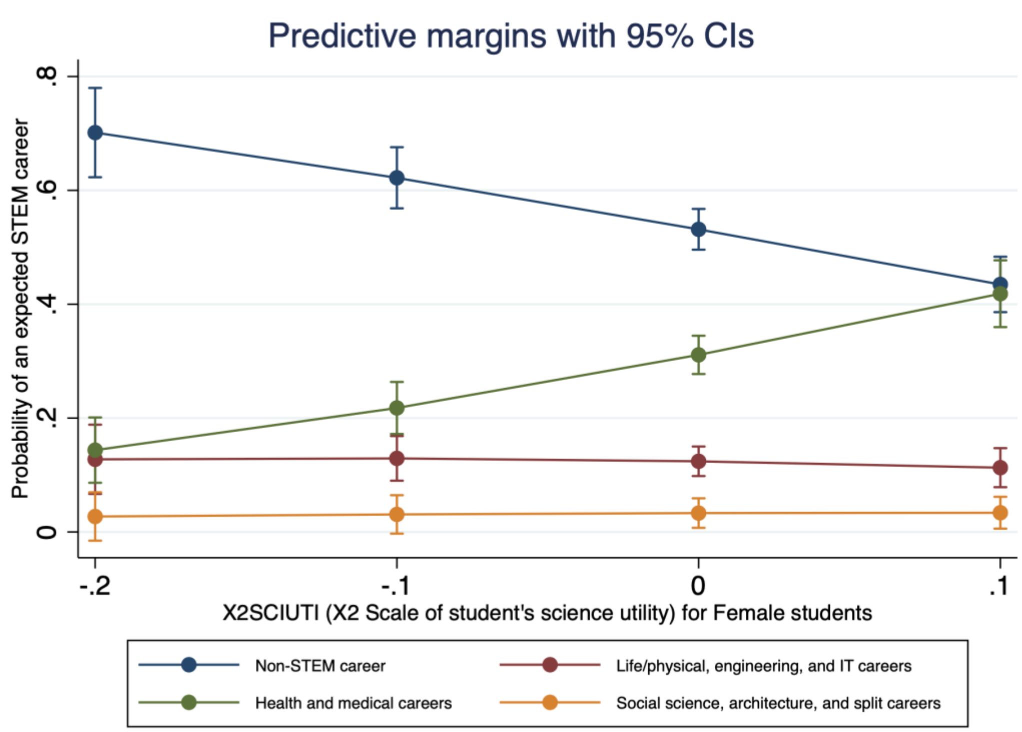


Figure 23. *Wave 4 MNLM by Gender for STEM1*



Another significant finding based on gender shows as the far-term effects of early gender bias (Figures 26-27) in the 9th-grade mathematics courses on the expectations of traditional and health STEM careers in the postsecondary years (traditional = 3.61 odds ratio; health = 3.16 odds ratio). Gender bias in the study is shown to effect both male and female students, with the latter most affected (see Figures 26-27). The far-term results are a shifting expectation amongst female students toward health and medical professions. These results coincided with the large significant effect of positive science utility in the 11th-grade on female students' anticipated STEM career at the age of 30 in the health and medical professions ($t = 7.92$, $p < .001$).

Figure 24. *Wave 1 Outcomes mlogitplot (STEM1)*

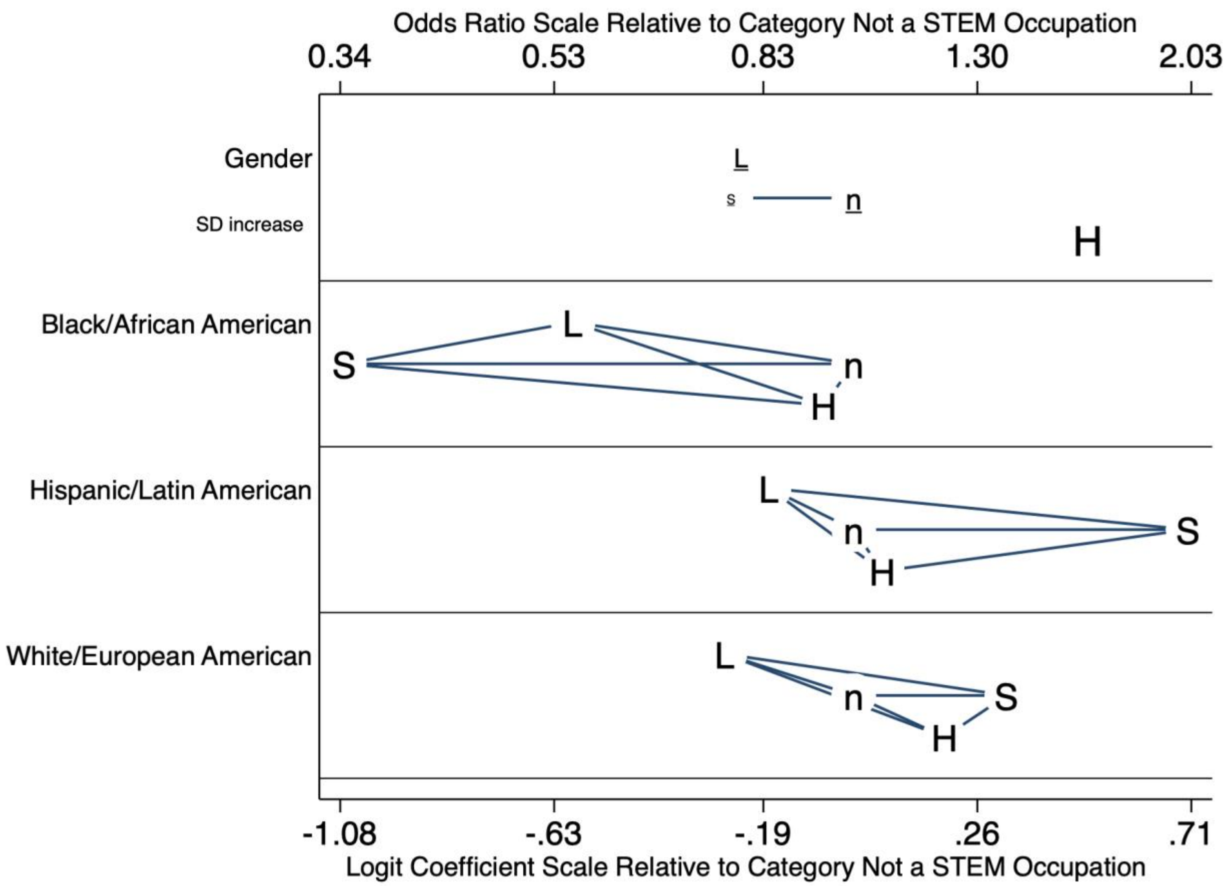


Figure 25. *Wave 4 Outcomes mlogitplot (STEM1)*

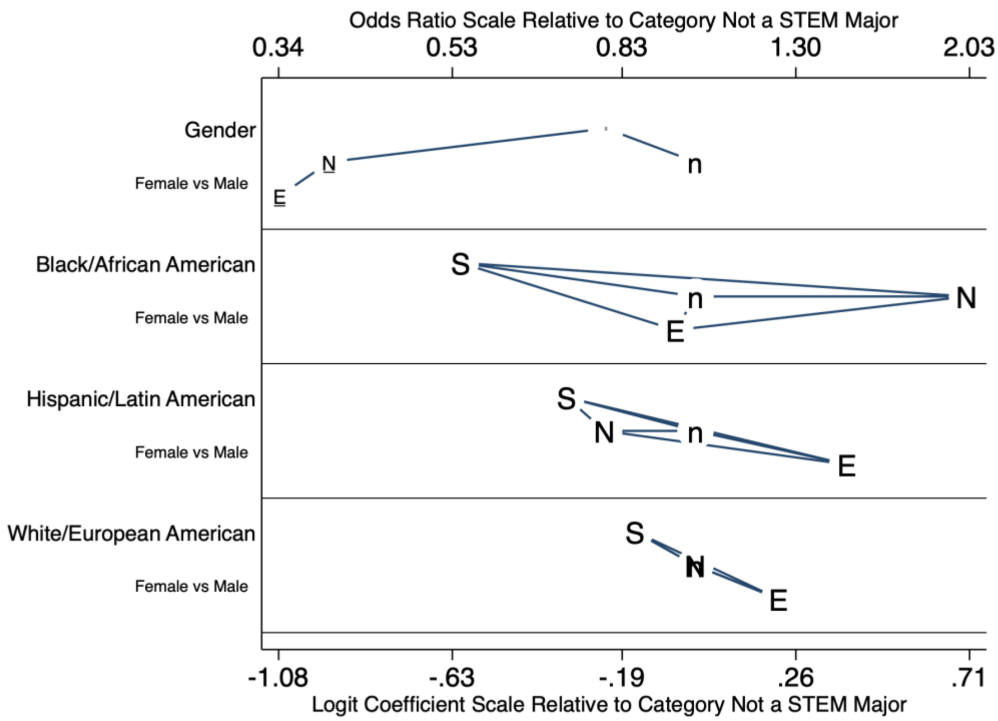
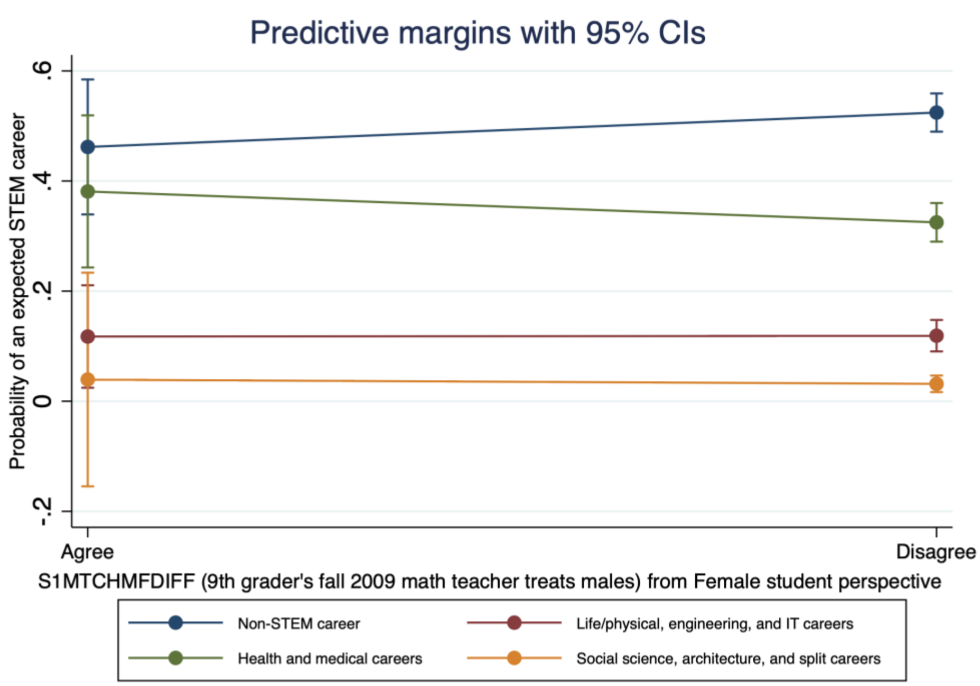


Figure 26. *Wave 4 MNLM by Gender (Female) and Gender Bias for STEM1*



Note. Significance in health and medical careers ($F_{(1,100)}$ = 33.05, p < .001).

Figure 27. *Wave 4 MNLM by Gender (Male) and Gender Bias for STEM1*

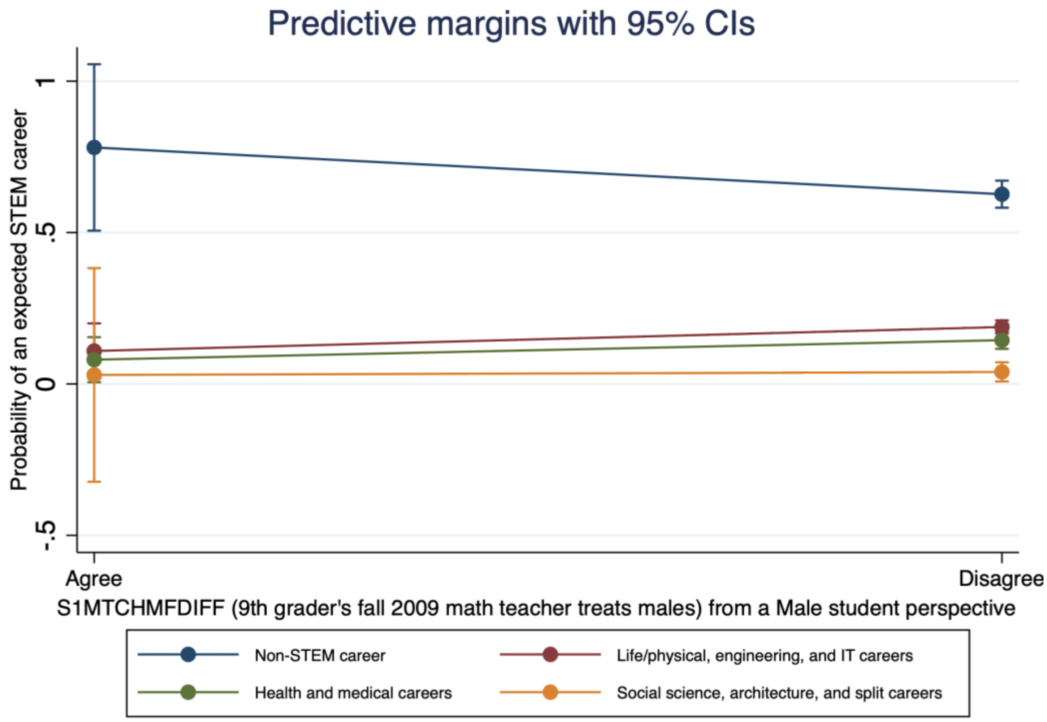
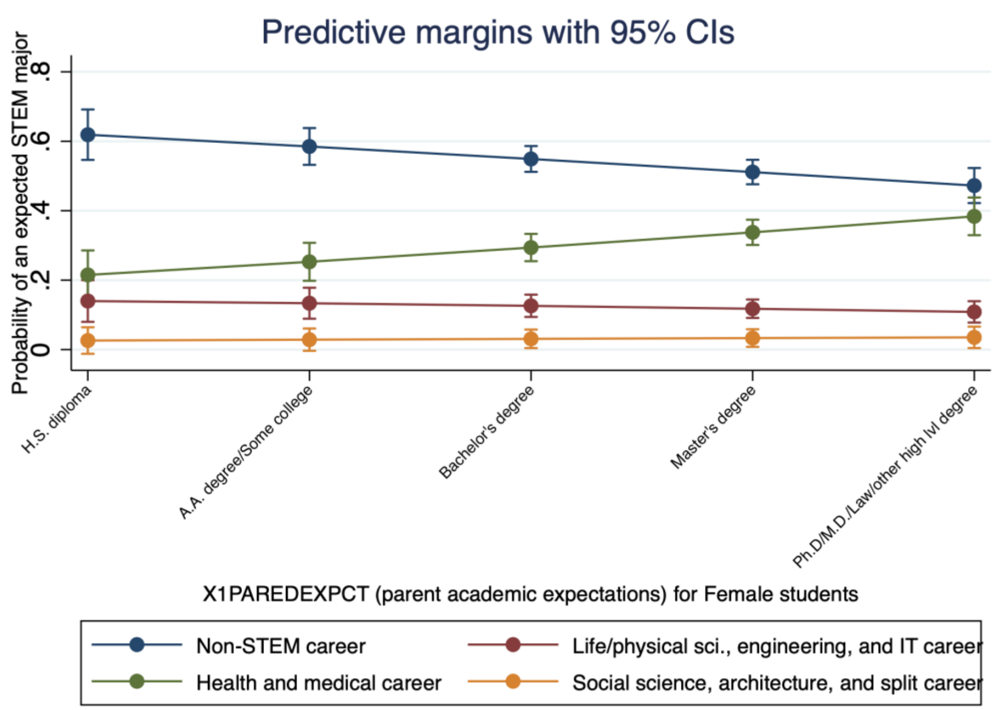
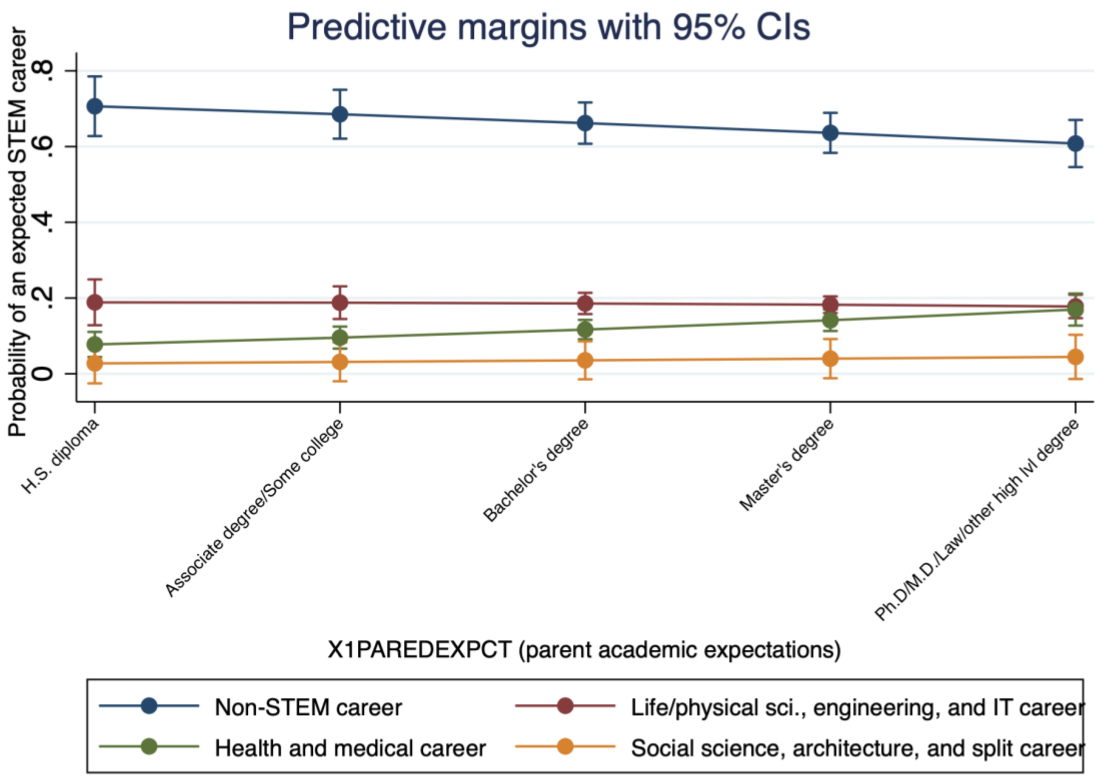


Figure 28. *Wave 4 MNLM by Gender (Female) and Parent Expectations for STEM1*



Note. Significance in health and medical careers ($F_{(1,190)}$ = 5.99, *p* = .015).

Figure 29. *Wave 4 MNLM by Gender (Male) and Parent Expectations for STEM1*



Results by Race and Ethnicity

The results by race and ethnicity are less statistically significant than those by gender, which dominate the analysis. Overall, though, there does exist factors of significant marginal change in model covariates by race and gender. For example, early anticipated career expectations of Black/African American students show greater odds of anticipating a non-STEM career when compared to similar White/European American students (Figure 20, 24-25). In the 11th-grade year, Black/African American students showed increased odds (Figure 20) of holding a positive anticipated STEM career in the health and medical fields versus more traditional STEM careers. Architecture, social science, health, and technician occupations showed more of an effect (Tables 46-48) on Latin American and European American subpopulations of the survey sample versus African American students.

Research Question 4: *What typological models predict the successful pursuit of underrepresented groups of students into STEM fields?*

Current research on student interest (Su & Rounds, 2015) and ability (Yang & Barth, 2017) typologies has been proven to predict student choices throughout their pursuit of a STEM career longitudinally. Su and Rounds (2015) description of how interests in people-oriented (e.g., health, medical, and social science) versus product-producing (e.g., engineering and the physical science) careers have explained pathways for female students pursuing STEM careers (Su & Rounds, 2015). Using tested typologies as well as evolving new ones, the research herein shows an explanatory alignment for underrepresented populations of students using a typological methodology.

Examining the relationship between people oriented versus product-producing careers underlines this typology as a significant predictor of pursuit for female students (see Figures 20-25). However, breaking apart this abstracted typology reveals that early math teacher and parental influence factors have a direct effect on this far-term typological generalization (illustrated in Figures 26 and 27). Although early parental expectations have a significant effect on the far-term STEM career expectations of students in their postsecondary years (1.27 and 1.84 odds ratios respectively), these give way to student-defined expectations in the 11th-grade year (3.92 odds ratio). What emerges from the results is a layered typological perspective. Longitudinally localized factors in the near-term (e.g., 9th- and 11th-grade) are shown to affect the far-term expectations (postsecondary years) of an anticipated STEM career path, when employing a STEM1 taxonomy. In addition to the layered perspective, STEM career outlooks undergo a transition from parent-influenced to independent career choices. Utilizing a STEM3 taxonomy reveals only one well-fitted model – an anticipated STEM career in engineering. This result reveals the interdisciplinary nature of the discipline. The modern engineer has both academically- and experientially orientated practices gained throughout their pursuit of a career in engineering. The alignment of model factors between near- and far-term expectations based on the STEM1 taxonomy illustrates a stability in the model (see fit and diagnostic measures in Figures B.16-B.27) regardless of perspective.

Research Question 5: *Is there a STEM taxonomy that encompasses inclusive typologies for underrepresented groups of students?*

A comparison between *STEM1* and *STEM3* taxonomies reveal a significant difference between models, waves, and perspectives. Two definitions of STEM – a BLS SOC career- versus a CIP college-focused one – produces two distinct model sets which align only along the expected engineering occupation at the age of 30. Both sets of taxonomies produce gradations of inclusive typologies for underrepresented groups of students, revealing significant findings (Tables 46-51) about current and longitudinal factors affecting women and students of color shown in Research Question 3.

Emerging, however, from both perspectives is the far-term (*STEM1*) approach. Although the marginal effects analysis reveals a significant longitudinal pull of underrepresented students into the health and medical professions due, in part, to early mathematics teacher gender bias ($F_{(1,99)} = 33.05$, $p < .001$), the focus of this perspective on future career outlooks (the applied sciences) highlights its significance to underrepresented students. Conversely, in the near-term (*STEM3*) perspective, only the engineering model emerges, another highly applied and pathway-aligned course of study. The results, therefore, show how an applied versus theoretical typology for STEM pursuit is inclusive of underrepresented students.

Another feature of the far-term taxonomy is the emergence of predictive variables that mirror the literature explored on motivation and persistence across a longitudinal continuum.

Unlike the near-term perspective, the far-term approach includes both barriers and supports to expectations of a STEM career for underrepresented students. For example, early math and science identities are predictors of early student STEM career expectations in the 9th-grade year. Similarly, parental expectations in the early secondary years yields to student STEM career expectations by the 11th-grade. Following the SCCT model for student career development, these variables shape and re-form perspectives that remain aligned within the STEM1 taxonomy.

Research Question 6: *How do these model results compare to traditional pipeline approaches to STEM pursuit?*

Traditional pipeline models subsume that a large initial supply of STEM capable students (in their early educational career) would select STEM majors and enter the respective careers. Giving rise to the "leaky pipeline" metaphor is the difference between the supply and production of students entering STEM careers. However, in this study, Tables A.4 – A.7 (and Figures A.1–A.2) indicate a fluctuation across the longitudinal waves with the significant addition of students ($\Delta n = 610$) with an expectation of a STEM career by the age of 30 during their 11th-grade year. These results alone dissolve the supply-side nature of a STEM pipeline for adequately predicting the movement of students into STEM careers. Moreover, since the movement of students across varying demographics is represented by a dynamic process, a linearized pipeline approach proves to be highly fallible in predicting STEM career pursuit. As indicated in Tables A.4 – A.7, if STEM pursuit is reduced to a supply-side input and demand-pulling output, a significant decrease in students with STEM career expectations emerges ($\Delta n = -2,370$), just as the leaky-pipeline model predicts. A more detailed, nuanced look at STEM career expectations throughout the pursuit continuum reveals the factors and effects on all students, in particular those who are historically underrepresented.

This study considered how two separate STEM taxonomic models would affect the expectation of a STEM career at the age of 30. Historical models maintained in the tradition, such as science, engineering, and mathematics, would not have revealed the typological connections between factor predictors of an anticipated STEM career, and gender and race representation as organized. A view of student pursuit at too high level of abstraction, has shown to be less productive in understanding student motivation and career attainment. Recent studies have shown large groups of "pipelined" students entering STEM health and medical positions (*STEM1*) which is not captured in the early models nor accounted for within the pipeline. This has led many researchers (Lucena, 2005; Teitelbaum, 2003) to acknowledge how pipeline model estimates are (a) flawed toward the supply-side, (b) one-dimensional with respect to career paths, and (c) represent a homogonous field (Hammonds & Subramaniam, 2003) of STEM professionals. These assessments are also reflected in this study. The differences between the fitted study factors across waves 1, 2, and 4 reveals the flaws in assuming a one-dimensional course pathway to a STEM career. Regardless of the perspective taken between STEM1 and STEM3 taxonomies, a clear distinction aligns against a one-dimensional approach to predicting STEM occupational expectations and towards a far-term outlook. Considering multiple student perspectives on career expectations leads to impactful results, these results support the unraveling of the manifold connections between students and their pursuit of STEM careers.

Chapter 5. Conclusions and Discussion

The purpose of the study herein was to develop a set of models describing the influencing factors that predict student pursuit patterns of STEM careers throughout their secondary and postsecondary careers. Prior research and scholarship around pursuit has provided a backdrop to developing an inclusive list of factors for a well-fitted, taxonometric-discriminating longitudinal model. Early mathematics self-concept (Howard, 2016; Sax et al., 2015; Wang et al., 2017) and parental involvement (Howard et al., 2019), course taking (Sadler et al., 2012), mathematics teacher gender bias (Starr et al., 2020), gender matching (Chen et al., 2020), and perspectives on viewing STEM pursuit supporting underrepresented groups of students (Su & Rounds, 2016; Yang & Barth, 2017) were particularly influential in the study. The results not only describe the experiences of students pursuing STEM careers throughout their secondary and postsecondary years but identifies important teacher/counselor practices and policy implications for supporting underrepresented students. Limitations inherent in the study will be discussed later in the Chapter as well as opportunities for future research in the coming years as more NCES data is released for HSLS:09.

Fit of Research Findings

Existing Literature and Conceptual Frameworks

As described in Chapter 2, the literature most aligned to the study are the factors that either support or are barriers to the longitudinal pursuit of a STEM career. An evaluation of current research over the last two decades provided a comprehensive list of potential factors (see Table 34) aligned to a social cognitive career theoretical construct that have been shown to alter the evolution of an expected STEM career outcome. Each factor was broken down into five major categories: (1) educational goals and outcomes; (2) psychometric influences; (3) experiential and learning influences; (4) contextual-environmental influences; and (5) demographic influences based on the research and underlying theories on motivation and retention (Table 2). Lent et al. (2002) has shown in their social cognitive theoretical framework that students are actively shaped by and shape their environment. This was particularly evident in the results showing significance across each model and data collection wave. Contextual-environmental influences had the greatest collective impact on positive and negative expectations of a STEM career at the age of 30. For example, parental/student expectations are specifically tied to career expectations and academic to career pursuit such as the connection between parental expectations of a Ph.D. and student pursuit of health and medical career outcomes. The corollary are parental expectations of a master's degree and the pursuit of a degree in the traditional STEM majors. Applied to the SCCT model, a bi-directional triadic relationship exists. It can be seen from the results that early parental expectations give way to student expectations in the 11th-grade. Additionally, self-efficacy, self-concept, and identity (personal determinants) are shown in the findings to be directly linked to expectations of a specific STEM career. As students are "products and producers of their environment" (Wood & Bandura, 1989), they also have an ability for self-regulation which fuels this triadic relationship undergirding Social Cognitive Career Theory. Compared to Expectancy-Value Theory post hoc, the SCCT framework provides a more complete explanation for this evolving set of constructs with underrepresented students.

STEM Pipeline

The educational goals and outcomes were further disaggregated into STEM taxonomies (see Table 1) using the BLS SOC, Bureau of Labor Statistics O*NET, NSF, Census Bureau, Department of Homeland Security, and ACT criteria that aligned to two distinct student perspectives, far-term (Figure 4) and near-term (Figure 5). Using the HSLS:09 general outcomes for STEM career expectations, near-term and far-term perspectives were evolved. The results provided a good fit and discrimination for each wave ($F_{(50,160)}$ = 30.54, p < .001; $F_{(50,150)}$ = 25.91, p < .001; $F_{(40,150)}$ = 17.96, p < .001) of the far-term student perspective on expectations of a STEM career. The near-term perspective, using the same modeled covariates in the former outcome models, produced a consistent result in the engineering category ($F_{(50,150)}$ = 7.88, p < .001; $F_{(50,150)}$ = 11.55, p < .001; $F_{(40,150)}$ = 17.96, p < .001). What is discerned from the analysis is an agreement to the differences in student perspectives on STEM career expectations and how those anticipations of a STEM career change across secondary and postsecondary years. This development is in stark contrast to the STEM pipeline models pushed around policy circles over that time. The inclusion of health and medical careers highlighted the observed up-and-down movement in students' career expectations within their secondary schooling. These results are consistent with the analysis of Lucena (2005), Teitelbaum (2003), and Xie and Killewald (2013).

Xie and Killewald (2013) considered if American science was in decline. Their discoveries, however, prompted a larger conversation around a surplus (not a shortage) when comparing STEM graduates to available careers. The upward jump in the current research showing an increase in 11th-grade STEM career expectations and subsequent drop ($\Delta n_{9th\text{-}11th}$ = +610; $\Delta n_{9th\text{-}postsecondary}$ = -2,370) in the postsecondary years reveals a similar trend across educational levels. On the surface it appears to be a significant overall drop (34%), however students are applying to degree programs available that far exceed supportable figures (Watanabe, 2022). Figures A.1-A.2 shows the changes between the 11th-grade and early postsecondary years by frequency and percentage across student demographic groupings. The drop is generated, at least in part, to the transition of students into higher educational majors. Although further research would need to be conducted to develop a strong correlation between the two, the remaining questions about a shortfall of qualified STEM students (those leaking out of the STEM pipeline) should be directed toward statewide policies that may "filter" students into available higher education majors.

Pursuit Factors

During the secondary years, a general reshuffling of STEM career expectations is evolving. This movement can be attributed to either the supports provided, or the barriers placed in front of students depending on the direction of move. Moreover, the decision point of choosing a STEM major is a significant milestone in the pursuit journey (.43, .50, and .60 odds ratios of not choosing a STEM major). As student STEM career expectations change, model factors also push and pull at this bifurcating career decision. Gender biases in the mathematics classroom were shown in the literature to be a large detractor for pursuing STEM careers (Starr et al., 2020). This effect was shown throughout the study as a becoming significant barrier in the longitudinal pursuit of STEM careers in the sciences, engineering, and information technology sectors. In fact, the results show using marginal effects, that gender biases push female students (with an interest in science) into health and medical related careers (2.69, 3.61, and 3.42 odds ratios). These effects are not contained to female students, as male students are also likely to choose different career paths when faced with gender biases in the mathematics classroom.

Science utility also emerged within the study as a highly significant factor in predicting student expectations of a STEM career in the health and medical professions. For female students, the odds of having an anticipated STEM career in the health-related professions dominated the analysis. These findings in connection with prior research by Rozek et al. (2017) and others, highlight the value of promoting STEM topics, research, and applications. A high science utility clearly increases students' career pursuit which is tied to motivations and achievement. However, the push into health and medical professions may not be as rosy as they seem. Figures 26-27 provides evidence that early mathematics teacher gender bias on female students who have an interest in STEM, pushes this group into health-related careers. These results have a significant implication on the effect secondary classroom teacher practices and local policies.

Although parental involvement – a scale which considers how parents involve themselves in discussing relevant topics on careers, college applications, and courses – follows alongside current research (Howard et al., 2019) as not proving to be a significant factor on predicting STEM career pursuit. However, parental expectations of a Master’s or Ph.D./professional degree did emerge as a pursuit factor in the early educational years (1.41 and 3.92). There is strong agreement in the literature (Howard et al., 2019; Jaynes, 2007) on the role of parental expectations and student attainment. The marginal effects plots (Figures 28-29) show how a higher parental expectation affects the academic achievement for female versus male students. Additionally, as a longitudinal effect, the models indicate the influences of parental expectations on student career pursuit by changing significance from one (parental expectation in the 9th-grade year; 1.41 odds ratio) to the other (student expectations in the 11th-grade year; 1.60 odds ratio).

Lastly, mathematics identity predicted greater significant odds of having an anticipated traditional STEM career in life and physical science, engineering, and/or information technology (1.52 odds ratio) in the 11th-grade. This important finding closely parallels the early work of Boaler et al. (2000) and later that of Ma et al. (2021) which both show a distinct connection between positive mathematics identity and student achievement. What is significant in this study is the connection to the life/physical sciences, engineering, and information technology professions. These results have further implications to policy and practice.

Policy and Practice

The implications of the study findings with practical classroom and curricular approaches with policy practices loom large. Early seminal reports on the state of STEM education shared commonly understood conclusions, with the following misunderstood beliefs: (1) the U.S. was producing lower quality science and engineering students and (2) the U.S. would be quickly surpassed by other nations in innovation, basing future policy decisions on this forecast. The resulting domination of the economic models used to make such future forecasts has transformed the educational landscape through a supply-side oriented model of human capital – the STEM pipeline. Views on the predictive capabilities of the STEM pipeline have long been challenged, however, lacking a clear operationalized definitions of STEM left the door open for many interpretations. STEM, STEAM, and SEM programs have flooded the elementary and secondary educational landscape over the last 20 years. However, a lack of understanding on how to define, implement, and connect these programs across educational levels has perpetuated the misrepresentation of STEM pursuit. For example, would an arts-based STEM program (referred to as STEAM) be appropriate at the secondary level for students interested in a STEM-based preparation program? Moreover, calling the aforementioned a preparation program in locales with a high concentration of underrepresented students is especially irresponsible as educators. There must be an operational redefinition of STEM at the federal level first, then devolved to the individual states and districts through policies such as the America COMPETES Act. The result could serve to assuage the large gradations of STEM across primary and secondary levels and avoid the conflicting messages portrayed to students who are in the process of discovering their agency.

Vertical alignment between levels of schooling continues to evolve based on new research and the resulting curricular changes. With the recent implementation of Common Core State and Next Generation Science Standards, a longitudinal set of 6-12th-grade math and science practices is leading a national push for a standard set of abilities and understandings. Synthesizing prior and current research has shown that identity building in math and science occurs within and beyond the formal classroom. Since positive early math and science identity results in an increased expectation of a STEM career, providing programs which center around the STEM subjects within a unique social culture (such as competition robotics or place-based scientific research, human-centered design projects for community problem solving, and/or industry internships) can build identity and self-efficacy in these critical discipline areas. Districts with secondary schools (middle and high) should identify vertical alignment in formal and informal settings so that these early identities don't fade by the 11th-grade year. Similarly, developing or continuing scientific research in the 10th-12th grades have the opportunity to grow the scientific utility amongst students – particularly those who are underrepresented in STEM. Providing practical applications to current student work is highly empowering and must be a constant in the educational curricular policies implemented in the future.

Limitations and Recommendations for Future Research

This study had several limitations which have the potential to be addressed with future research and the release of additional information from the HSLS survey data set. First, the data in the study considered a longitudinal range of measurement points from their 9th-grade through their postsecondary years of schooling. This limitation is model constraining since a final STEM career disposition cannot be gathered for the participant group to solidify the predictive nature of the study results. Since this occurs at a singular point in the data collection process (i.e., the twelfth year following the participant groups' high school graduation), capturing student dispositions of a STEM career as an "expected" outcome variable was necessary within the analysis. Although this approach was taken in-line with current research efforts, the release of future career data in 2025, the final wave of the High School Longitudinal Study, will further validate the predictive results herein with the actual careers obtained by the study participants.

Another longitudinal limitation is the clustering of contextual factors within the early secondary academic years. Although the decision to cluster these factors within the first year of data collection (2009) is based on current research, it provides a limitation to the study by constraining the factors that can be assessed longitudinally across secondary and postsecondary settings. However, longitudinal research on psychometric factors, such as identity change (Cassidy et al., 2001), shows stability across secondary and postsecondary transitions.

Second, the survey questions were tied to self-assessments and aligned to an Expectancy-Value Theory of motivation and academic attainment. Whereas a social cognitive career theoretical construct was employed in determining an initial set of STEM career predictive factors, other methodologies may produce differing results. SCCT was used as a methodology due to its current positive association to underrepresented groups of students. However, future researchers should be cautioned that deviating from this construct while using the collection of factors could produce differing results.

Third, there exists many survey participants who either did not select a response to to which occupation they expect or plan to have at the age of 30. Although these numbers represent a significant limitation on the study sample, it illustrates how expected outcomes evolve based on individual student experiences. Throughout the longitudinal pursuit of a STEM career, our thoughts on future career outcomes are constantly evolving as we build agency from the many influencing factors affecting our motivational behaviors.

Fourth, many constructs were limited to specific waves of data collection. Each of the psychological influences retain in the study were assessed in the first and second waves. This decision point by Ingels et al. (2018) was a constraint to the final wave model results. For example, early constructs that had a significant effect on the predictions of an anticipated STEM career (such as mathematics identity, science utility, math teacher gender bias, and mentorship) could not be paired with their current assessment in the latter models. Future research on the longitudinal changes in these factors could provide a more granulated understanding of underrepresented students' chosen majors of study and career choices by comparing changes in psychological factors throughout secondary and postsecondary schooling. The lack of a more robust data collection effort on student mentorship, throughout this same period, would have also provided insightful evidence into the contextual-environmental influences on students' STEM careers. A series of mentorship questions exists in HSLS, with some of them retained in the univariate analysis, however, these occur in either the 9th-grade or 11th-grade years and are mostly school-centered rather than student-centered. Mentorship at the postsecondary level has been proven to support student career development and entry into the traditional STEM careers (Tai et al., 2017). Providing more data on mentorship could prove especially valuable in understanding the postsecondary relationships with STEM career pursuit.

Fifth, teacher instructional methods were considered for inclusion within the study, however they were eliminated prior to the univariate analysis. Due to the data collection start date, an assessment of important STEM skills – such as those associated with mathematics identity and science utility – could not be directly understood or implemented into the secondary models. With recent changes to the math and science curriculum through the adoption of Common Core State Standards and Next Generation Science Standards nationwide, it is not clear how these methodological shifts are affecting student entry into STEM majors and careers. Future research should seek answers to the roles of student psychological influences on their career expectations through these large-scale shifts in teaching practice.

Finally, defining STEM careers by varying the taxonometric lenses used in a model building approach may produce additional positive typologies for underrepresented groups of students. Another perspective may be attained by utilizing the STEM2 coded variables in HSLS. These variables look at the far-term (BLS SOC dominated) taxonomy from the perspective of STEM career skills. Another final research direction lies in the development of more qualitive and grounded theoretical studies to expand the nuanced ways in which students view their pursuit of STEM careers from the influences detailed in this study.

Conclusion

This study led to the identification, comparison, and development of multiple models for understanding and predicting STEM career pursuit longitudinally. Implications to traditionally underrepresented groups of students were explored through the establishment of positive typologies that included internal pursuit factors (such as motivation and persistence) as well as external environmental, school, and parental ones. Additionally, two taxonomies for STEM career pursuit were informed through a review of the literature, designed based on a synthesis of results, and implemented in the final model analysis. Depending on the near-term or far-term perspective on STEM careers, variations were discovered in the pathways to STEM pursuit, the impacts by gender and race/ethnicity, and an unraveling of the STEM pipeline. For decades policy makers have focused on an abstracted view of student pursuit of STEM careers. These approaches have routinely enveloped a false view of who enters the STEM “pipeline”, why these students continue to pursue STEM career outcomes, their manifold pathways toward pursuit, and what defines a STEM career. The broad utilization of a “leaky path” pipeline analogizes a systemic laziness in the policy sphere for understanding, empathizing, and solving the underrepresented problem in STEM pathways and careers.

Echoing a call from some researchers to policy makers, STEM must be clearly defined. The addition of specific health and medical professions exist in the STEM workforce and are critical to the development of our collective future. With the COVID-19 global pandemic, we are witness to a sizable punctuation event. As seen within this study, policy windows will begin to open that could connect the health and medical professions to the mainstream STEM careers. National funding for the research and development of future global pandemic prevention measures will undoubtedly reveal a shortage of qualified health and medical professionals including managers, technicians, clinicians, and researchers. The door is open for resetting our understanding of STEM. Operationalizing STEM will go a long way in aligning its stratified uses throughout education. Continuing to develop educational policies alongside public perceptions on the status of the STEM workforce would continue to be deleterious. Removing pipeline analogies that promote unsupported outlooks present in the current data and their associated large-scale supply-side pushes for students will support policies and practices that positively promote underrepresented students into STEM career pathways to pursuit. Forecasting the manifold relationships between students and their pursuit of STEM careers reveals both the complex dynamics involved in achieving these career outcomes and how the power of a STEM pipeline model has drifted from its early origins in wake of our collective fear of failure.

References

Ahmed, W. & Mudrey, R. R. (2019). The role of motivational factors in predicting STEM career aspirations. *International Journal of School & Educational Psychology*, *7*(3), 201-214. https://doi.org/10.1080/21683603.2017.1401499

Allen, C. D. & Eisenhart, M. (2017). Fighting for desired versions of a future self: How young women negotiated STEM-related identities in the discursive landscape of educational opportunity. *Journal of the Learning Sciences*, *26*(3), 407-436. https://doi.org/10.1080/10508406.2017.1294985

Alvarado, S. E., & Muniz, P. (2018). Racial and ethnic heterogeneity in the effect of MESA on AP STEM coursework and college STEM major aspirations. *Research in Higher Education*, *59*(7), 933-957. https://doi.org/10.1007/s11162-018-9493-3

Andersen, L., & Chen, J. A. (2016). Do high‐ability students disidentify with science? A descriptive study of US ninth graders in 2009. *Science Education*, *100*(1), 57-77. https://doi.org/10.1002/sce.21197

Asim, M., Kurlaender, M., & Reed, S. (2019). 12th Grade Course-taking and the Distribution of Opportunity for College Readiness in Mathematics. https://files.eric.ed.gov/fulltext/ED600439.pdf

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*, 23-28.

Bandura, A., Freeman, W. H., & Lightsey, R. (1999). Self-efficacy: The exercise of control. https://doi.org/10.1891/0889-8391.13.2.158

Begg, C., & Gray, R. (1984). Calculation of polychotomous logistic regression parameters using individualized regressions. *Biometrika*, *71*(1), 11-18. https://doi.org/10.2307/2336391

Beier, M. E., Kim, M. H., Saterbak, A., Leautaud, V., Bishnoi, S., & Gilberto, J. M. (2019). The effect of authentic project-based learning on attitudes and career aspirations in STEM. *Journal of Research in Science Teaching*, *56*(1), 3-23. https://doi.org/10.1002/tea.21465

Bloom, B. S. (1985). Generalizations about talent development. *Developing talent in young people*, 507-549.

Boaler, J., & Greeno, J. G. (2000). *Identity, agency, and knowing in mathematics worlds*. Multiple Perspectives on Mathematics Teaching and Learning, 171-200. Ablex Publishing.

Bodnar, K., Hofkens, T. L., Wang, M. T., & Schunn, C. D. (2020). Science Identity Predicts Science Career Aspiration Across Gender and Race, but Especially for Boys. *International Journal of Gender, Science and Technology*, *12*(1), 32-45. http://genderandset.open.ac.uk/index.php/genderandset/article/view/675/1116

Bozick, R., & Ingels, S. J. (2007). Mathematics coursetaking and achievement at the end of high school: Evidence from the Education Longitudinal Study of 2002 (ELS:2002) (NCES 2008-319). Washington, DC: U.S. Department of Education, National Center for Education Statistics. http://files.eric.ed.gov/fulltext/ED497754.pdf

Bozick, R., and Ingels, S. J. (2008). *Mathematics Coursetaking and Achievement at the End of High School* (NCES 2008-319). National Center for Education Statistics, Institute of

Education Sciences, U.S. Department of Education. Washington, DC. http://files.eric.ed.gov/fulltext/ED499546.pdf

Braxton, J. M. (2019). Leaving college: Rethinking the causes and cures of student attrition by Vincent Tinto. *Journal of College Student Development*, *60*(1), 129-134. https://doi.org/10.1353/csd.2019.0012

Brown, S. D., & Lent, R. W. (1996). A social cognitive framework for career choice counseling. *The career development quarterly*, *44*(4), 354-366. https://doi.org/10.1002/j.2161-0045.1996.tb00451.x

Cassidy, C., & Trew, K. (2001). Assessing identity change: A longitudinal study of the transition from school to college. *Group Processes & Intergroup Relations*, *4*(1), 49-60. https://doi.org/10.1177%2F1368430201041004

Chen, C., Sonnert, G., & Sadler, P. M. (2020). The effect of first high school science teacher's gender and gender matching on students' science identity in college. *Science Education*, *104*(1), 75-99. https://doi.org/10.1002/sce.21551

Cheng, S., & Long, J. S. (2007). Testing for IIA in the multinomial logit model. *Sociological methods & research*, *35*(4), 583-600. https://doi.org/10.1177%2F0049124106292361

Cilluffo, A., & Cohn, D. (2019). 6 demographic trends shaping the U.S. and the world in 2019. https://www.pewresearch.org/fact-tank/2019/04/11/6-demographic-trends-shaping-the-u-s-and-the-world-in-2019/

Cook, D. A., & Artino Jr, A. R. (2016). Motivation to learn: an overview of contemporary theories. *Medical education*, *50*(10), 997-1014. https://doi.org/10.1111/medu.13074

Cooper, C. (2016). The Changing Space of Aerospace in Southern California. *Los Angeles County Economic and Development Corporation Institute for Applied Economics*. https://laedc.org/wp-content/uploads/2016/03/LAEDC_Aerospace_FINAL_20160331b.pdf

Cox, N. (2017). EXTREMES: Stata module to list extreme values of a variable. Statistical Software Components. *Boston College Department of Economics*.

DeBoer, G. (1984). Factors related to the decision of men and women to continue taking science courses in college. Journal of Research in Science Teaching, 21(3), 325 – 329. https://doi.org/10.1002/tea.3660210309

DeBoer, G. (1986). Perceived science ability as a factor in the course selections of men and women in college. Journal of Research in Science Teaching, 23(4), 343 – 352. https://doi.org/10.1002/tea.3660230408

Degol, J. L., Wang, M. T., Zhang, Y., & Allerton, J. (2018). Do growth mindsets in math benefit females? Identifying pathways between gender, mindset, and motivation. *Journal of youth and adolescence*, *47*(5), 976-990. https://doi.org/10.1007/s10964-017-0739-8

Desilver, D. (2017). U.S. students' academic achievement still lags that of their peers in many other countries. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2017/02/15/u-s-students-internationally-math-science/

Dixon-Román, E. J., Everson, H. T., & McArdle, J. J. (2013). Race, poverty and SAT scores: Modeling the influences of family income on black and white high school students' SAT performance. *Teachers College Record*, *115*(4), 1-33. https://www.academia.edu/download/50171775/Race_Poverty_SAT_TC_Record.pdf

Eccles, J., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J., & Midgley, C. (1983). Expectancies, values and academic behaviors. In Spence, J. T. (ed.), *Achievement and Achievement Motives*. W. H. Freeman.

Eccles, J. S. & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual review of psychology*, *53*(1), 109-132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Edwin, M., Prescod, D. J., & Bryan, J. (2019). Profiles of High School Students' STEM Career Aspirations. *The Career Development Quarterly*, *67*(3), 255-263. https://doi.org/10.1002/cdq.12194

Engberg, M. E., & Gilbert, A. J. (2014). The counseling opportunity structure: Examining correlates of four-year college-going rates. *Research in Higher Education*, *55*(3), 219-244. https://doi.org/10.1007/s11162-013-9309-4

Fouad, N. A., & Santana, M. C. (2017). SCCT and underrepresented populations in STEM fields: Moving the needle. *Journal of Career Assessment*, *25*(1), 24-39. https://doi.org/10.1177%2F1069072716658324

Fry, T. R., & Harris, M. N. (1996). A Monte Carlo study of tests for the independence of irrelevant alternatives property. *Transportation Research Part B: Methodological*, *30*(1), 19-30. https://doi.org/10.1016/0191-2615(95)00019-4

Funk, C. & Parker, K. (2018). Women and men in the STEM workforce varies widely across jobs. https://www.pewsocialtrends.org/2018/01/09/diversity-in-the-stem-workforce-varies-widely-across-jobs/

Gottfried, M. A. (2015). The influence of applied STEM coursetaking on advanced mathematics and science coursetaking. *The Journal of Educational Research*, *108*(5), 382-399. https://doi.org/10.1080/00220671.2014.899959

Gottlieb, J. J. (2018). STEM career aspirations in Black, Hispanic, and White ninth-grade students. *Journal of Research in Science Teaching*, *55*(10), 1365-1392. https://doi.org/10.1002/tea.21456

Hausman, J., & McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica*, 52(5). https://doi.org/10.2307/1910997

Haynes, J. E., & Klehr, H. (2006). *Early Cold War Spies: The Espionage Trials That Shaped American Politics*. Cambridge University Press.

Heeringa, S. G., West, B. T., & Berglund, P. A. (2017). *Applied survey data analysis*. Chapman and Hall/CRC.

Hernandez, P. R., Hopkins, P. D., Masters, K., Holland, L., Mei, B. M., Richards-Babb, M., ... & Shook, N. J. (2018). Student integration into STEM careers and culture: A longitudinal examination of summer faculty mentors and project ownership. *CBE—Life Sciences Education*, *17*(3). https://doi.org/10.1187/cbe.18-02-0022

Howard, N. R., Howard, K. E., Busse, R. T., & Hunt, C. (2019). Let's Talk: An Examination of Parental Involvement as a Predictor of STEM Achievement in Math for High School Girls. *Urban Education*. https://doi.org/10.1177%2F0042085919877933

Holzman, B., Klasik, D., & Baker, R. (2019). Gaps in the College Application Gauntlet. *Research in Higher Education*, 1-28. https://doi.org/10.1007/s11162-019-09566-8

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398). John Wiley & Sons.

Ikenberry, J. (October 2005). The World is Flat: A Brief History of the Twenty-first Century. https://www.foreignaffairs.com/reviews/capsule-review/2005-09-01/world-flat-brief-history-twenty-first-century

Ingels, S.J., Pratt, D.J., Herget, D., Bryan, M., Fritch, L.B., Ottem, R., Rogers, J.E., and Wilson, D. (2018). *High School Longitudinal Study of 2009 (HSLS:09) Base Year to Second Follow-Up and High School Transcript Data File Documentation* (NCES 2018-140). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Jackson, L., Ford, J., Randolph, C., Schleiden, C., Harris-McKoy, D., & McWey, L. (2020). School climate as a link between high school Black males' math identity and outcomes. *Education and Urban Society*, 0013124520931453. https://doi.org/10.1177%2F0013124520931453

James, A. G., Rudy, D., & Dotterer, A. (2019). Longitudinal Examination of Relations between School-and Home-Based Parent Involvement and GPA across Ethnic Groups. *Journal of Child* *and Family Studies*, *28*(11), 3000-3010. https://doi.org/10.1007/s10826-019-01475-9

Jeynes, W. H. (2007). The relationship between parental involvement and urban secondary school student academic achievement: A meta-analysis. *Urban Education, 42*(1), 82-110. https://doi.org/10.1177%2F0042085906293818

Jang, S. T. (2019). Schooling experiences and educational outcomes of Latinx secondary school students living at the intersections of multiple social constructs. *Urban Education*. https://doi.org/10.1177%2F0042085919857793

Kelly, A. M. (2016). Social cognitive perspective of gender disparities in undergraduate physics. *Physical Review Physics Education Research*, *12*(2), 020116. https://doi.org/10.1103/PhysRevPhysEducRes.12.020116

Ketenci, T., Leroux, A., & Renken, M. (2020). Beyond Student Factors: A Study of the Impact on STEM Career Attainment. *Journal for STEM Education Research,* 1-19. https://doi.org/10.1007/s41979-020-00037-9

Kitchen, J. A., Sonnert, G., & Sadler, P. M. (2018). The impact of college-and university-run high school summer programs on students' end of high school STEM career aspirations. *Science Education*, *102*(3), 529-547. https://doi.org/10.1002/sce.21332

Kliebard, H. M. (2004). *The struggle for the American curriculum, 1893-1958*. Routledge.

Koppman, S., Cain, C. L., & Leahey, E. (2015). The joy of science: disciplinary diversity in emotional accounts. *Science, Technology, & Human Values*, *40*(1), 30-70. https://doi.org/10.1177%2F0162243914537527

Kremer, K. P. (2020). Predictors of College Success Outcomes in Emerging Adults: The Role of High School Dual Enrollment Courses. *Emerging Adulthood*, 2167696820916639.

Launius, R. D. (2009). United States space cooperation and competition: Historical reflections. *Astropolitics*, *7*(2), 89-100. https://doi.org/10.1080/14777620903073853

Lent, R., Brown, S., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. Journal of Vocational Behavior, 45(1), 79-122. https://doi.org/10.1006/jvbe.1994.1027

Lent, R., Brown, S., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. Journal of Counseling Psychology, 47(1), 36 – 49. https://psycnet.apa.org/doi/10.1037/0022-0167.47.1.36

Lent, R. W., Sheu, H. B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. Journal of Vocational Behavior, 73(2), 328 – 335. https://doi.org/10.1016/j.jvb.2008.07.005

Levinson, M. (January 2014). Ownership and agency will propel STEM learning. https://www.edutopia.org/blog/ownership-agency-propel-stem-learning-matt-levinson

Li, J., Mau, W. C. J., & Bray, S. S. (2017). Examining the role and practices of high school counselors in helping students make career transition. http://hdl.handle.net/10057/16356

Lichtenberger, E., & George-Jackson, C. (2013). Predicting high school students' interest in majoring in a STEM field: Insight into high school students' postsecondary plans. *Journal of*

Career and Technical Education, *28*(1), 19-38. http://files.eric.ed.gov/fulltext/EJ1043177.pdf

Lindahl, M. G., Folkesson, A. M., & Zeidler, D. L. (2019). Students' recognition of educational demands in the context of a socioscientific issues curriculum. *Journal of Research in Science Teaching*, *56*(9), 1155-1182. https://doi.org/10.1002/tea.21548

Liu, Y., Hau, K. T., & Zheng, X. (2019). Do both intrinsic and identified motivations have long-term effects? *The Journal of Psychology*, *153*(3), 288-306. https://doi.org/10.1080/00223980.2018.1516611

Long, J. S., & Freese, J. (2014). *Regression models for categorical dependent variables using Stata*. Stata press.

Lucena, J. C. (2000). Making women and minorities in science and engineering for national purposes in the United States. *Journal of Women and Minorities in Science and Engineering*, *6*(1). https://doi.org/10.1615/JWomenMinorScienEng.v6.i1.10

Lucena, J. C. (2005). Defending the nation: US policymaking to create scientists and engineers from sputnik to the 'war against terrorism. University Press of America.

Lynch, S. J., Burton, E. P., Behrend, T., House, A., Ford, M., Spillane, N., ... & Means, B. (2018). Understanding inclusive STEM high schools as opportunity structures for underrepresented students: Critical components. *Journal of Research in Science Teaching*, *55*(5), 712-748. https://doi.org/10.1002/tea.21437

Lyon, G. H., Jafri, J., & St Louis, K. (2012). Beyond the Pipeline: STEM Pathways for Youth Development. *Afterschool Matters*, *16*, 48-57. http://files.eric.ed.gov/fulltext/EJ992152.pdf

Ma, Y., & Xiao, S. (2021). Math and Science Identity Change and Paths into and out of STEM: Gender and Racial Disparities. *Socius*. https://doi.org/10.1177/23780231211001978

Mau, W. C. (2003). Factors that influence persistence in science and engineering career aspirations. Career Development Quarterly, 51(3), 234 – 243. https://doi.org/10.1002/j.2161-0045.2003.tb00604.x

Mazuzan, G. (1994). The National Science Foundation: A Brief History. National Science Foundation. Retrieved from https://www.nsf.gov/about/history/nsf50/nsf8816.jsp

Means, B., Wang, H., Wei, X., Iwatani, E., & Peters, V. (2018). Broadening participation in STEM college majors: Effects of attending a STEM-focused high school. *AERA Open*. https://doi.org/10.1177%2F2332858418806305

Miller, D. I., & Wai, J. (2015). The bachelor's to Ph.D. STEM pipeline no longer leaks more women than men: A 30-year analysis. *Frontiers in psychology*, *6*, 37. https://doi.org/10.3389/fpsyg.2015.00037

Mullis, I. V. S., Martin, M. O., Foy, P., Kelly, D. L., & Fishbein, B. (2020). *TIMSS 2019 International Results in Mathematics and Science.* Retrieved from Boston College, TIMSS & PIRLS International Study Center.

Murphy, S., MacDonald, A., Wang, C. A., & Danaia, L. (2019). Towards an understanding of STEM engagement: A review of the literature on motivation and academic emotions. *Canadian Journal of Science, Mathematics and Technology Education*, *19*(3), 304-320. https://doi.org/10.1007/s42330-019-00054-w

Mwangi, C. A. G., Cabrera, A. F., & Kurban, E. R. (2019). Connecting school and home: Examining parental and school involvement in readiness for college through multilevel SEM. *Research in Higher Education*, *60*(4), 553-575. https://doi.org/10.1007/s11162-018-9520-4

National Academy of Engineering. (2005). Educating the Engineer of 2020: Adapting engineering education to the new century. Washington, DC: The National Academies Press. https://www.nap.edu/catalog/11338/educating-the-engineer-of-2020-adapting-engineering-education-to-the

National Academy of Sciences, National Academy of Engineering, and Institute of Medicine. 2007. *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future*. Washington, DC: The National Academies Press. https://doi.org/10.17226/11463.

National Academy of Sciences, National Academy of Engineering, and Institute of Medicine. 2010. *Rising Above the Gathering Storm, Revisited: Rapidly Approaching Category 5*. Washington, DC: The National Academies Press. https://doi.org/10.17226/12999.

National Academies of Sciences, Engineering, and Medicine. 2016. *Barriers and Opportunities for 2-Year and 4-Year STEM Degrees: Systemic Change to Support Students' Diverse Pathways*. Washington, DC: The National Academies Press. https://doi.org/10.17226/21739

National Academies of Sciences, Engineering, and Medicine. 2016. *Barriers and Opportunities for 2-Year and 4-Year STEM Degrees: Systemic Change to Support Students' Diverse Pathways*. Washington, DC: The National Academies Press. https://doi.org/10.17226/21739

National Academies of Sciences, Engineering, and Medicine. (2017). *Building America's skilled technical workforce*. National Academies Press.

National Center for Education Statistics. (2019). Digest of Education Statistics. Retrieved from https://nces.ed.gov/programs/digest/

National Commission on Excellence in Education. (1983). A nation at risk: The imperative for educational reform. *The Elementary School Journal*, *84*(2), 113-130. Retrieved from https://www.edreform.com/wp-content/uploads/2013/02/A_Nation_At_Risk_1983.pdf

National Economic Council, Council of Economic Advisers, & Office of Science and Technology Policy. (2015). A Strategy for American Innovation. *The White House*, (October), 76. https://obamawhitehouse.archives.gov/sites/default/files/strategy_for_american_innovation_october_2015.pdf

National Governors Association. (2007). Innovation America: Building a Science, Technology, Engineering, and Mathematics Agenda. https://files.eric.ed.gov/fulltext/ED496324.pdf

National Research Council. (2002). *Attracting PhDs to K-12 education: a demonstration program for science, mathematics, and technology*. National Academies Press. https://www.nap.edu/catalog/10433/attracting-phds-to-k-12-education-a-demonstration-program-for

National Research Council. (2012). *Rising to the challenge: US innovation policy for the global economy*. National Academies Press. https://www.nap.edu/read/13386/ chapter/1

National Science Board & National Science Foundation. (2019). Higher Education in Science and Engineering. *Science and Engineering Indicators 2020*. NSB-2019-7. Alexandria, VA. https://ncses.nsf.gov/pubs/nsb20197/

National Science Board & National Science Foundation. (2020). *Science and Engineering Indicators 2020: The State of U.S. Science and Engineering*. NSB-2020-1. https://ncses.nsf.gov/pubs/nsb20201/

Piketty, T., & Goldhammer, A. (2014). Capital in the twenty-first century. Cambridge Massachusetts: The Belknap Press of Harvard University Press.

Plasman, J., Gottfried, M., Williams, D., Ippolito, M., & Owens, A. Parents' occupations and students' success in STEM fields: A systematic review and narrative synthesis. https://doi.org/10.1007/s40894-020-00136-z

Rinn, A. (2013). Family context predictors of math self-concept among undergraduate STEM majors: An analysis of gender differences. *Journal of the Scholarship of Teaching and Learning,* 116-132. https://scholarworks.iu.edu/journals/index.php/josotl/article/view/3108

Rodriguez, S. L., & Blaney, J. M. (2020). "We're the unicorns in STEM": Understanding how academic and social experiences influence sense of belonging for Latina undergraduate students. *Journal of Diversity in Higher Education*. https://psycnet.apa.org/doi/10.1037/dhe0000176

Romero, J. D. (2016, January 29). Study urges a movement away from traditional STEM pipelines to embrace diversity of STEM educational pathways. *AAAS*. https://www.aaas.org/news/study-urges-movement-away-traditional-stem-pipelines-embrace-diversity-stem-educational

Rosen, J. A., Porter, S. R., & Rogers, J. (2017). Understanding student self-reports of academic performance and course-taking behavior. *AERA Open*, *3*(2). https://doi.org/10.1177%2F2332858417711427

Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents: A promising start, but further to go. *Educational Psychologist*, *51*(2), 146-163. https://psycnet.apa.org/doi/10.1080/00461520.2016.1154792

Rothwell, J. (2013). *The hidden STEM economy*. Metropolitan Policy Program at Brookings. https://www.brookings.edu/research/the-hidden-stem-economy/

Rozek, C. S., Svoboda, R. C., Harackiewicz, J. M., Hulleman, C. S., & Hyde, J. S. (2017). Utility-value intervention with parents increases students' STEM preparation and career pursuit. *Proceedings of the National Academy of Sciences*, *114*(5), 909-914. https://doi.org/10.1073/pnas.1607386114

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. *Science education*, *96*(3), 411-427. https://doi.org/10.1002/sce.21007

Sansone, D. (2017). Why does teacher gender matter? *Economics of Education Review*, *61*, 9-18. https://doi.org/10.1016/j.econedurev.2017.09.004

Saw, G., Chang, C. N., & Chan, H. Y. (2018). Cross-sectional and longitudinal disparities in STEM career aspirations at the intersection of gender, race/ethnicity, and socioeconomic status. *Educational Researcher, 47*(8), 525-531. https://doi.org/10.3102%2F0013189X18787818

Sax, L. J., Kanny, M. A., Riggers-Piehl, T. A., Whang, H., & Paulson, L. N. (2015). "But I'm not good at math": The changing salience of mathematical self-concept in shaping women's and men's STEM aspirations. *Research in Higher Education*, *56*(8), 813-842. https://doi.org/10.1007/s11162-015-9375-x

Sax, L. J., Lim, G., Lehman, K., & Lonje-Paulson, L. (2018). Reversal of the gender gap: the biological sciences as a unique case within science, technology, engineering, and mathematics (STEM). *Journal of Women and Minorities in Science and Engineering*, *24*(4). http://doi.org/10.1615/JWomenMinorScienEng.2018019995

Seo, E., Shen, Y., & Alfaro, E. C. (2019). Adolescents' beliefs about math ability and their relations to STEM career attainment: Joint consideration of race/ethnicity and gender. *Journal of youth and adolescence, 48*(2), 306-325. https://doi.org/10.1007/s10964-018-0911-9

Seitz, F. (2007). *A Selection of Highlights from the History of the National Academy of Sciences, 1863-2005*. University Press of America.

Shi, Y. (2018). The puzzle of missing female engineers: Academic preparation, ability beliefs, and preferences. *Economics of Education Review, 64,* 129-143. https://doi.org/10.1016/j.econedurev.2018.04.005

Shi, Q., & Brown, M. H. (2020). School counselors' impact on school-level academic Outcomes: caseload and use of time. *Professional School Counseling*, *23*(1). https://doi.org/10.1177%2F2156759X20904489

Starr, C. R., Hunter, L., Dunkin, R., Honig, S., Palomino, R., & Leaper, C. (2020). Engaging in science practices in classrooms predicts increases in undergraduates' STEM motivation, identity, and achievement: A short-term longitudinal study. *Journal of Research in Science Teaching*. https://doi.org/10.1002/tea.21623

Svoboda, R. C., Rozek, C. S., Hyde, J. S., Harackiewicz, J. M., & Destin, M. (2016). Understanding the relationship between parental education and STEM course taking through identity-based and expectancy-value theories of motivation. *AERA Open*. https://doi.org/10.1177%2F2332858416664875

The United States Department of Education. (2016). *STEM 2026: A Vision for Innovation in STEM Education*. U.S. Department of Education Workshop, *55*. http://www.air.org/system/files/downloads/report/STEM-2026-Vision-for-Innovation-September-2016.pdf

Tabachnick, B., & Fidell, L. (2015). Using multivariate statistics (7th ed.). Pearson.

Tai, R. H., Kong, X., Mitchell, C. E., Dabney, K. P., Read, D. M., Jeffe, D. B., ... & Wathington, H. D. (2017). Examining summer laboratory research apprenticeships for high school students as a factor in entry to MD/PhD programs at matriculation. *CBE—Life Sciences Education*, *16*(2), ar37. https://doi.org/10.1187/cbe.15-07-0161

Tai, R. H., Liu, C. Q., Maltese, A. V., & Fan, X. (2006). Planning early for careers in science. *Life sci*, *1*(0.2). https://doi.org/10.1126/science.1128690

Tanenbaum, C. (2016). STEM 2026: A vision for innovation in STEM education. *US Department of Education, Washington, DC*. https://www.air.org/system/files/downloads/report/STEM-2026-Vision-for-Innovation-September-2016.pdf

Teitelbaum, P. (2003). The influence of high school graduation requirement policies in mathematics and science on student course-taking patterns and achievement. *Educational Evaluation and Policy Analysis*, *25*(1), 31-57. https://doi.org/10.3102/01623737025001031

Tinto, V. (1993). Leaving college: Rethinking the causes and cures of student attrition. Chicago: University of Chicago Press.

Trusty, J. (2002). Effects of High school course-taking and other variables on choice of science and mathematics college majors. Journal of Counseling and Development, 80, 464 – 474. https://doi.org/10.1002/j.1556-6678.2002.tb00213.x

Tyson, W., Lee, R., Borman, K. M., & Hanson, M. A. (2007). Science, technology, engineering, and mathematics (STEM) pathways: High school science and math coursework and postsecondary degree attainment. *Journal of Education for Students placed at risk*, *12*(3), 243-270. https://doi.org/10.1080/10824660701601266

Unfried, A., Faber, M., & Wiebe, E. N. (2014). Student Interest in Engineering and Other STEM Careers: An Examination of School-Level, Gender, Race/Ethnicity, and Urbanicity. In *ASEE Annual Conference & Exposition, Indianapolis, IN*. https://eval.fi.ncsu.edu/wp-content/uploads/2016/03/ASEE-2014-Unfried-Faber-Wiebe.pdf

United States Department of Labor. (2007). *The STEM workforce challenge: The role of the public workforce system in a national solution for a competitive Science, Technology, Engineering, and Mathematics (STEM) workforce*. Washington, DC: Author. http://digitalcommons.ilr.cornell.edu/key_workplace/637

Vollmeyer, R. & Rheinberg, F. (2000). Does motivation affect performance via persistence? Learning and Instruction, 10, 293-309. Learning and Instruction. 10. 293–309. https://doi.org/10.1016/S0959-4752(99)00031-6

Wang, M. T., Chow, A., Degol, J. L., & Eccles, J. S. (2017). Does everyone's motivational beliefs about physical science decline in secondary school?: Heterogeneity of adolescents' achievement motivation trajectories in physics and chemistry. *Journal of youth and adolescence*, *46*(8), 1821-1838. https://doi.org/10.1007/s10964-016-0620-1

Wang, M. T., Ye, F., & Degol, J. L. (2017). Who chooses STEM careers? Using a relative cognitive strength and interest model to predict careers in science, technology, engineering, and mathematics. *Journal of youth and adolescence*, *46*(8), 1805-1820. https://doi.org/10.1007/s10964-016-0618-8

Wang, J., & Staver, J. R. (2001). Examining relationships between factors of science education and student career aspirations. Journal of Educational Research, 94(5), 312 – 319. https://doi.org/10.1080/00220670109598767

Wang, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*(5), 1081-1121. https://doi.org/10.3102%2F0002831213488622

Wantanabe, T. (2022, February 24). UC smashes record for first-year fall applications, with gains in most racial groups. *Los Angeles Times*. https://www.latimes.com/california/story/2022-02-24/uc-breaks-fall-2022-college-admission-application-records

Warne, R. T., Sonnert, G., & Sadler, P. M. (2019). The relationship between advanced placement mathematics courses and students' STEM career interest. *Educational Researcher*, *48*(2), 101-111. https://doi.org/10.3102%2F0013189X19825811

Wigfield, A. & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental review*, *12*(3), 265-310. https://doi.org/10.1016/0273-2297(92)90011-P

Wigfield, A. & Eccles, J. S. (2002). The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In *Development of achievement motivation* (pp. 91-120). Academic Press. https://doi.org/10.1016/B978-012750053-9/50006-1

Wolniak, G. C. (2016). Examining STEM bachelor's degree completion for students with differing propensities at college entry. *Journal of College Student Retention: Research, Theory & Practice*, *18*(3), 287-309. https://doi.org/10.1177%2F1521025115622782

Xie, Y. & Killewald, A. A. (2012). Is American Science in Decline? Harvard University Press.

Xing, X., & Gordon, H. R. (2020). Mediating Effects of School Engagement between High School on-Time Completion and Career and Technical Education. *Vocations and Learning*, 1-21. https://doi.org/10.1007/s12186-020-09252-2

Xue, Y., & Larson, R. C. (2015). STEM crisis or STEM surplus? Yes and yes. *Monthly labor review*, *2015*. https://doi.org/10.21916/mlr.2015.14

Yang, Y. & Barth, J. M. (2017). A Q factor analysis approach to understanding female college students' attitudes toward multiple STEM disciplines. *Methodological Innovations*. https://doi.org/10.1177%2F2059799117738704

Young, J. L., Ero-Tolliver, I., Young, J. R., & Ford, D. Y. (2017). Maximizing opportunities to enroll in advanced high school science courses: Examining the scientific dispositions of Black girls. *Journal of Urban Learning, Teaching, and Research*, *13,* 174-183. http://files.eric.ed.gov/fulltext/EJ1149860.pdf

Young, J., & Young, J. L. (2018). We can Achieve if We Receive: Examining the Effects of Out-of-School Time Activities on Black Student Achievement in Mathematics. *Equity & Excellence in Education*, *51*(2), 182-198. https://doi.org/10.1080/10665684.2018.1506952

Young, J., Young, J., & Witherspoon, T. (2019). Informing Informal STEM Learning: Implications for Mathematics Identity in African American Students. *Journal of Mathematics Education*, *12*(1), 39-56. http://educationforatoz.com/images/2019-1-3-Young_et_al_LM_AS_Final.pdf

Yu, R., & Singh, K. (2018). Teacher support, instructional practices, student motivation, and mathematics achievement in high school. *The Journal of Educational Research*, *111*(1), 81-94. https://doi.org/10.1080/00220671.2016.1204260

Zhang, Y. L. (2019). Early academic momentum: Factors contributing to community college transfer students' STEM degree attainment. *Journal of College Student Retention: Research, Theory & Practice*. https://doi.org/10.1177%2F1521025119881130

Appendix A. Descriptive Statistics

A.1 Descriptive Statistics for STEM Code 1 by Gender and Race

The following data tables and figures provide a detailed view of student participants in the study by race and gender.

Table A.1. *Descriptive Statistics for X1STU30OCC_STEM1 by Student Demographics (X1SEX)*

[b]STEM Sub-Domain	Female				Male			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.61	.012	.59	.64	.77	.010	.75	.78
2	.06	.005	.05	.13	.12	.006	.10	.13
3	.31	.011	.29	.33	.09	.007	.08	.11
4	.02	.003	.01	.02	.02	.004	.02	.03
Total	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A.2*. Descriptive Statistics for X2STU30OCC_STEM1 by Student Demographics (X1SEX)*

[b]STEM Sub-Domain	Female				Male			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.58	.010	.56	.60	.73	.010	.71	.75
2	.05	.005	.04	.06	.14	.008	.13	.16
3	.34	.010	.32	.36	.10	.007	.09	.12
4	.04	.003	.03	.04	.03	.004	.02	.04
Total	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A.3*. Descriptive Statistics for X4OCC30STEM1 by Student Demographics (X1SEX)*

[b]STEM Sub-Domain	Female				Male			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.53	.017	.50	.57	.72	.012	.70	.75
2	.06	.006	.05	.08	.16	.010	.14	.18
3	.37	.069	.08	.11	.09	.007	.08	.11
4	.03	.005	.03	.05	.02	.004	.02	.03
Total	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A. 4. *Descriptive Statistics for X1STU30OCC_STEM1 by Race/Ethnicity*

[b]STEM Sub-Domain	Black/African American				Hispanic/Latin American				White/European American			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.72	.025	.67	.766	.70	.024	.65	.75	.68	.008	.67	.70
2	.05	.010	.04	.08	.07	.01	.05	.10	.10	.004	.09	.11
3	.22	.021	.18	.26	.20	.023	.16	.25	.20	.007	.18	.21
4	.01	.006	.004	.03	.02	.007	.01	.04	.02	.003	.02	.03
Total	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A.5. *Descriptive Statistics for X2STU30OCC_STEM1 by Race/Ethnicity*

[b]STEM Sub-Domain	Black/African American				Hispanic/Latin American				White/European American			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.64	.025	.59	.69	.66	.021	.61	.70	.66	.008	.64	.67
2	.07	.012	.05	.10	.08	.012	.06	.11	.10	.006	.09	.12
3	.27	.022	.22	.31	.23	.017	.19	.26	.21	.006	.20	.22
4	.02	.008	.01	.05	.04	.009	.03	.06	.03	.003	.03	.04
Total	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A.6. *Descriptive Statistics for X4OCC30STEM1 by Race/Ethnicity*

[b]STEM Sub-Domain	Black/African American				Hispanic/Latin American				White/European American			
	Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI		Proportion	Std. Err.[a]	95% CI	
1	.61	.031	.55	.67	.64	.029	.58	.69	.63	.01	.61	.65
2	.07	.02	.05	.11	.10	.013	.07	.13	.12	.008	.11	.14
3	.28	.033	.22	.35	.23	.030	.17	.29	.22	.009	.21	.24
4	.04	.01	.02	.07	.04	.011	.02	.07	.03	.003	.02	.03
Total	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (1) not a STEM occupation; (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains.

Table A.7. *Descriptive Statistics for STEM Code 1 by Race/Ethnicity and Gender*

Wave	[b]Sub-Domain	Black/African American		Hispanic/Latin American		White/European American	
		Prop.	Std. Err.[a]	Prop.	Std. Err.[a]	Prop.	Std. Err.[a]
1	2	.04 (.07)	.011 (.016)	.04 (**.10**)	.011 (.019)	.06 (**.13**)	.005 (.007)
	3	**.31 (.09)**	.028 (.015)	**.31** (.09)	.031 (.024)	**.31** (.09)	.010 (.007)
	4	.01 (.02)	.004 (.014)	.02 (.03)	.009 (.011)	.02 (.03)	.003 (.004)
2	2	.04 (.10)	.013 (.019)	.04 (**.12**)	.012 (.021)	.05 (**.16**)	.004 (.009)
	3	**.39 (.11)**	.031 (.020)	**.35** (.10)	.029 (.017)	**.33** (.10)	.009 (.007)
	4	.03 (.01)	.013 (.005)	.02 (.05)	.007 (.015)	.04 (.02)	.004 (.004)
3	2	.05 (**.11**)	.018 (.03)	.06 (**.14**)	.014 (.023)	.07 (**.18**)	.010 (.011)
	3	**.41** (.08)	.045 (.022)	**.36** (.09)	.046 (.020)	**.36** (.09)	.013 (.008)
	4	.04 (.03)	.017 (.011)	.04 (.03)	.020 (.013)	.03 (.02)	.004 (.005)

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM sub-domains correspond to the following: (2) life and physical science, engineering, mathematics, and IT occupations; (3) health occupations; and (4) split across two sub-domains. Each entry is broken by gender, formatted as “female(male)” for maximum category values. Not a STEM occupation was excluded in the table.

Note. (1) is omitted to only include accepted STEM sub-domains.

Table A.8. *Descriptive Statistics for STEM Code 3 by Race/Ethnicity and Gender*

Wave	[b]Sub-Domain	Black/African American		Hispanic		White/European American	
		Prop.	Std. Err.[a]	Prop.	Std. Err.[a]	Prop.	Std. Err.[a]
1	2	.030(.040)	.006 (.007)	.072 (.033)	.007 (.007)	.064 (.060)	.004 (.004)
	3	.006 (**.076**)	.003 (.009)	.006 (.075)	.002 (.008)	.009 (**.102**)	.001 (.005)
	4	.034 (.057)	.006 (.008)	.047 (**.078**)	.006 (.008)	.041 (.084)	.003 (.004)
2	2	.056 (.022)	.008 (.005)	.065 (.034)	.007 (.006)	.072 (.045)	.004 (.003)
	3	.017 (**.088**)	.004 (.010)	.017 (**.097**)	.004 (.009)	.020 (**.124**)	.002 (.006)
	4	.029 (.057)	.006 (.008)	.036 (.072)	.005 (.008)	.026 (.077)	.003 (.004)
3	2	.044 (.028)	.008 (.007)	.050 (.030)	.008 (.007)	.050 (.043)	.004 (.004)
	3	.013 (**.065**)	.004 (.011)	.017 (.066)	.004 (.009)	.022 (**.089**)	.003 (.005)
	4	.021 (.049)	.006 (.010)	.020 (**.068**)	.005 (.009)	.024 (.066)	.003 (.005)

[a] Balanced Repeated Replication (BRR) analysis for the complex survey data.

[b] STEM occupational types correspond to the following: (2) science; (3) engineering; and (4) non-science and engineering. Each entry is broken by gender, formatted as “female(male)” for maximum category values. Not a STEM occupation was excluded in the table.

Figure A.1. *Percentages of Students Identifying a STEM Career by Race (X1RACE) and Gender (X1SEX) for Each Wave (1,2, and 4)*

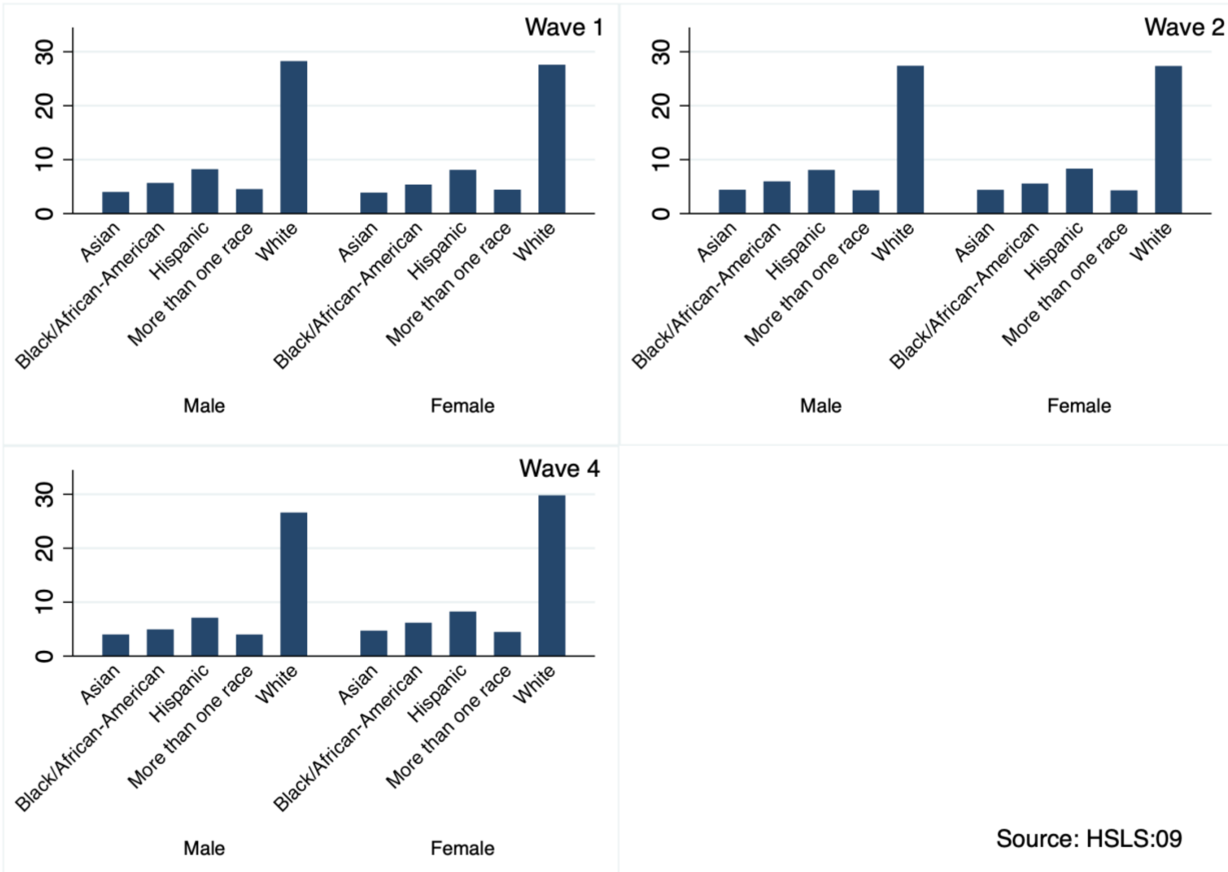
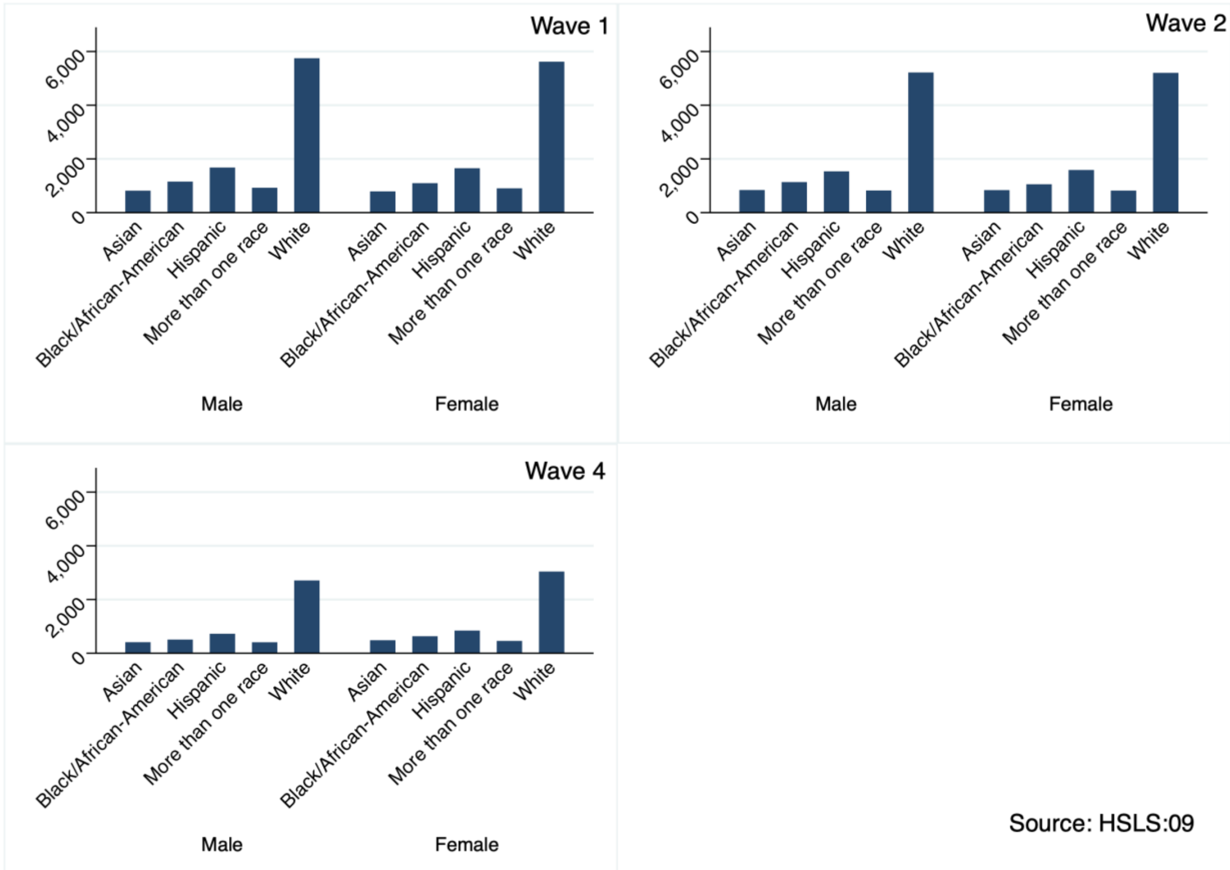


Figure A.2. *Frequencies of Students Identifying a STEM Career by Race (X1RACE) and Gender (X1SEX) for Each Wave (1,2, and 4)*



Appendix B. Model Development Statistics

B.1 Fit and Diagnostics

B.1.1 Linearization of Continuous Covariates

Below are a set of figures showing the linearization of continuous covariates throughout each wave (1, 2, and 3) in the STEM code 1 model.

Figure B.1. *Wave 1 Linearization of Continuous Covariates*

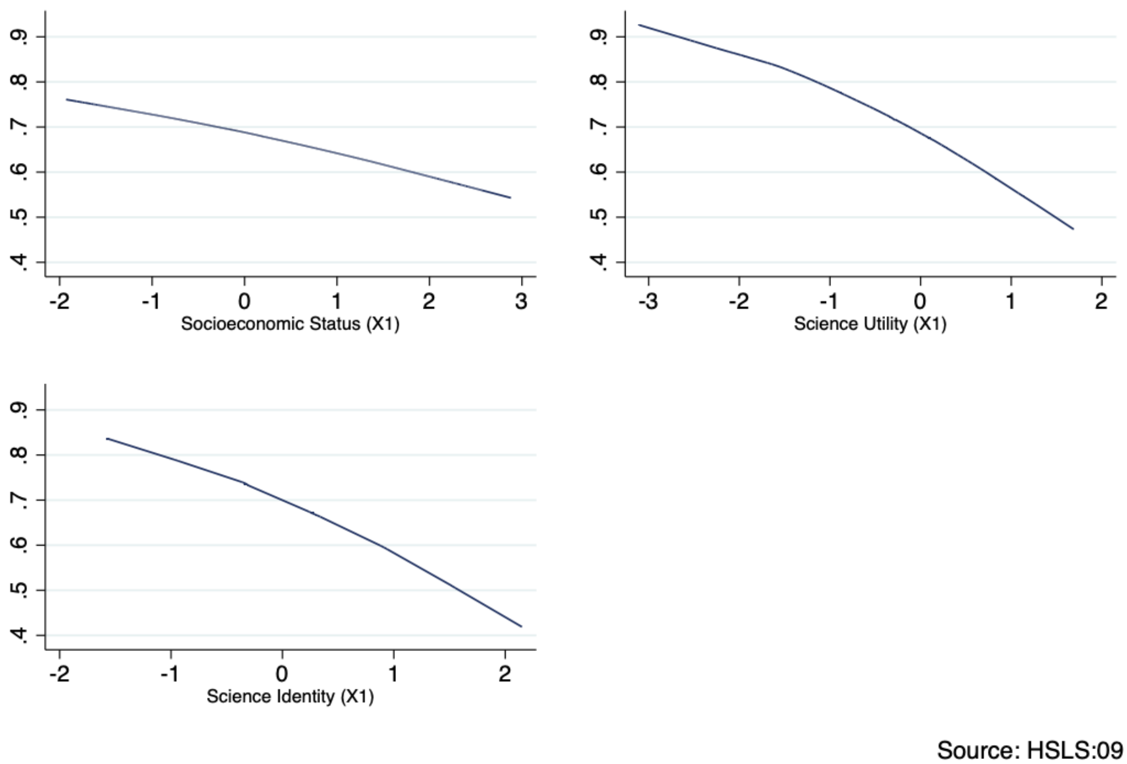
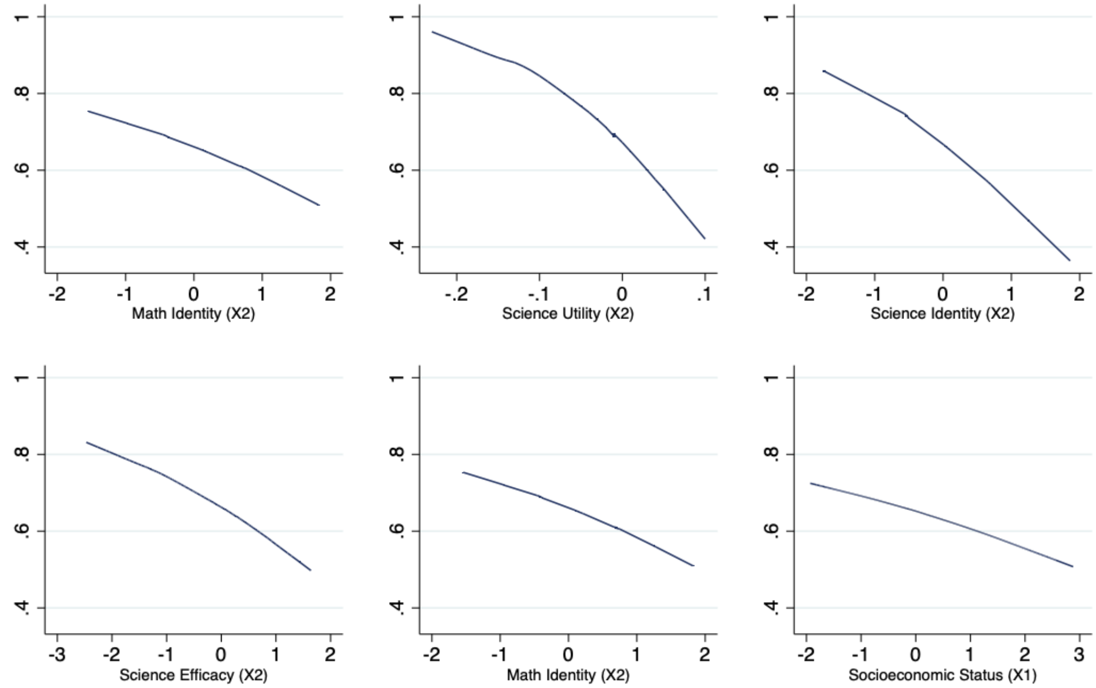
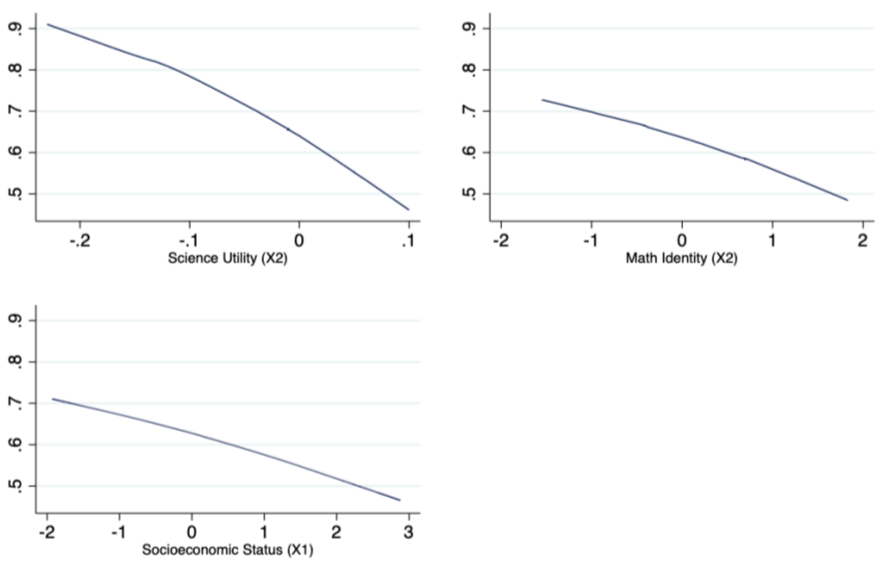


***Figure B.2**. Wave 2 Linearization of Continuous Covariates*



Source: HSLS:09

***Figure B.3.** Wave 4 Linearization of Continuous Covariates*



Source: HSLS:09

B.1.2 Fit and Diagnostics for STEM Code 1

Figure B.4. *Individual Logit Fit and Diagnostics of STEM1 – Wave 1 Model 1*

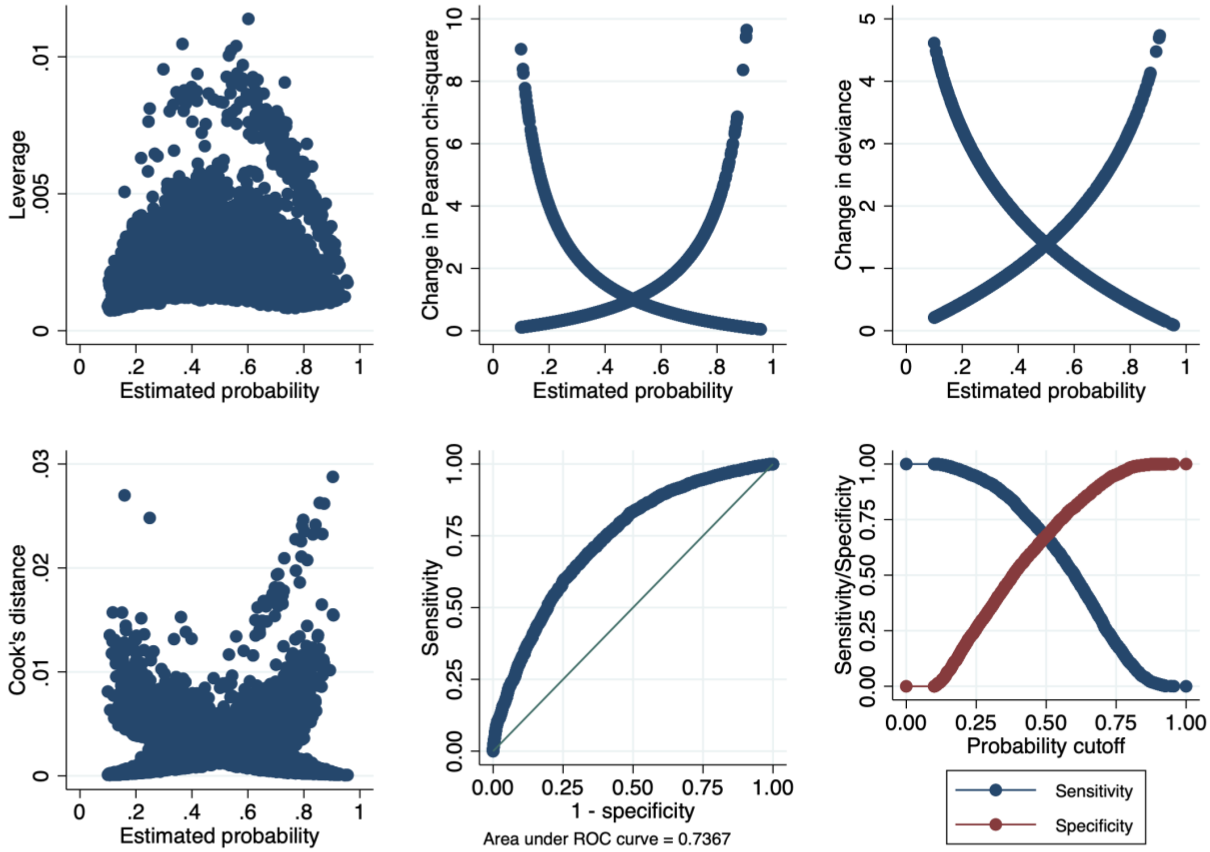


Figure B.5. *Individual Logit Fit and Diagnostics of STEM1 – Wave 1 Model 2*

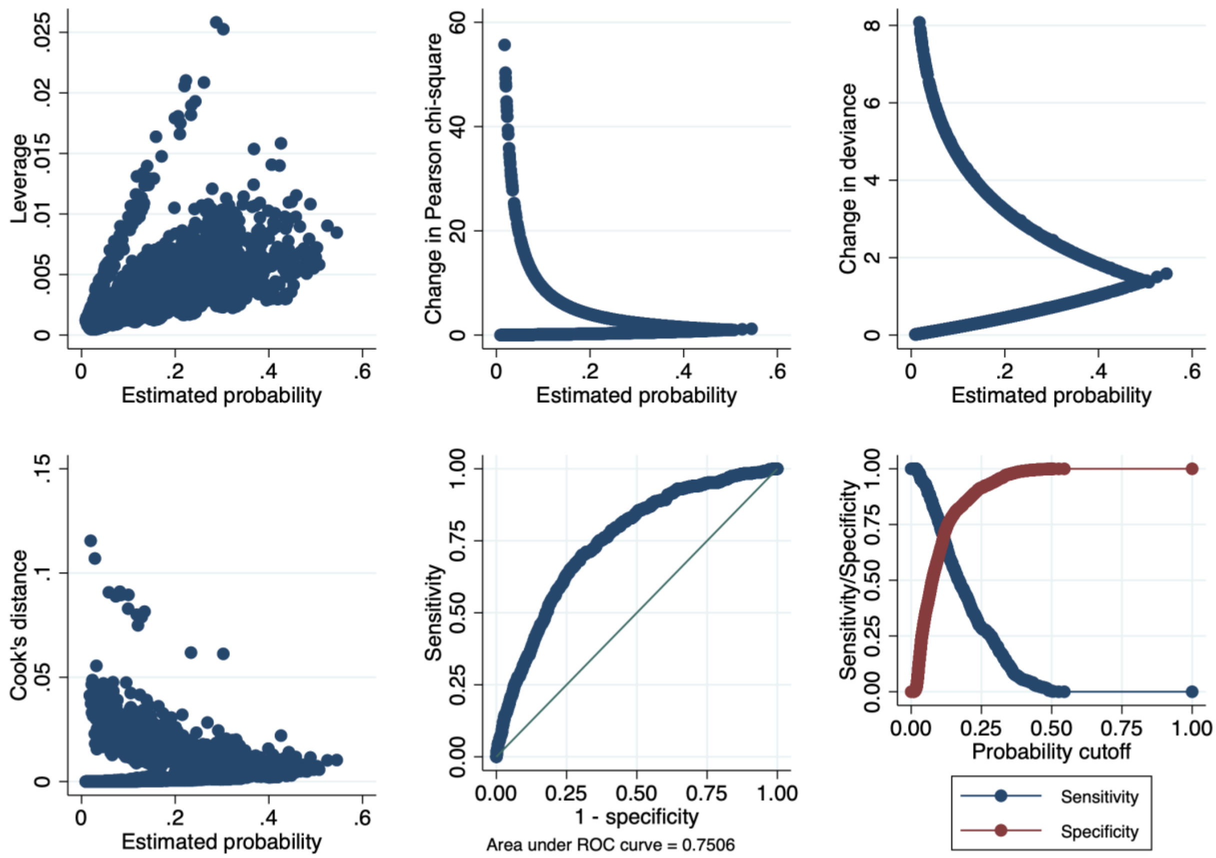


Figure B.6. *Individual Logit Fit and Diagnostics of STEM1 – Wave 1 Model 3*

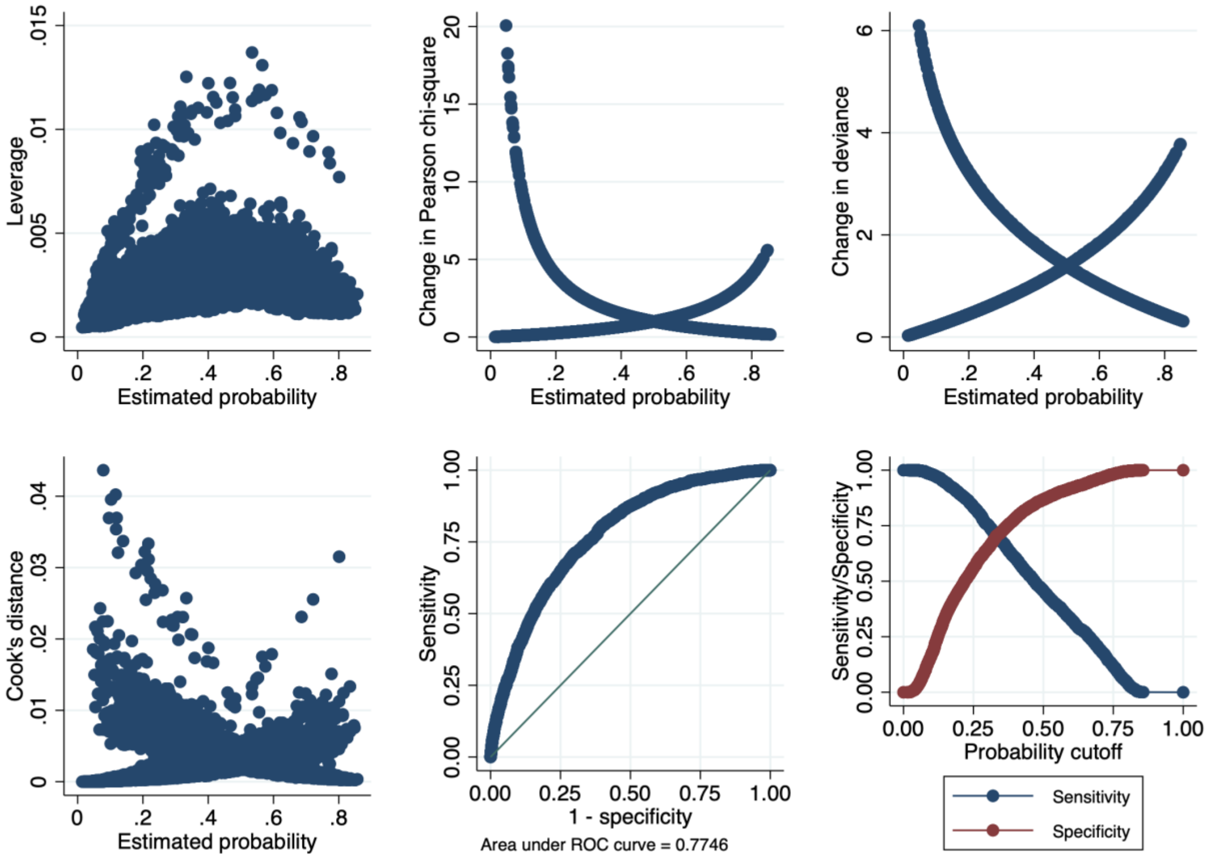


Figure B.7. *Individual Logit Fit and Diagnostics of STEM1 – Wave 1 Model 4*

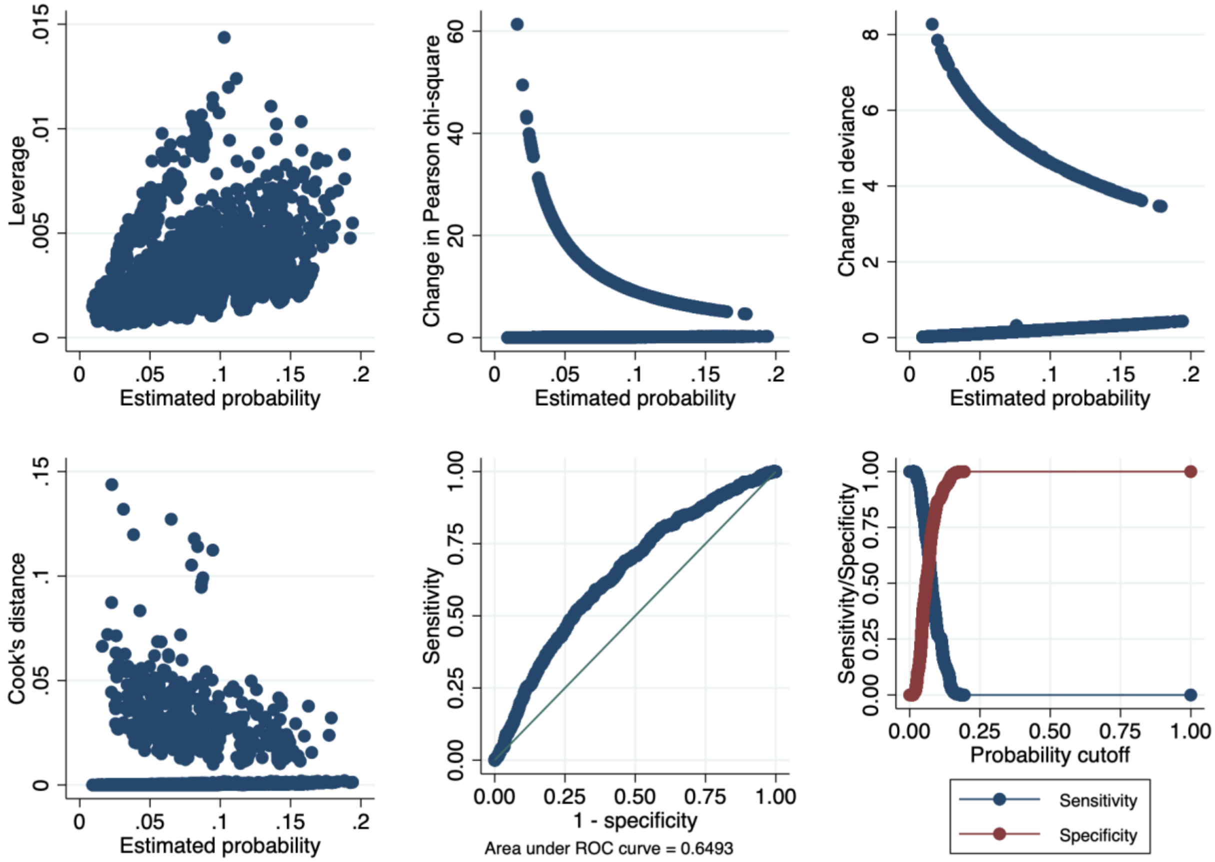


Figure B.8. *Individual Logit Fit and Diagnostics of STEM1 – Wave 2 Model 1*

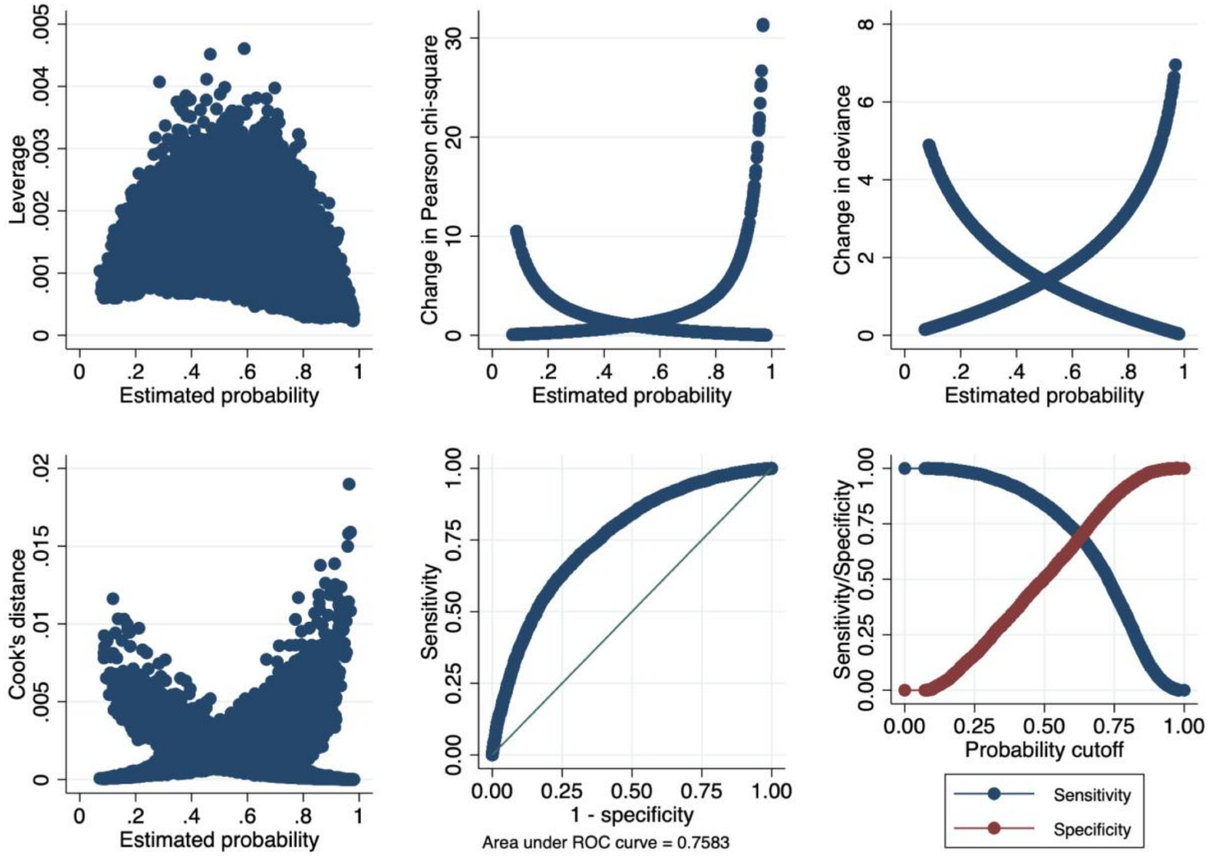


Figure B.9. *Individual Logit Fit and Diagnostics of STEM1 – Wave 2 Model 2*

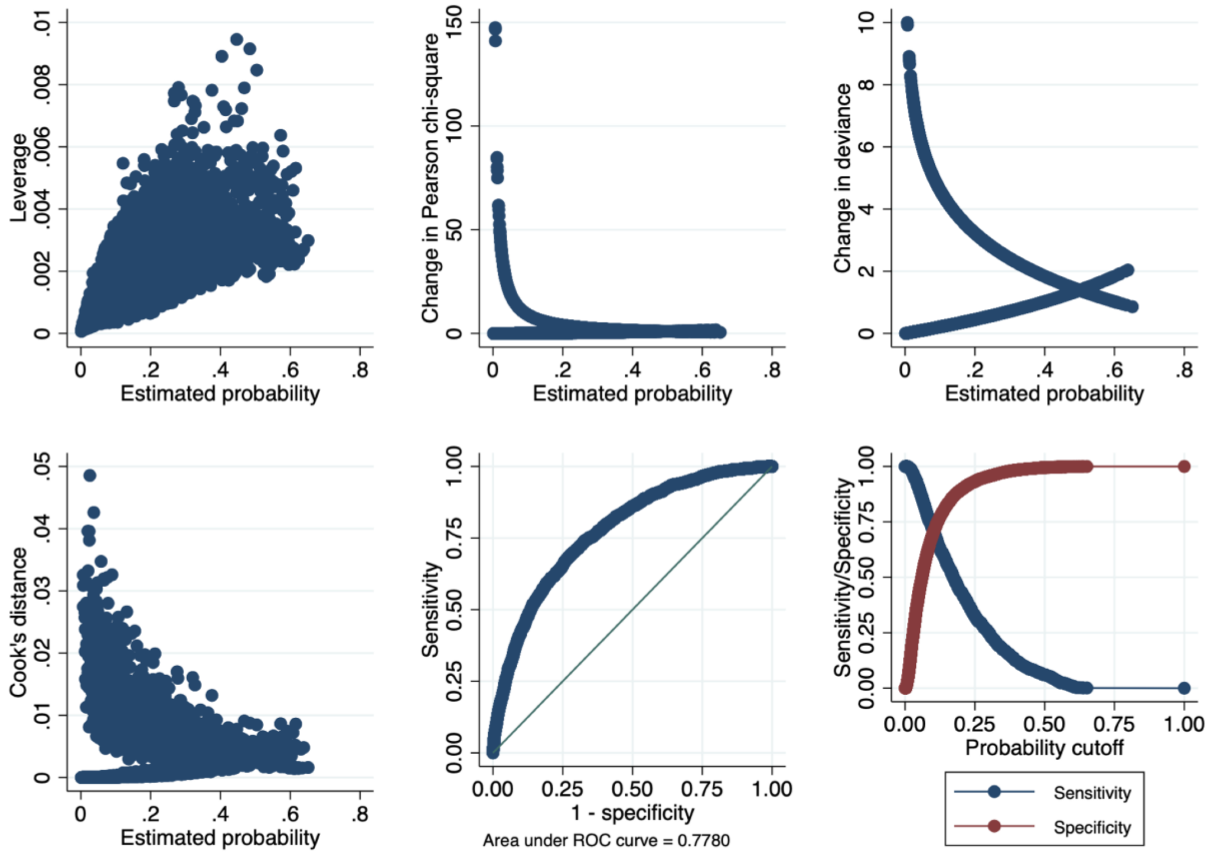


Figure B.10. *Individual Logit Fit and Diagnostics of STEM1 – Wave 2 Model 3*

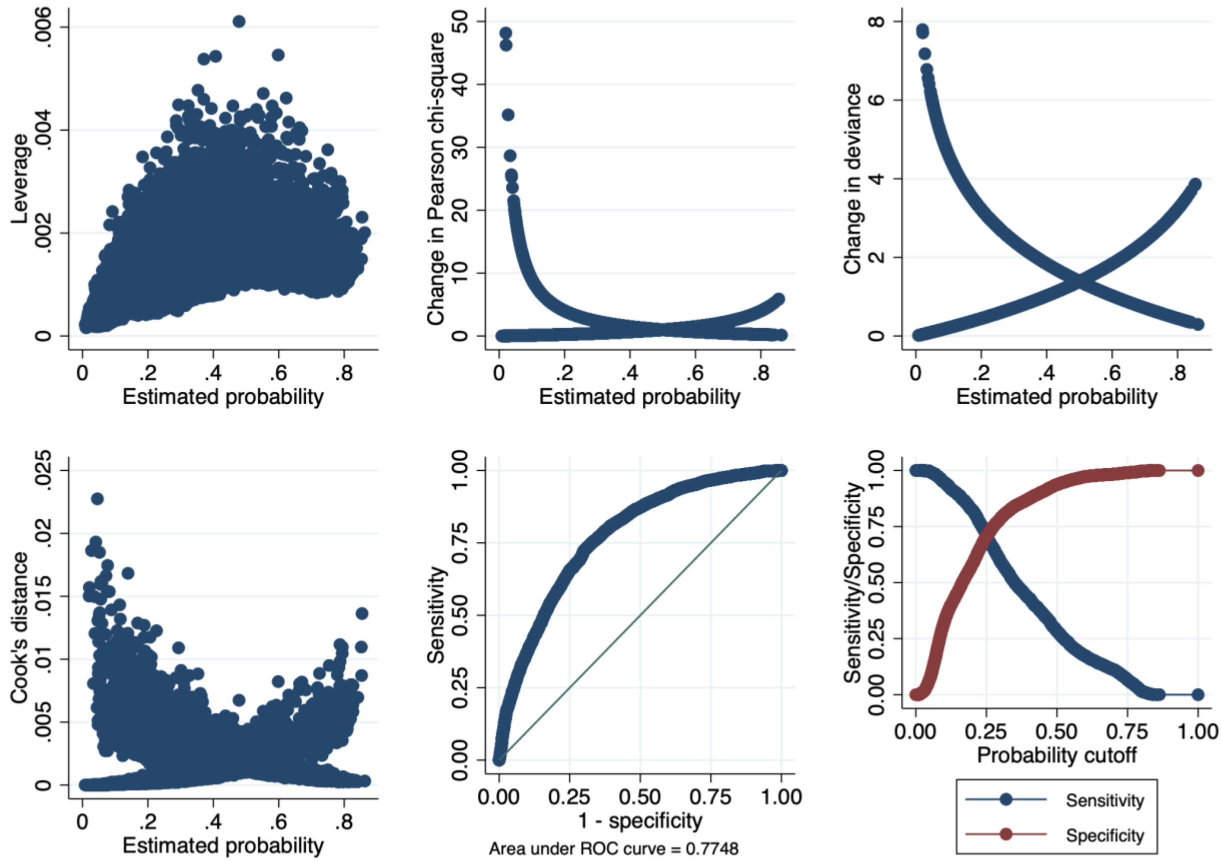


Figure B.11. *Individual Logit Fit and Diagnostics of STEM1 – Wave 2 Model 4*

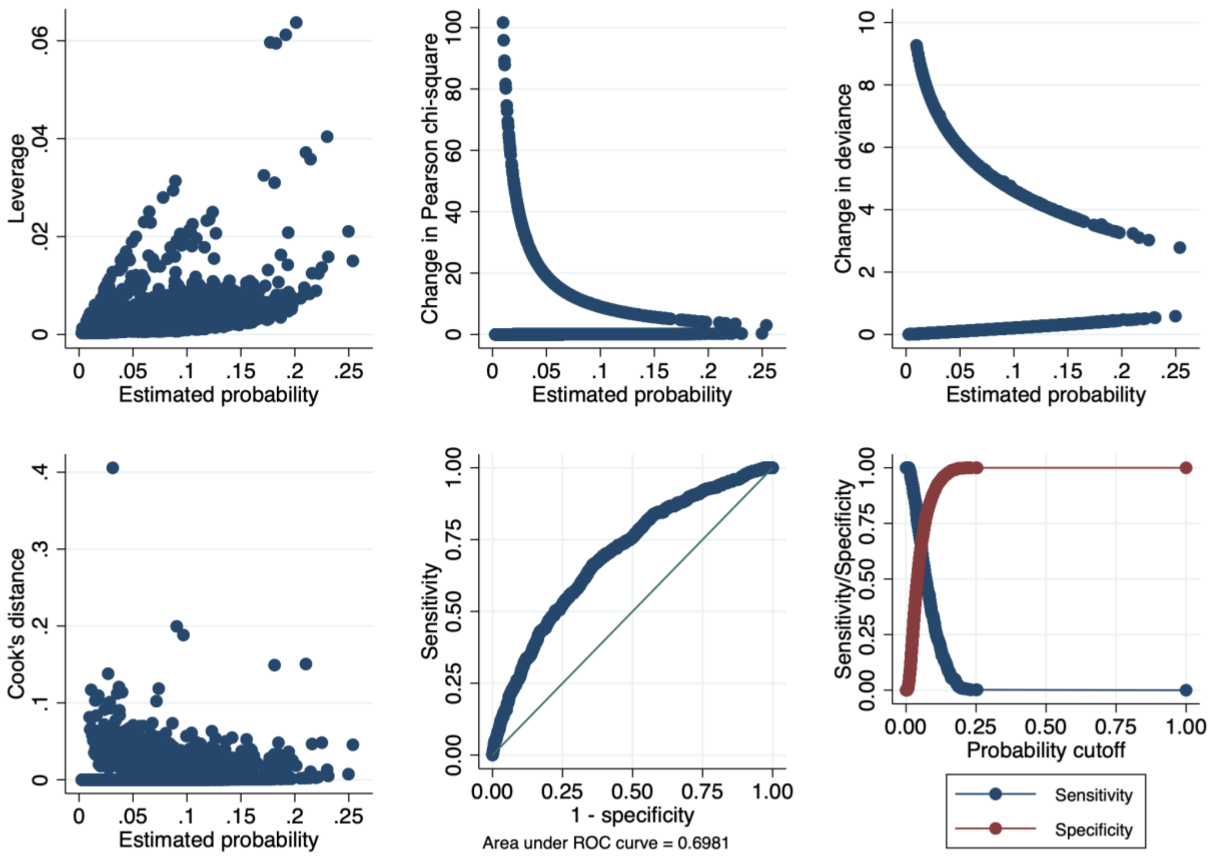


Figure B.12. *Individual Logit Fit and Diagnostics of STEM1 – Wave 4 Model 1*

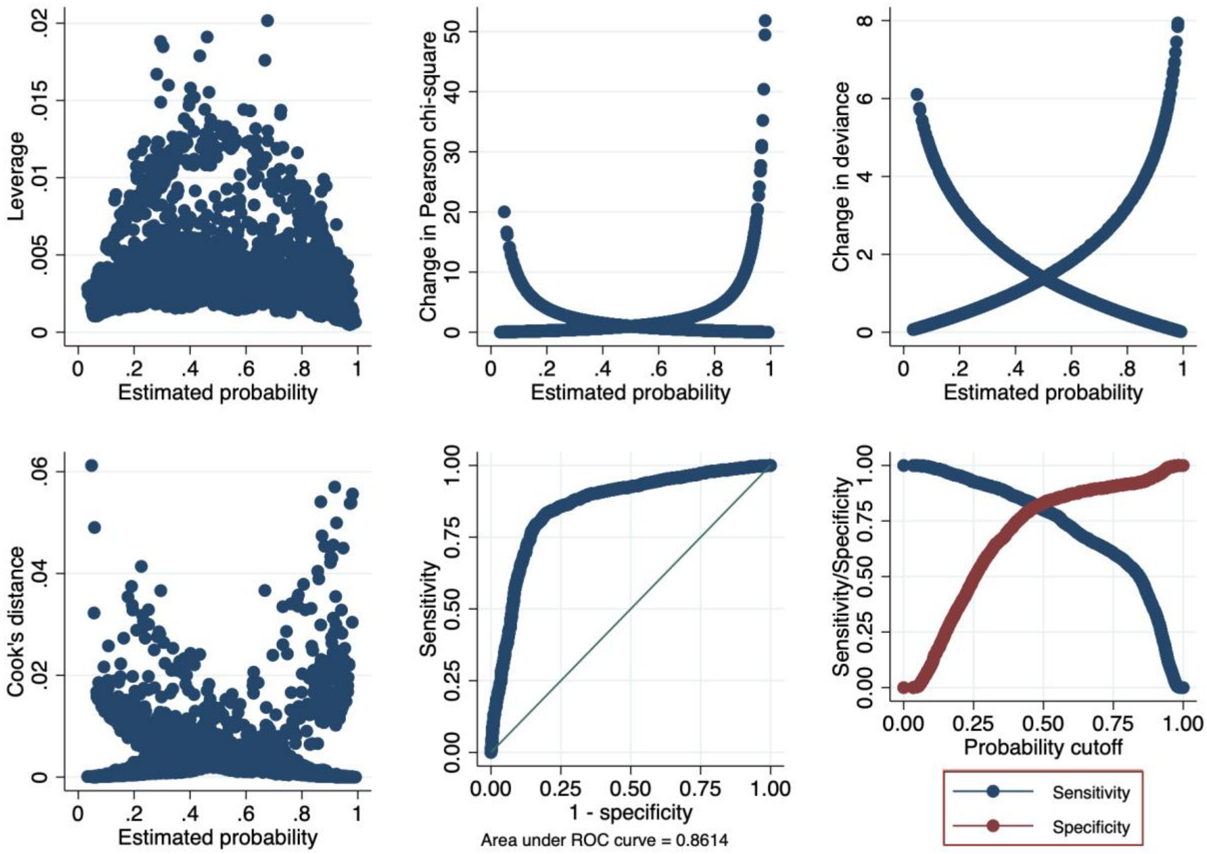


Figure B.13. *Individual Logit Fit and Diagnostics of STEM1 – Wave 4 Model 2*

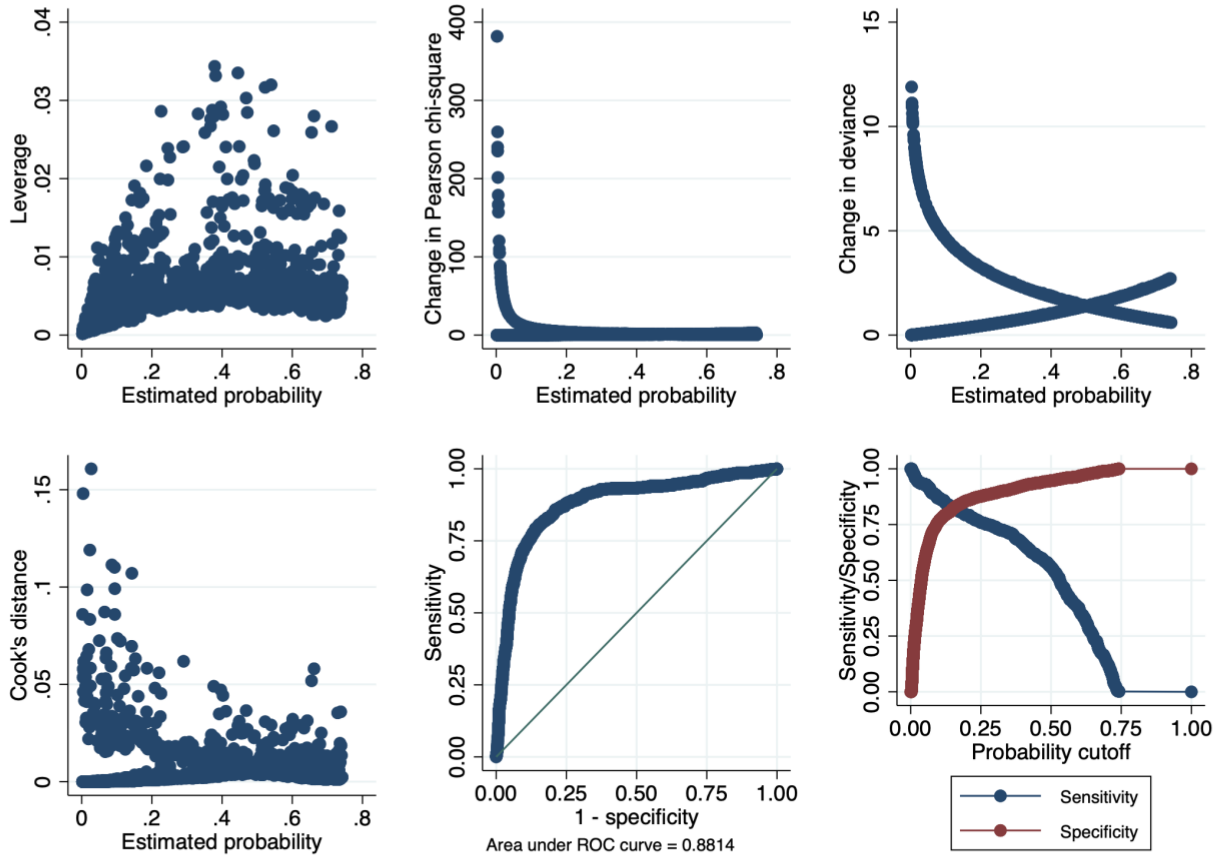


Figure B.14. *Individual Logit Fit and Diagnostics of STEM1– Wave 4 Model 3*

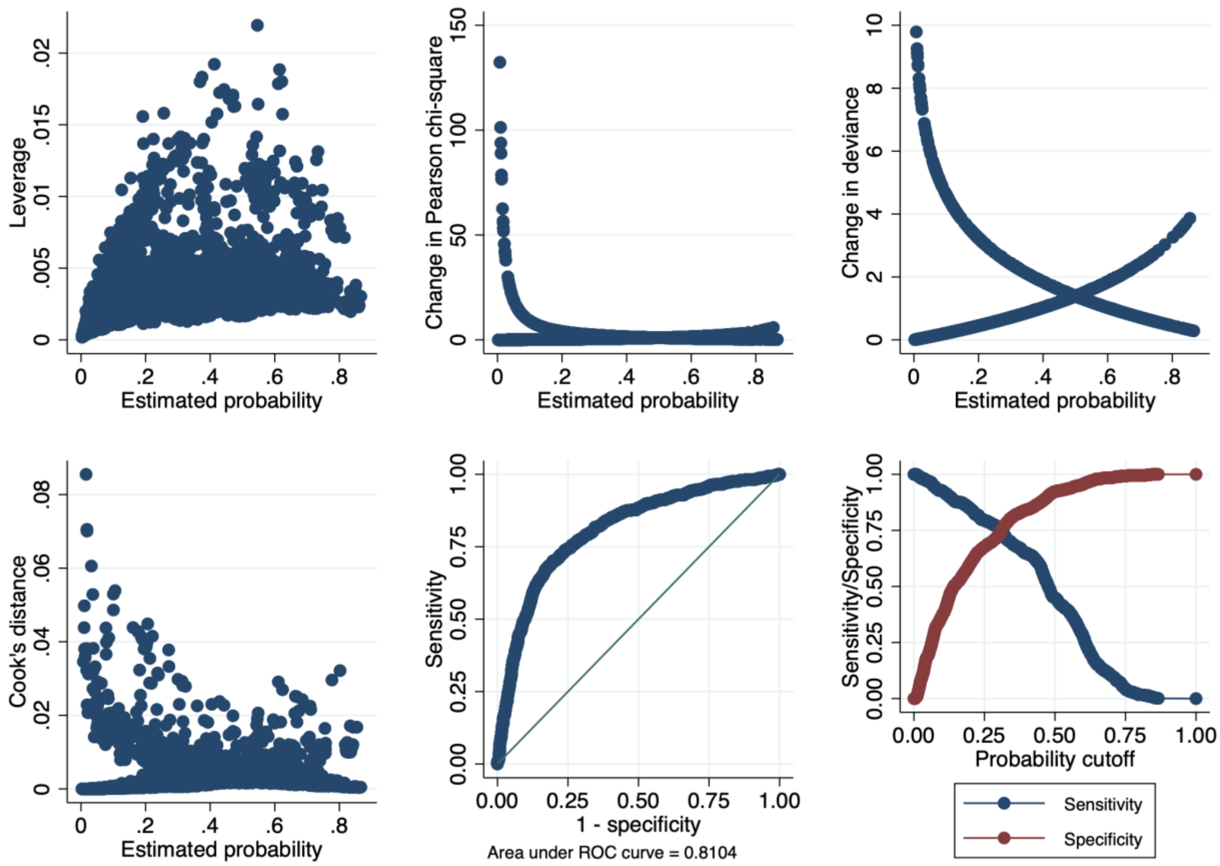
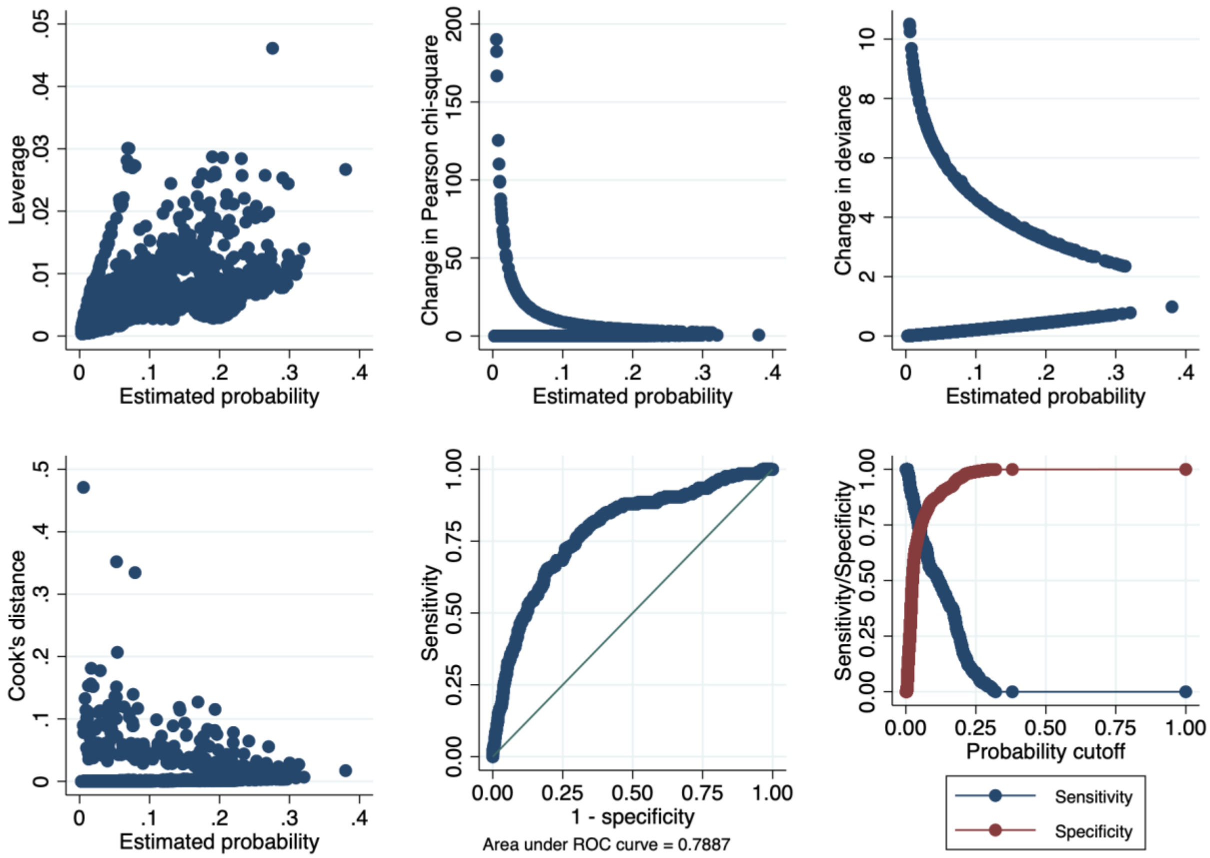


Figure B.15. *Individual Logit Fit and Diagnostics of STEM1 – Wave 3 Model 4*



B.1.3 Fit and Diagnostics for STEM Code 3

Figure B.16. *Individual Logit Fit and Diagnostics of STEM3 – Wave 1 Model 1*

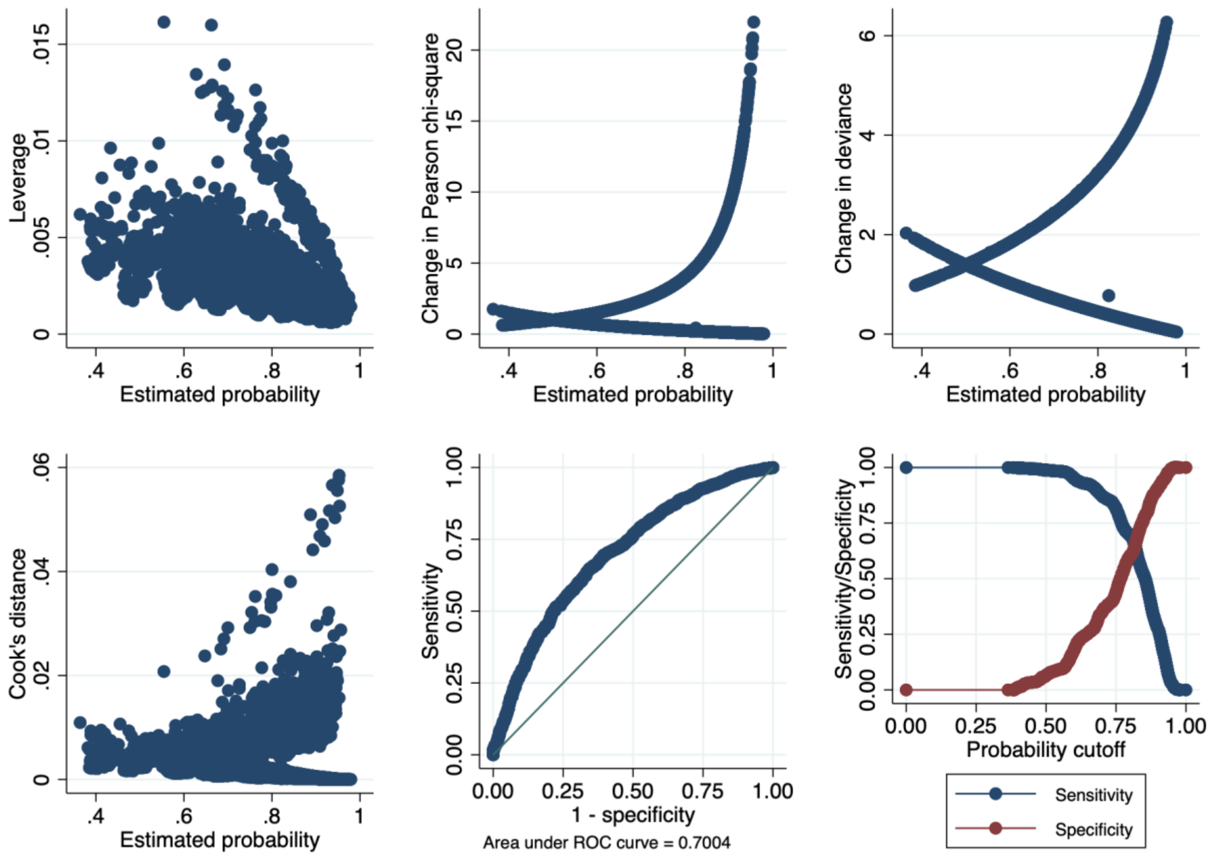


Figure B.17. *Individual Logit Fit and Diagnostics of STEM3 – Wave 1 Model 2*

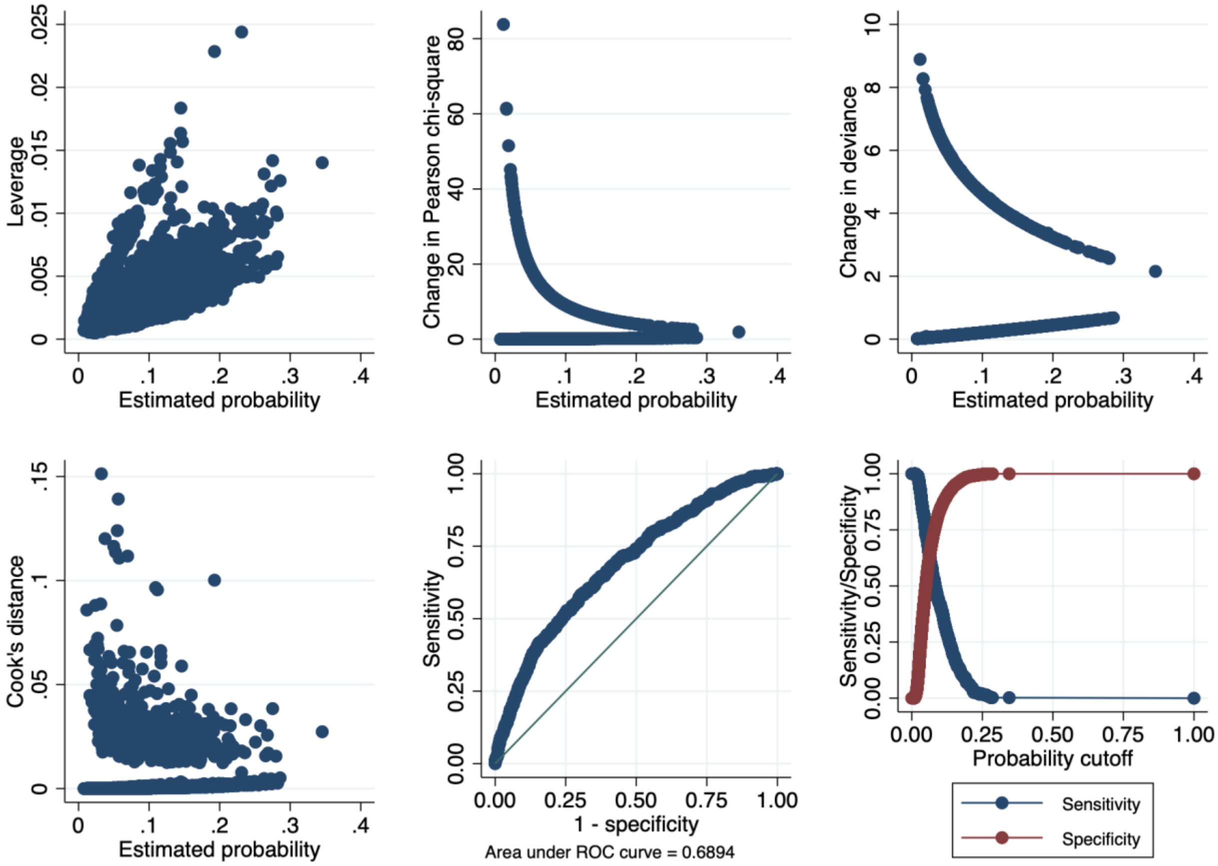


Figure B.18. *Individual Logit Fit and Diagnostics of STEM3 – Wave 1 Model 3*

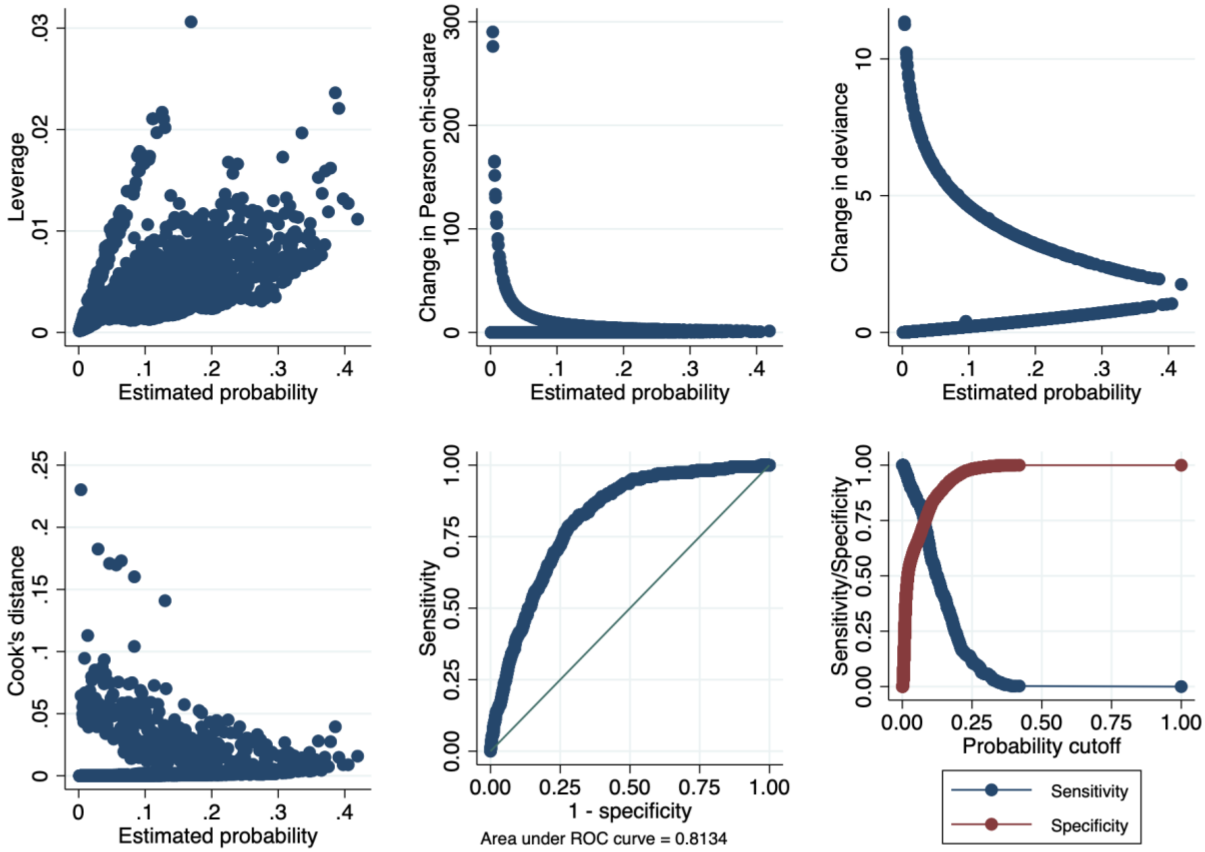


Figure B.19. *Individual Logit Fit and Diagnostics of STEM3 – Wave 1 Model 4*

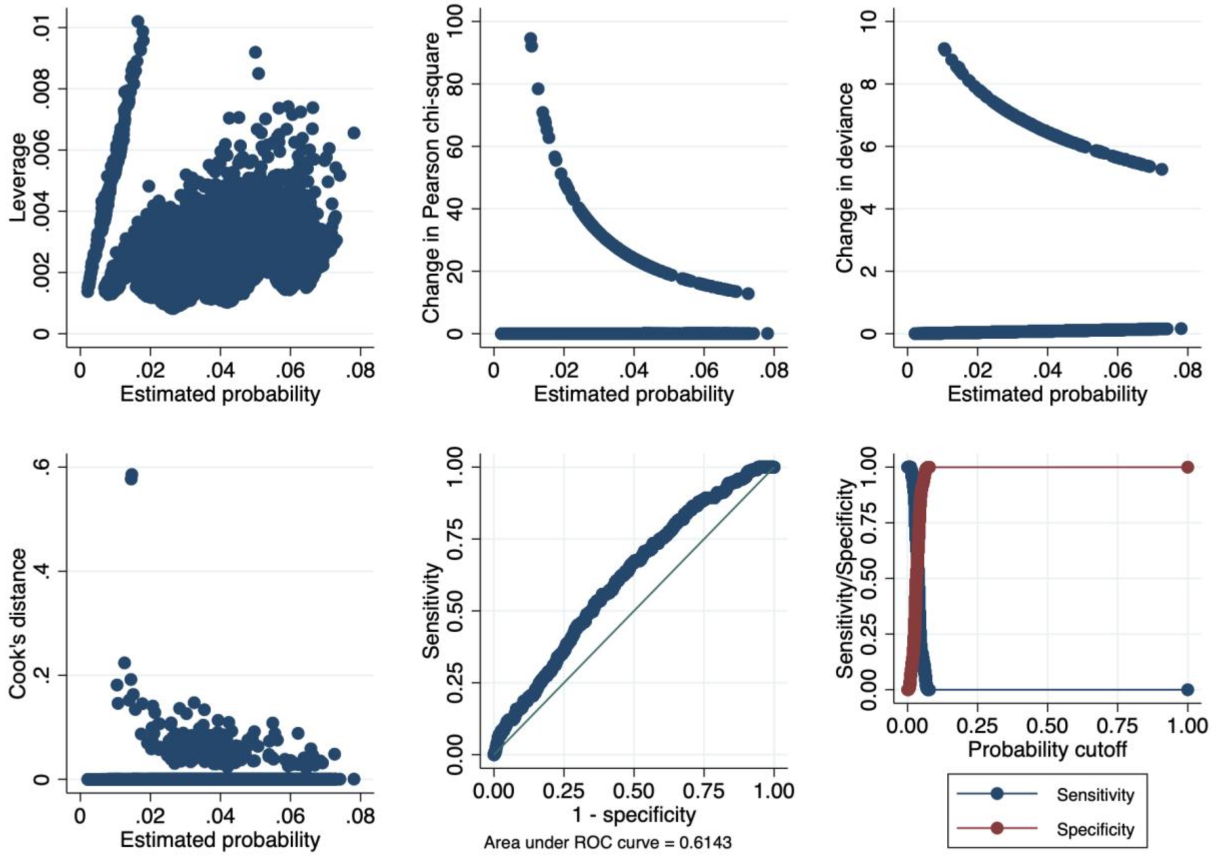


Figure B.20. *Individual Logit Fit and Diagnostics of STEM3 – Wave 2 Model 1*

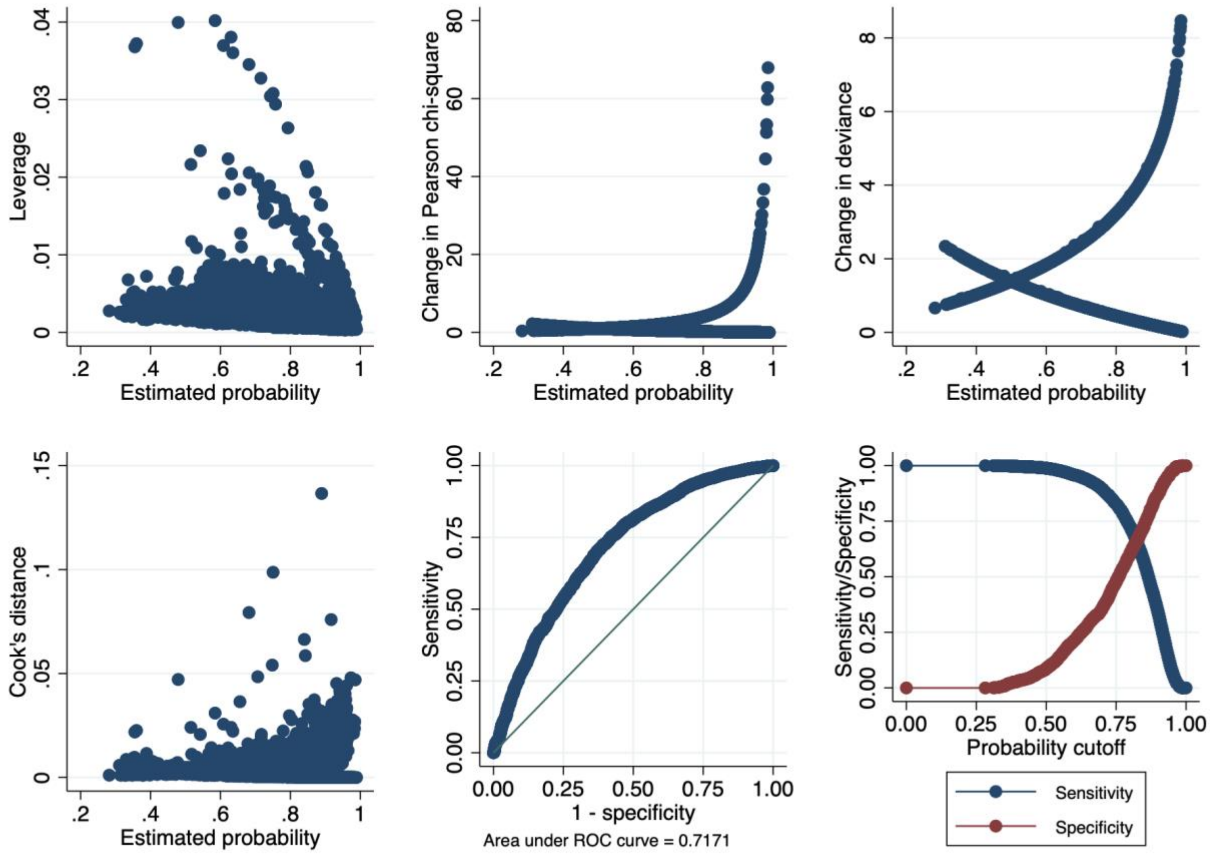


Figure B.21. *Individual Logit Fit and Diagnostics of STEM3 – Wave 2 Model 2*

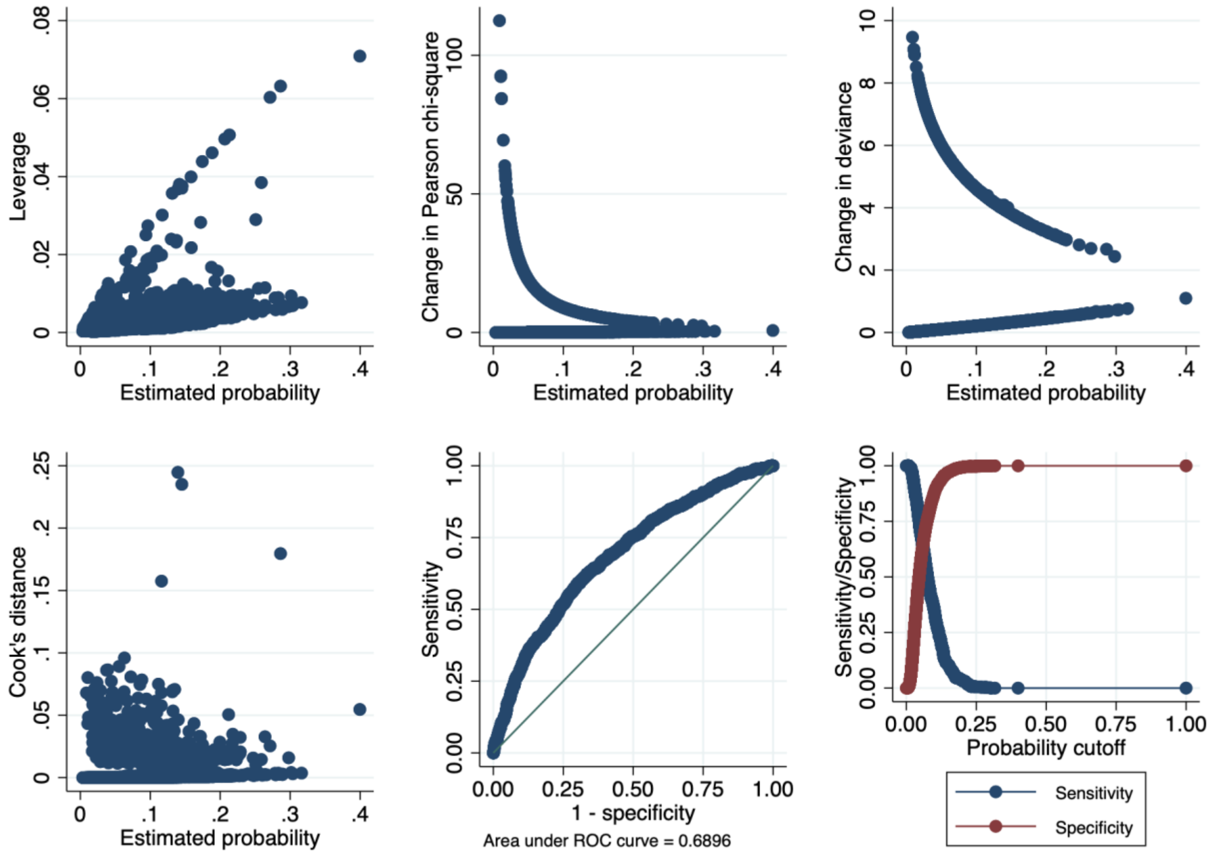


Figure B.22. *Individual Logit Fit and Diagnostics of STEM3 – Wave 2 Model 3*

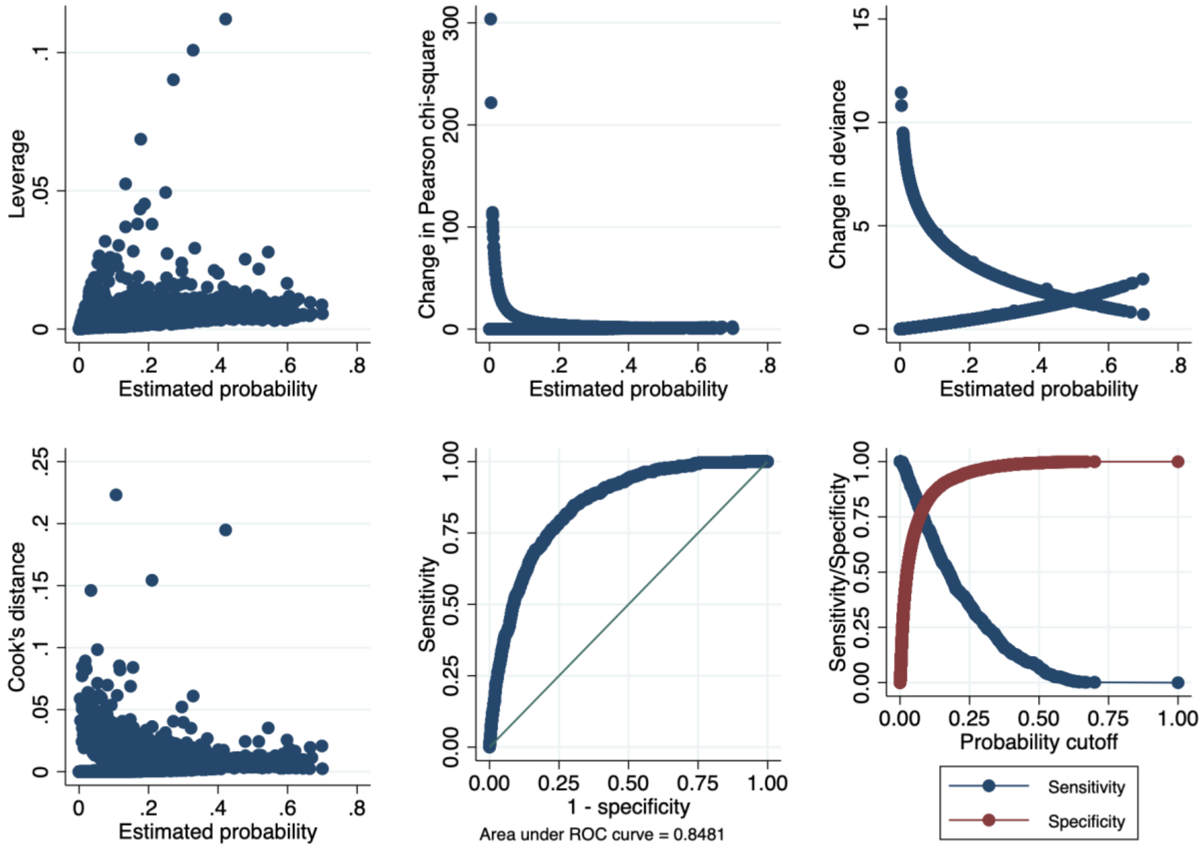


Figure B.23. *Individual Logit Fit and Diagnostics of STEM3 – Wave 2 Model 4*

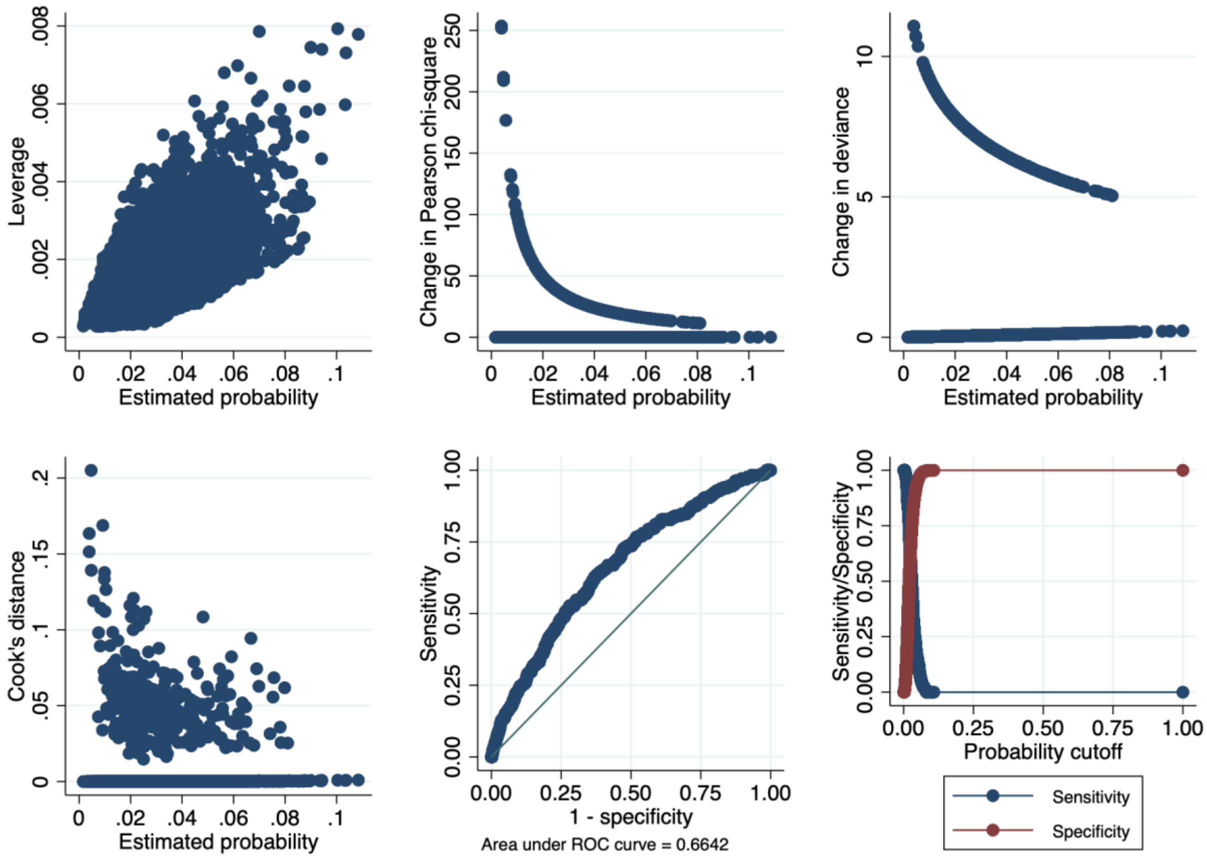


Figure B.24. *Individual Logit Fit and Diagnostics of STEM3 – Wave 4 Model 1*

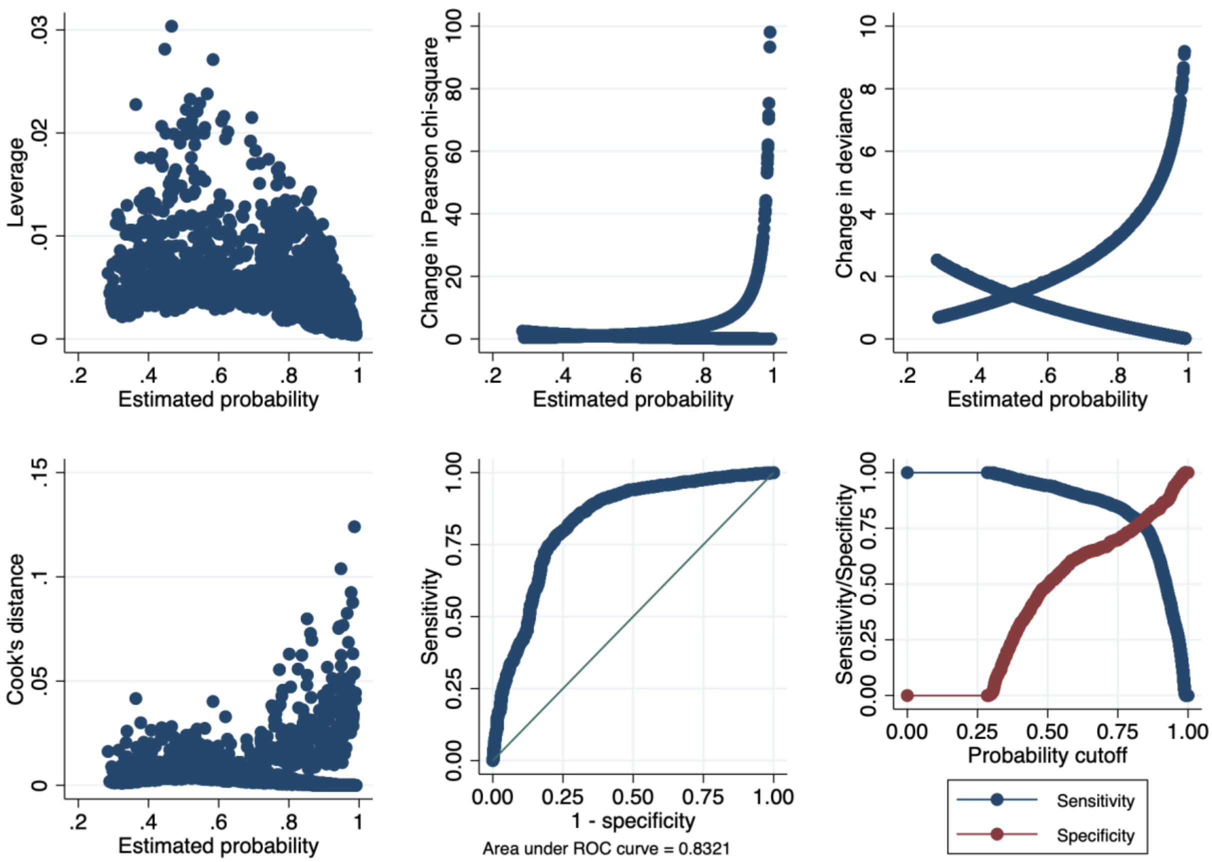


Figure B.25. *Individual Logit Fit and Diagnostics of STEM3 – Wave 4 Model 2*

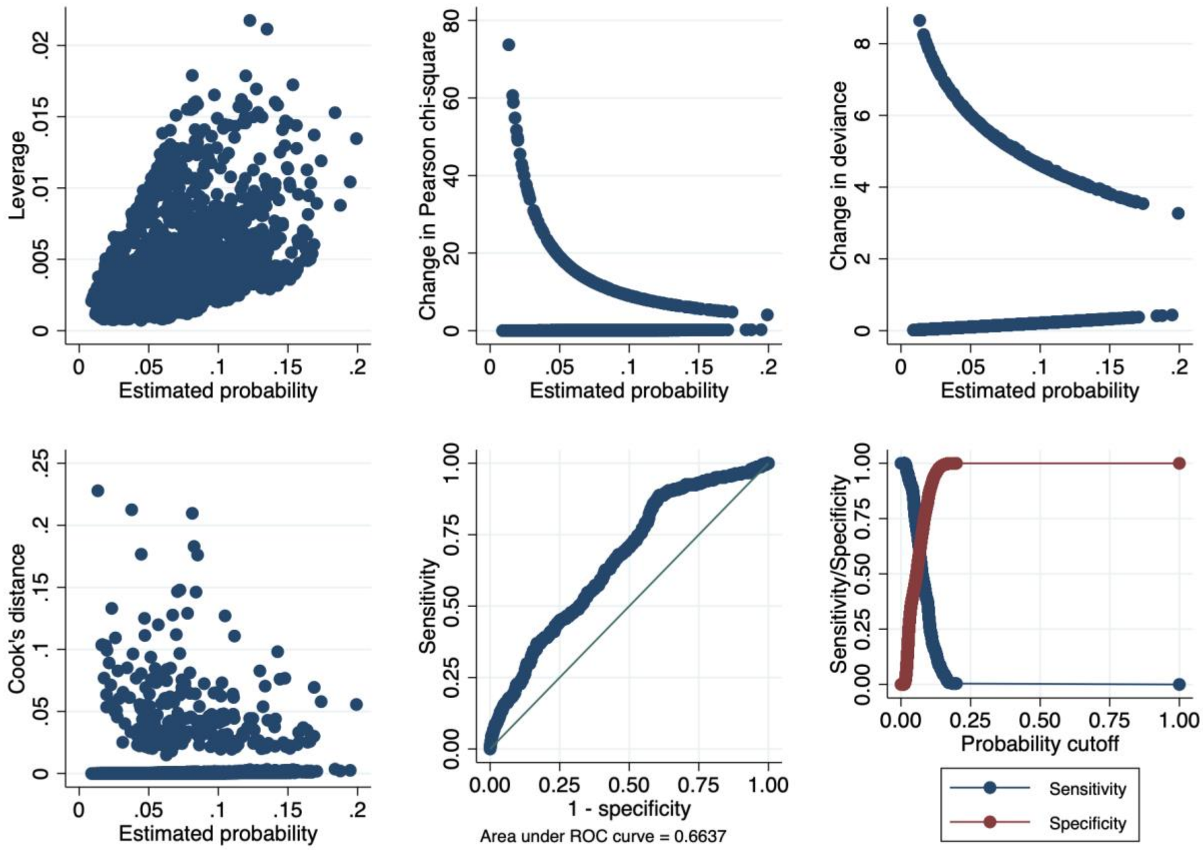


Figure B.26. *Individual Logit Fit and Diagnostics of STEM3 – Wave 4 Model 3*

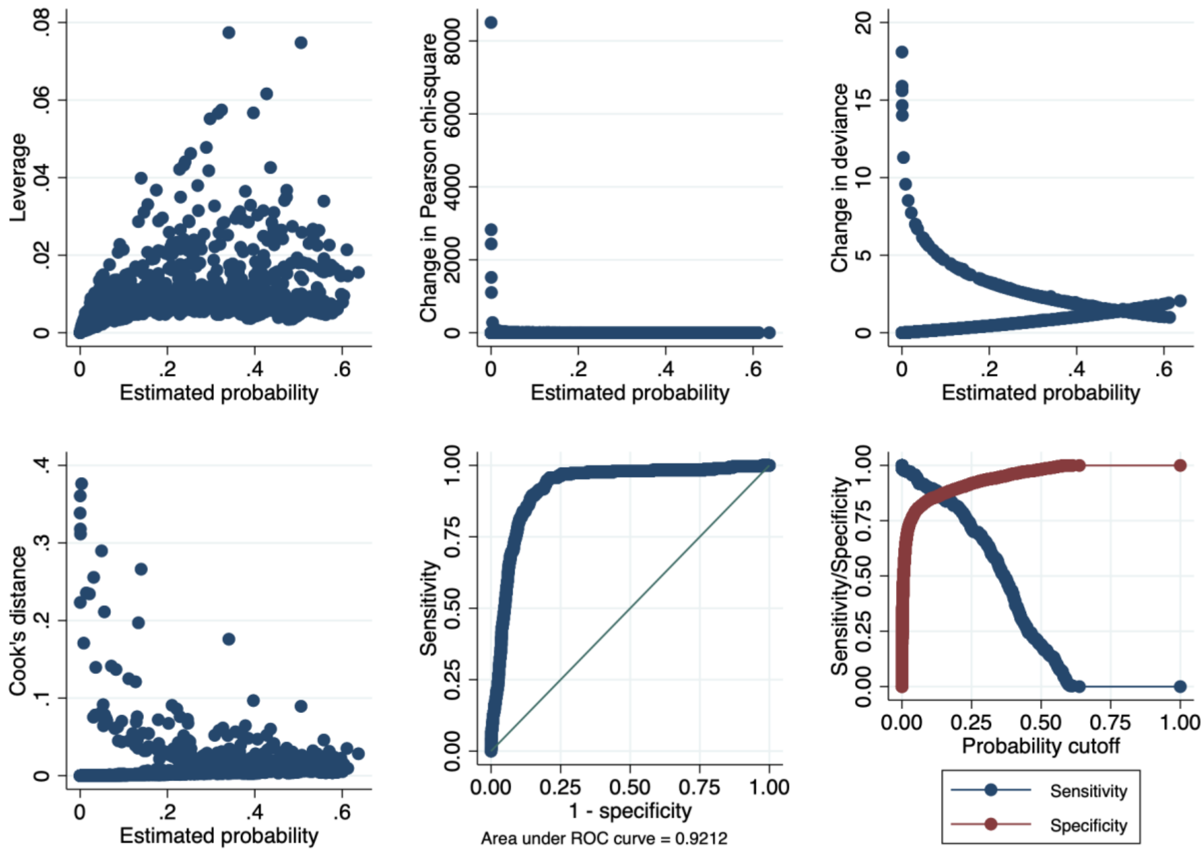


Figure B.27. *Individual Logit Fit and Diagnostics of STEM3 – Wave 4 Model 4*